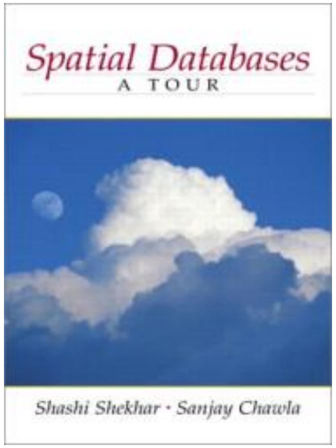
Transforming Smart Cities with Spatial Computing

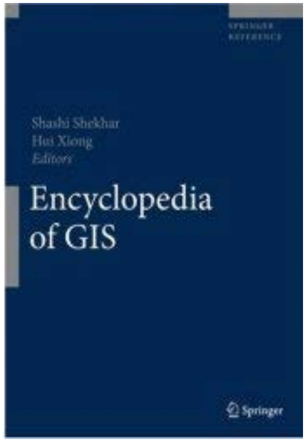
Workshop on New mobility and cities: *Exploring a research network of urban sustainability observatories via data-enabled university-community partnerships*, Ohio State University: July 15th, 2019.

Shashi Shekhar

McKnight Distinguished University Professor, University of Minnesota

www.cs.umn.edu/~shekhar : shekhar@umn.edu





Transforming Smart Cities with Spatial Computing

Ack.: NSF S&CC Award 1737633.

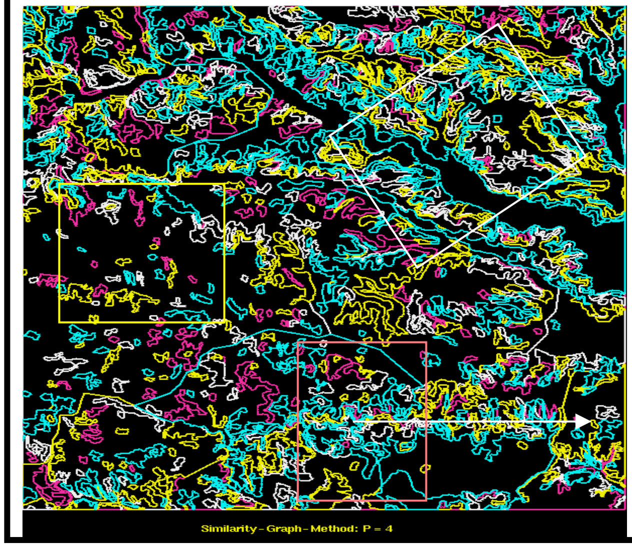
Details: Transforming Smart Cities with Spatial Computing, *Proc. IEEE International Smart Cities Conference,* 2018 (w/ Y. Xie et al.).

Acknowledgements

- P.I., Connecting the Smart-City Paradigm with a Sustainable Urban Infrastructure Systems Frame- work to Advance Equity in Communities, NSF(1737633), $2.5 M, 9/17 - 8/20.
- Co-P.I., Planning Grant: Engineering Research Center for Intelligent Infrastructure for Safe, Efficient and Resilient Mobility, NSF,(1840432), 97K, 9/18-8/20, (P.I.: A. Misra, U of Kansas).
- Co-P.I., *Cloud-Connected Delivery Vehicles: Boosting Fuel Economy Using Physics-Aware Spatio- temporal Data Analysis and Real-Time Powertrain Control*, USDOE ARPA-E, $1.78M (1.4M fed.), 2/17 - 2//20. (P.I.: W. Northrop)
- Co-P.I., *Increasing Low-Input Turfgrass Adoption Through Breeding, Innovation, and Public Education*, USDA/NIFA/SCRI (2017-51181-27222), $5.4 M, 9/17 - 8/21. (with E. Watkins et al.).
- P.I., III: Medium: *Investigating Spatio-Temporal Informatics to Advance Transportation Science*, NSF, 1.2M, 9/19-8/23 (*recommended*), w/ W. Northrop.
- Also part of (a) Ford Motor Company University Research Program, (b) NSF Midwest Big Data Hub: Building Communities to Harness the Data Revolution, $4M, 6/19-5/23; and (c) NIH Clinical and Translational Science Award (CTSA), $42M, 3/18 - 2/23. (P.I.: B. Blazar).

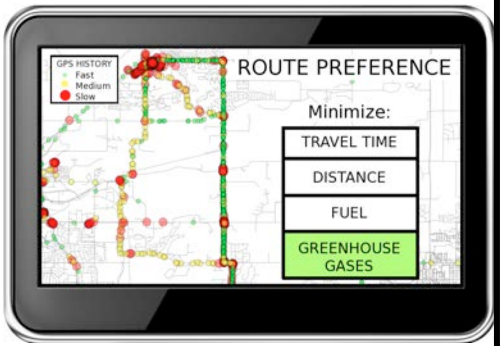
Spatial Databases: Representative Projects

Parallelize Range Queries



Storing graphs on disk

Eco-Routing



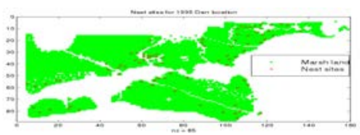
Evacutation Route Planning

Details: (1) Spatial Computing, MIT Press (Essential Knowledge Series), 2020 (expected).
(2) Spatial Databases: A Tour, Prentice Hall, 2003.
(3) Spatial Database: Accomplishments and Research Needs, IEEE Trans. on Knowledge and Data Engineering, 11(1), 1999.

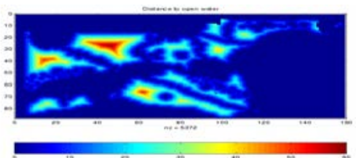
Spatial Data Mining: Representative Projects

Location prediction: nesting sites

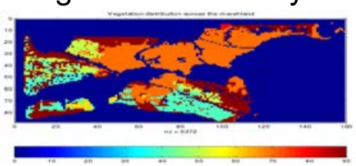
Nest locations



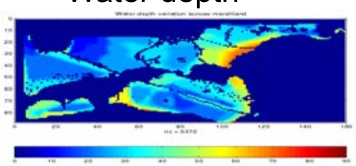
Distance to open water



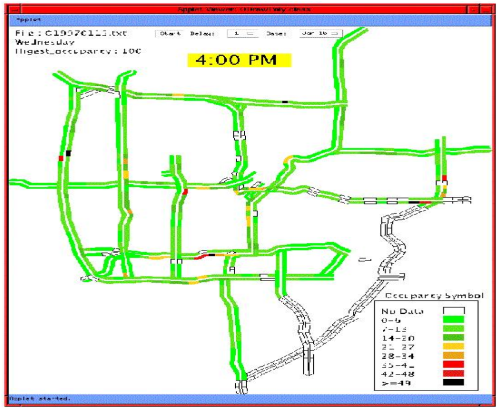
Vegetation durability

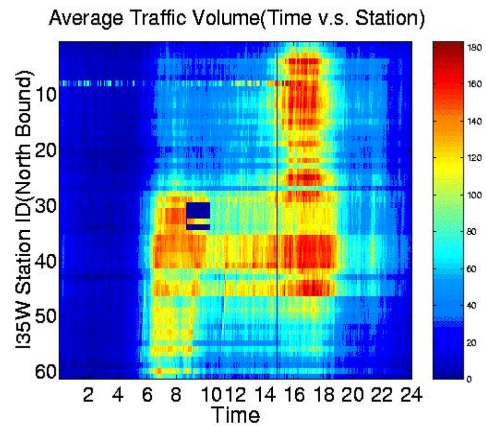


Water depth

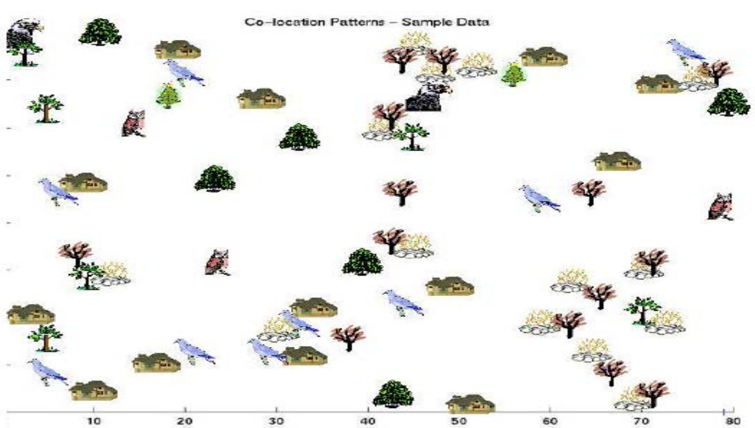


Spatial outliers: sensor on I-35





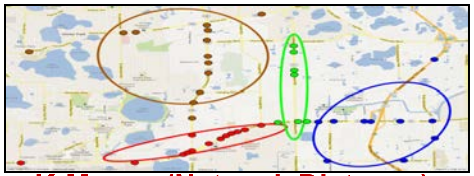
Co-location Patterns



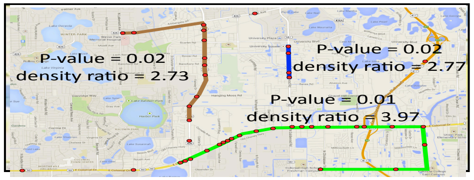
Spatial Network Activity Summarization

Input: k = 4, 43 fatalities

K-Means (Euclidean Distance)



K-Means (Network Distance)



Linear Hotspots

Details: (a) Transdisciplinary Foundations of Geospatial Data Science, ISPRS Intl.Jr. of Geo-Informatics, 6(12), 2017. doi:10.3390/ijgi6120395.
(b) Identifying patterns in spatial information: a survey of methods, Wiley Interdisc. Reviews: Data Mining and Know. Discovery , 1(3):193-214, May/June 2011

OUTLINE

- Motivation
  - Spatial Methods and Industrial Cities
  - Spatial Computing in Modern Cities
- Knowledge Co-production (KC)
- KC Story 1: Evacuation Planning
- KC Story 2: A S&CC Project
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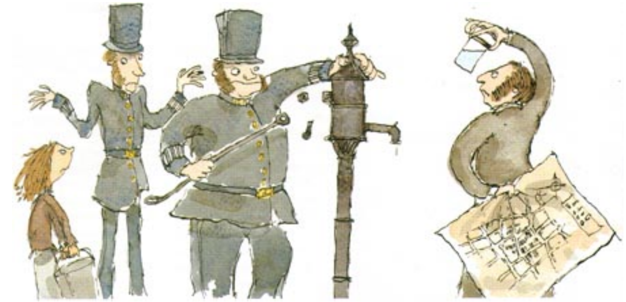
History of Transforming Cities with Spatial Computing

<u>1854: What causes Cholera?</u>

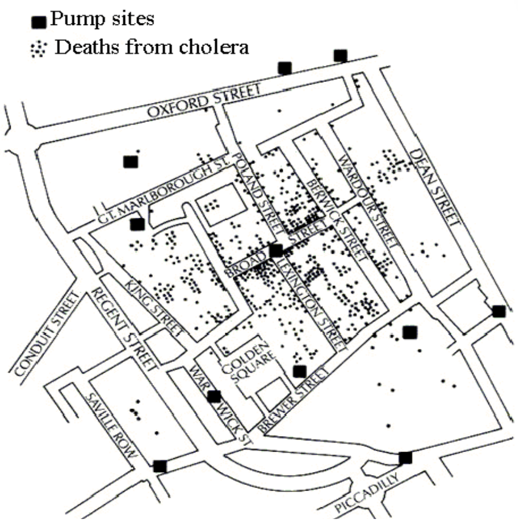


Collect & Curate Data ⇨ Discover Patterns, Generate Hypothesis ⇨ Test Hypothesis (Experiments) ⇨ Develop Theory

? water pump

Remove pump handle

Germ Theory



Impact on cities:
Health & well-being, parks, sewer system to protect drinking water, …

Q? What are Choleras of today?
Q? How may Spatial Computing Help?

Spatial Computing Examples

ArcGIS ESRI GIS X

SaTScan™
Software for the spatial, temporal, and space-time scan statistics

OGC™
Open Geospatial Consortium, Inc.

ORACLE SPATIAL

IBM Smarter Planet

vs

Google Earth

OpenStreetMap

Ushahidi

waze
Outsmarting Traffic, Together.

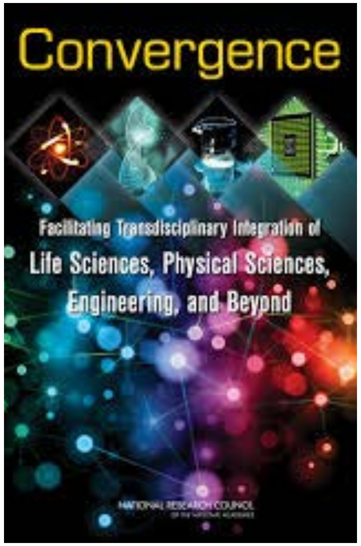
Google Earth Engine

MONSANTO

THE CLIMATE CORPORATION

What is Spatial Computing?

- A convergence of revolutions in sub-areas
  - Positioning, e.g., GPS, wi-fi, …
  - Remote Sensing, e.g., nano-satellites, cloud-hosted data
  - GIS, e.g., virtual globes, Geo-design, …
  - Spatial Data Science, e.g., spatial data mining, …
  - Spatial DBMS, e.g., SQL3/OGC



- To solve Societal Problems
  - Food : Precision Agriculture, Global Agriculture Monitoring, …
  - Mobility : Navigation, e.g., Google Maps
  - Mobility : Ride-sharing services, e.g., Uber, Didi, …

- Details:
  - Spatial Computing, Communications of the ACM, 59(1), Jan. 2016.

The Changing World of Spatial Computing

	Last Century	Last Decade
Map User	Well-trained few	Billions
Mappers	Well-trained few	Billions
Software, Hardware	Few layers, e.g., Applications: Arc/GIS, Databases: SQL3/OGIS	Almost all layers
User Expectations & Risks	Modest	Many use-case & Geo-privacy concerns

Spatial Computing is a Critical Infrastructure Today!

- 2 billion GPS receivers in use, will hit 7 billion by 2022.
- Besides location, it reference time for critical infrastructure
  - Telecommunications industry
  - Banks
  - Airlines...
- GPS is the single point of failure for the entire modern economy.
- 50,000 incidents of deliberate (GPS) jamming last two years
  - Against Ubers, Waymo's self-driving cars, delivery drones from Amazon

Bloomberg Businessweek

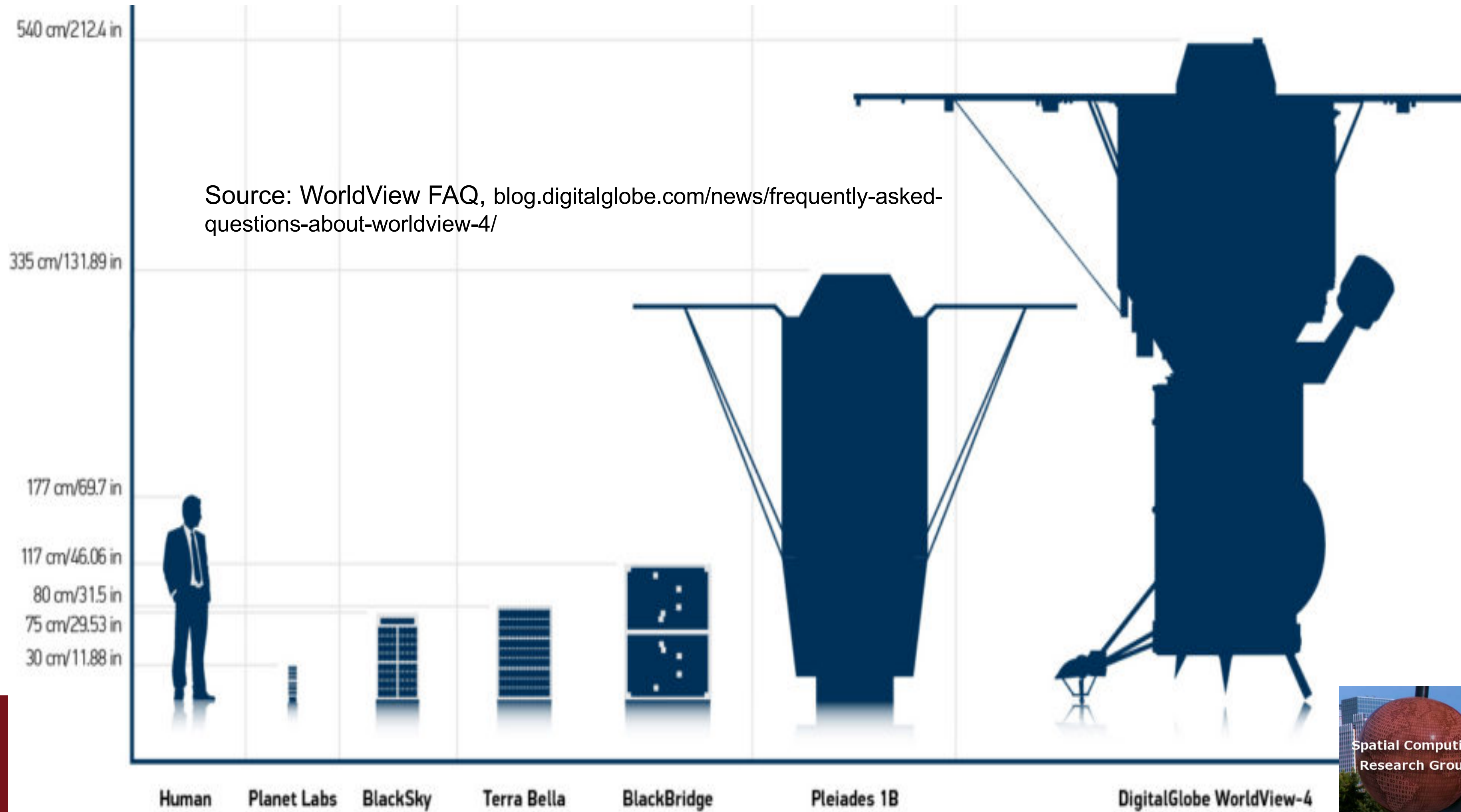
July 25, 2018, 4:00 AM CDT

The World Economy Runs on GPS. It Needs a Backup Plan

Source: *https://www.bloomberg.com/news/features/2018-07-25/the-world-economy-runs-on-gps-it-needs-a-backup-plan*

Large Constellations of Small Satellites

- Hi-frequency time-series of imagery of entire earth
- Large Constellations Ex. Planet Labs: 100 satellites: daily scan of Earth at 1m resolution



Source: WorldView FAQ, blog.digitalglobe.com/news/frequently-asked-questions-about-worldview-4/

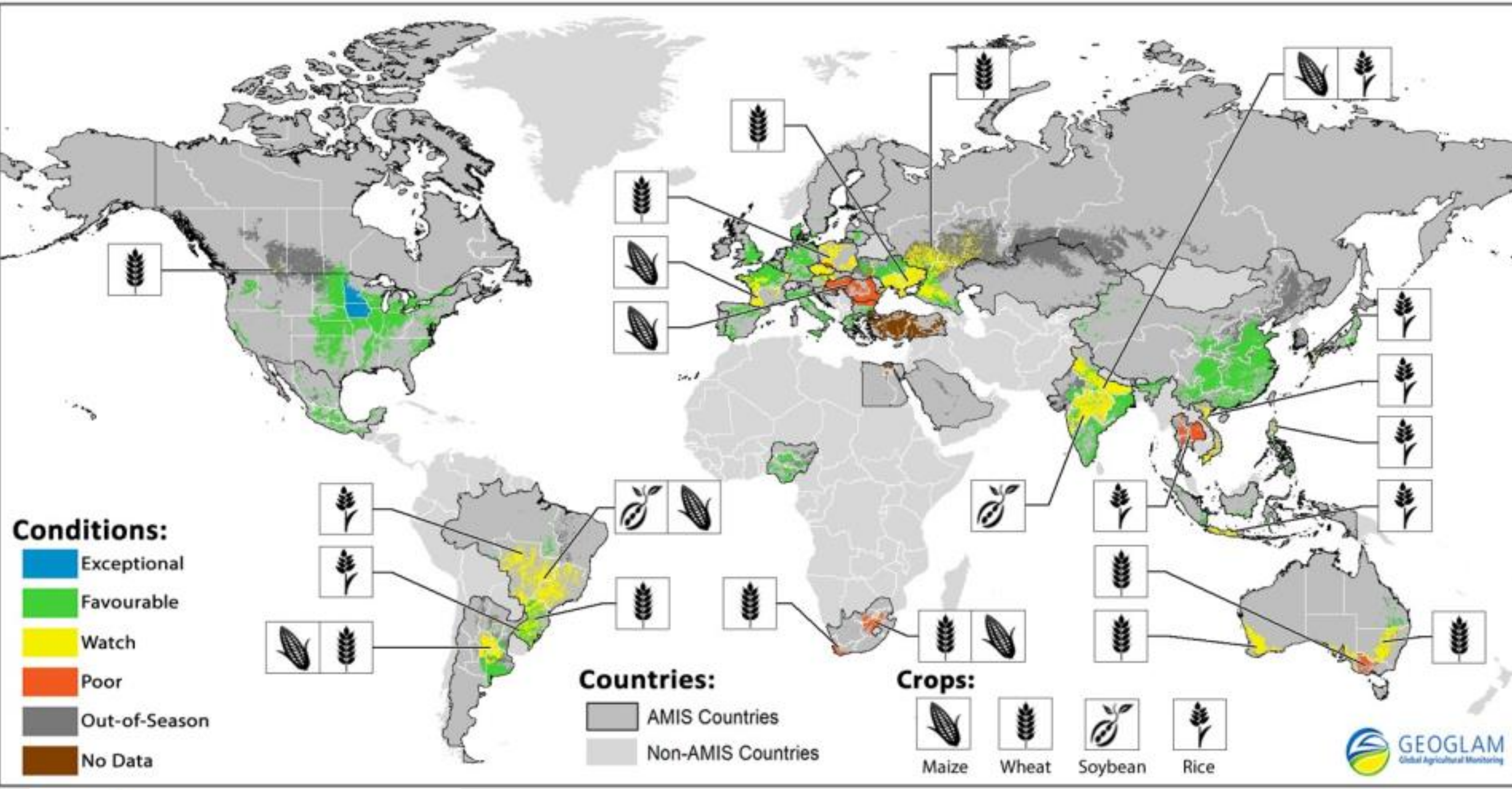
Spatial Computing Research Group

Cheap (or free) satellite data on cloud computers

- 2008: USGS gave away 35-year LandSat satellite imagery archive
  - Analog of public availability of GPS signal in late 1980s
- 2017: Many cloud-based Virtual collaboration environment
  - Explosion in machine learning on satelliite imagery to map crops, water, buildings, roads, …

	Google Earth Engines	NEX	AWS Earth
Elevation, Landsat, LOCA, MODIS, NAIP	x	x	x
NOAA	x		x
AVHRR, FIA, GIMMM, GlobCover, NARR, TRIMM, Sentinel-1	x	x	
IARPA, GDELT, MOGREPS, OpenStreetMap, Sentinel-2, SpaceNet (building/road labels for ML)			x
CHIRPS, GeoScience Australia, GSMap, NASS, Oxford Map, PSDI, WHRC, WorldClim, WorldPop, WWF,	x		
BCCA, FLUXNET		x	

Global Agriculture Monitoring



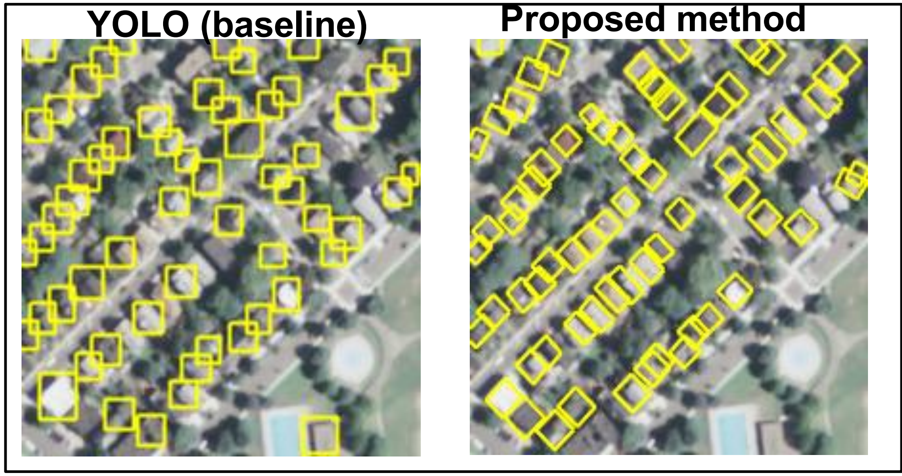
AMIS Agricultural Market Information System

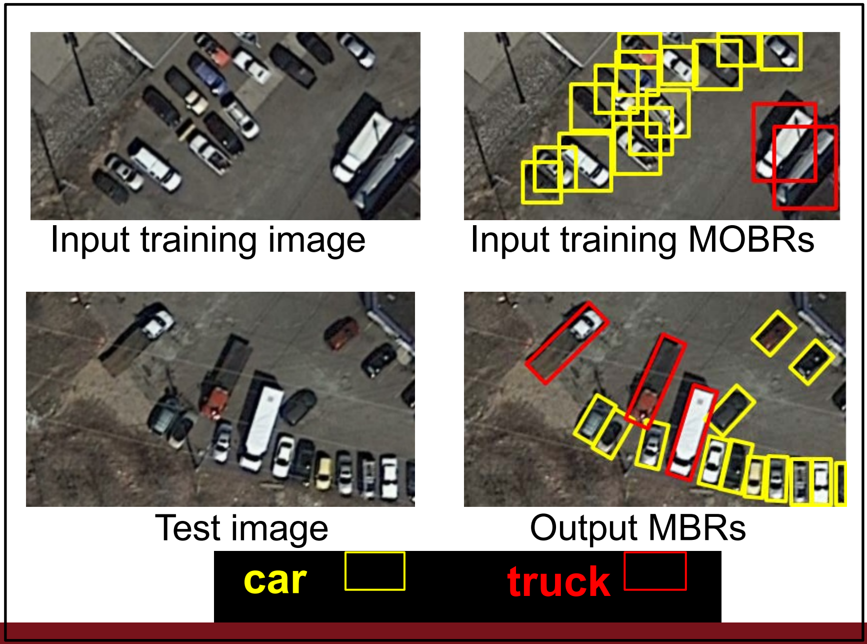
GEOGLAM Global Agricultural Monitoring

UNIVERSITY OF MINNESOTA Driven to Discover®

Mapping Urban Objects: Buildings, Vehicles, …

- **Q:?** How many building does a City have?
- **Q?** Estimate truck supply in a city (CH Robinson).
- **Data:**
  - Buildings: NAIP Imagery (1 meter pixels)
    - MA Buildings Dataset, 2017 https://www.cs.toronto.edu/~vmnih/data/
  - Vehicles: Aerial imagery (3 inch pixels)
    - Hennepin & Ramsey counties
- **Method:**
  - YOLO Deep Learning
- **Patterns:**
  - Detected geospatial objects
    - Houses
    - Cars, trucks, …





Y. Xie,, R. Bhojwani, S. Shekhar, and J. Knight, An unsupervised augmentation framework for deep learning based geospatial object detection: A summary of results. In Proc. 26th ACM SIGSPATIAL Intl. Conf. on Adv. in GIS (pp. 349-358), 2018

A UCGIS Call to Action:
Bringing the Geospatial Perspective to Data Science Degrees and Curricula

Data that are geographically referenced or contain some type of location markers are both common and of high value (e.g., data subject to state-specific policies, laws and regulations; demographic data from the census; location traces of smartphones and vehicles; remotely sensed imagery from satellites, aircraft and small unmanned aerial vehicles; volunteered geographic information; geographically referenced social media postings). A 2011 McKinsey Global Institute report estimates a value of "about $600 billion annually by 2020" from leveraging personal location data[2] to reduce fuel waste, improve health outcomes, and better match products to consumer needs. Spatial data are critical for societal priorities such as national security, public health & safety, food, energy, water, smart cities, transportation, climate, weather, and the environment. For example, remotely-sensed satellite imagery is used to monitor not only weather and climate but also global crops[3] for early warnings and planning to avoid food shortages.

University Consortium for GEOGRAPHIC INFORMATION SCIENCE

Summer 2018

One Size Data Science Does not Fit All Data!

However, spatial data presents unique data science challenges. Recent court cases that address gerrymandering, the manipulation of geographic boundaries to favor a political party, offer a high-profile example. Instances of such exploitation of the modifiable areal unit problem (or dilemma) is not limited to elections since the MAUP affects almost all traditional data science methods in which results (e.g., correlations) change dramatically by varying geographic boundaries of spatial partitions. The fundamental geographic qualities of spatial autocorrelation, which assumes properties of geographically proximate places to be similar, and geographic heterogeneity, where no two places on Earth are exactly alike, violate assumptions of sample independence and randomness that underlie many conventional statistical methods. Other spatial challenges include how to choose between a plurality of projections and coordinate systems and how to deal with the imprecision, inaccuracy, and uncertainty of location

A UCGIS Call to Action:

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Summer 2018

Spatial Data Science Tools

measurements. To deal with such challenges, practitioners in many fields including agriculture, weather forecast, mining, and environmental science incorporate *geospatial data science*[4] methods such as spatially-explicit models, spatial statistics[5], geo-statistics, geographic data mining[6], spatial databases[7], etc.

[4] Y. Xie et al., Transdisciplinary Foundations of Geospatial Data Science, *ISPRS Intl. Jr. of Geo-Informatics*, 6(12):395-418, 2017. DOI: 10.3390/ijgi6120395.
[5] N. Cressie, *Statistics for Spatial Data*, Wiley, 1993 (1st ed.), 2015 (Revised ed.).
[6] H. Miller and J. Han, *Geographic Data Mining and Knowledge Discovery*, CRC Press, 2009 (2nd Ed.).
[7] S. Shekhar and S. Chawla, *Spatial Databases: A Tour*, Prentice Hall, 2003.

A UCGIS Call to Action:

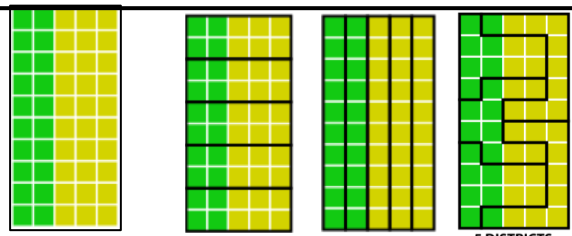
Bringing the Geospatial Perspective to Data Science Degrees and Curricula

University Consortium for GEOGRAPHIC INFORMATION SCIENCE

Summer 2018

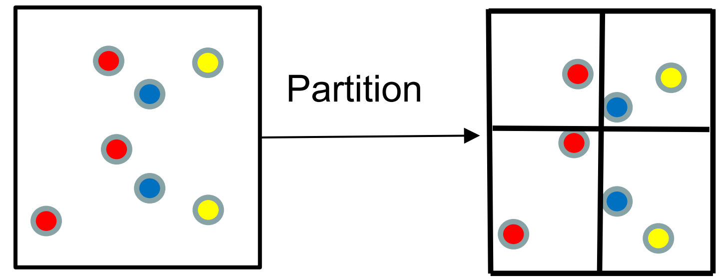
Spatial Partitioning: Gerrymandering

- Space partitioning affects statistical results!
  - Gerrymandering Elections, Correlations
  - Modifiable Areal Unit Problem (MAUP) Dilemma



Election Results	0 - 5	2 - 3	3 - 2

Gini-Index	0.47	0.47	0	0.36

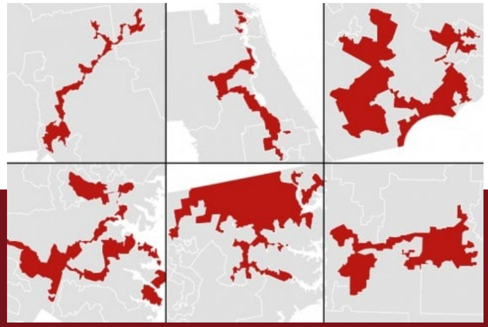


	Partition Based Pearson's Correlation	Support
● - ●		0
● - ●		1

Gerrymandering, a Tradition as Old as the Republic, Faces a Reckoning

Supreme Court to hear arguments on whether contorted voting maps drawn by both parties to cement power have finally gone too far

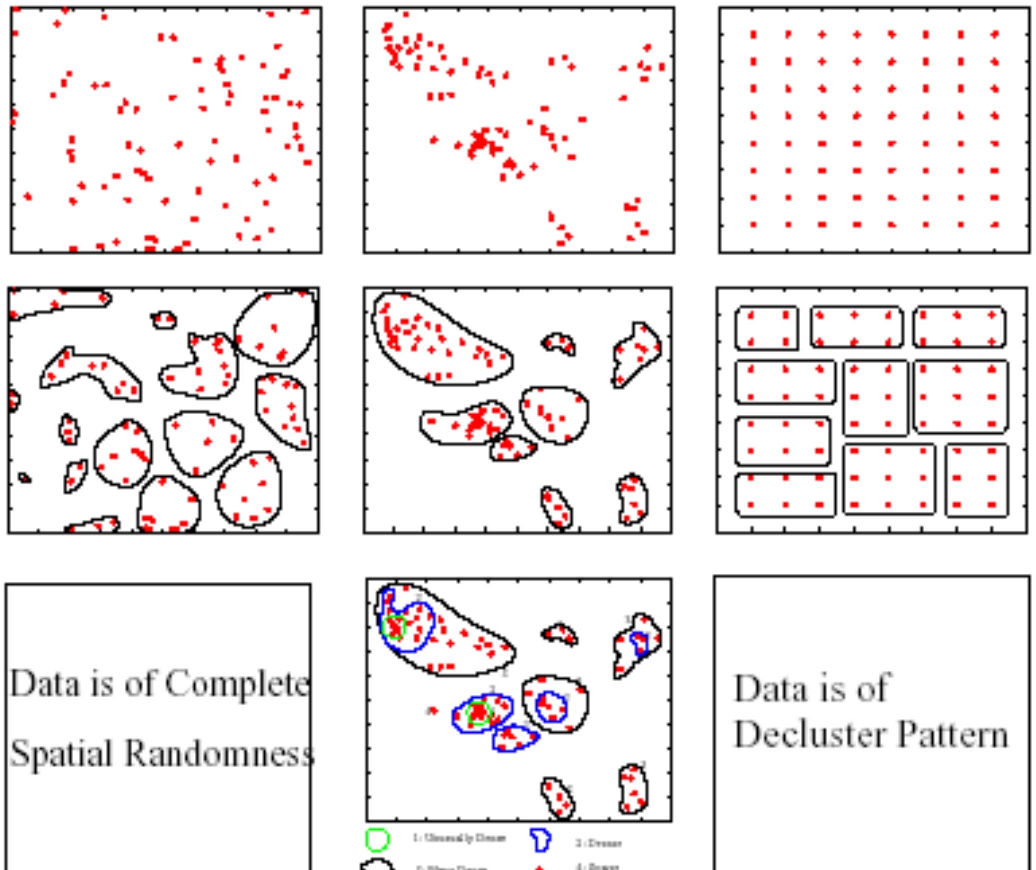
THE WALL STREET JOURNAL.



US Electoral District with Irregular shapes(Source: Washington Post)

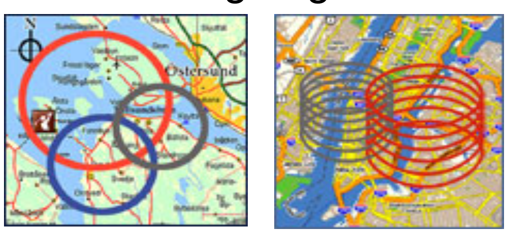
Limitation of Traditional Clustering

- Challenge: One size does not fit all
  - Prediction error vs. model bias, Cost of false positives, …
- Example. Clustering: Find groups of points



Traditional Clustering
(K-means always finds clusters)

Spatial Clustering begs to differ!



SaTScan™
Software for the spatial, temporal, and space-time scan statistics

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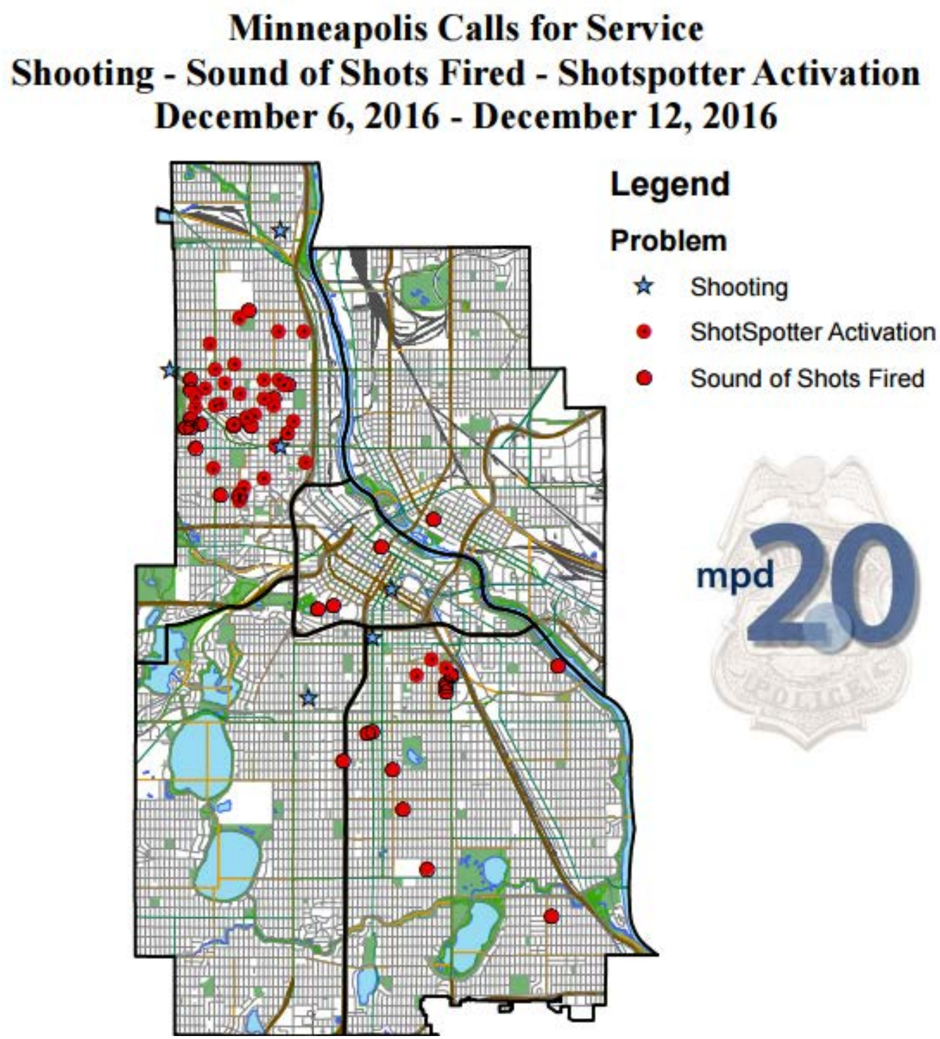
Spatial Computing in Modern Cities

Rank	2015	2016	2017
1	**(69%) Geospatial / Mapping**	(93%) Public Meeting records	**(53%) GeoSpatial / Mapping**
2	(67%) Virtualization	(92%) Wireless Infrastructure	(48%) Cybersecurity
3	(60%) Performance Benchmarks	(91%) Redundant/ Offsite Data Storage	(34%) Predictive Policing
4	(58%) Transaction Processing	(90%) Endpoint Security	(32%) eDiscovery
5	(57%) Project Management	(85%) Broadband Infrastructure	(20%) Predictive Analytics

Source: Digital Cities Survey, Center for Digital Government, GovTech.com, 11/9/2017.

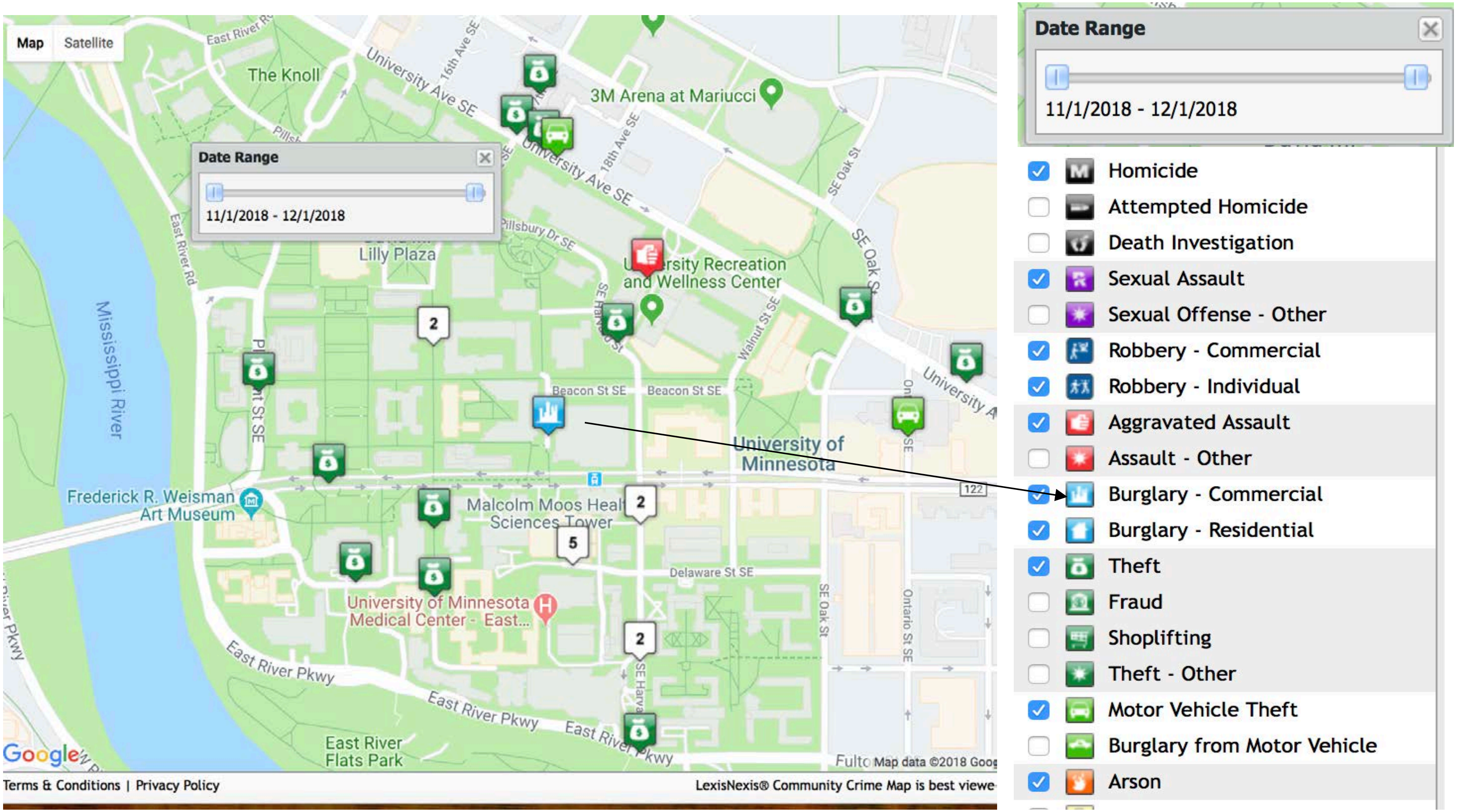
Operational Use: Emergency Services

- Gun-shot detection
  - triangulate from microphones
- E-911: Locate cell-phone calling 911
- Reverse 911
- CMAS, PLAN: Geo-targeted Alert &
- …



mpd 2.0

Operational Use: **Crime Mapping**



- Sources: www.ci.minneapolis.mn.us/police/statistics, communitycrimemap.com

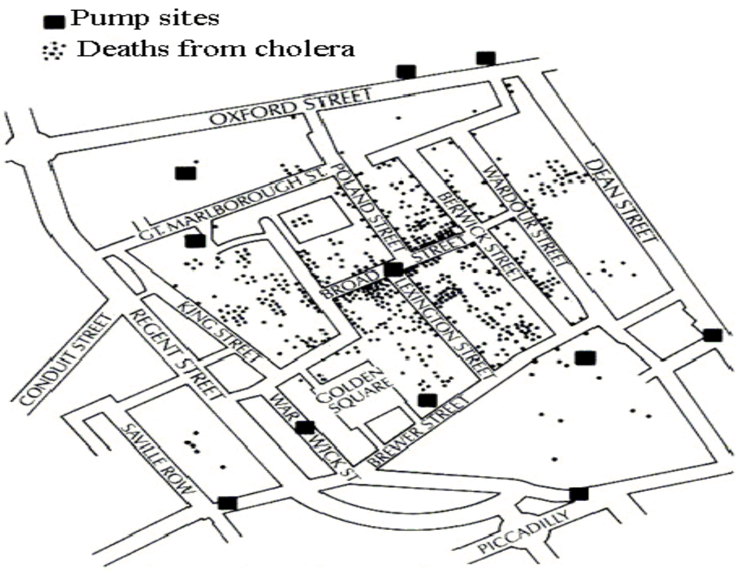
Operational Use: **Early Warning Systems**

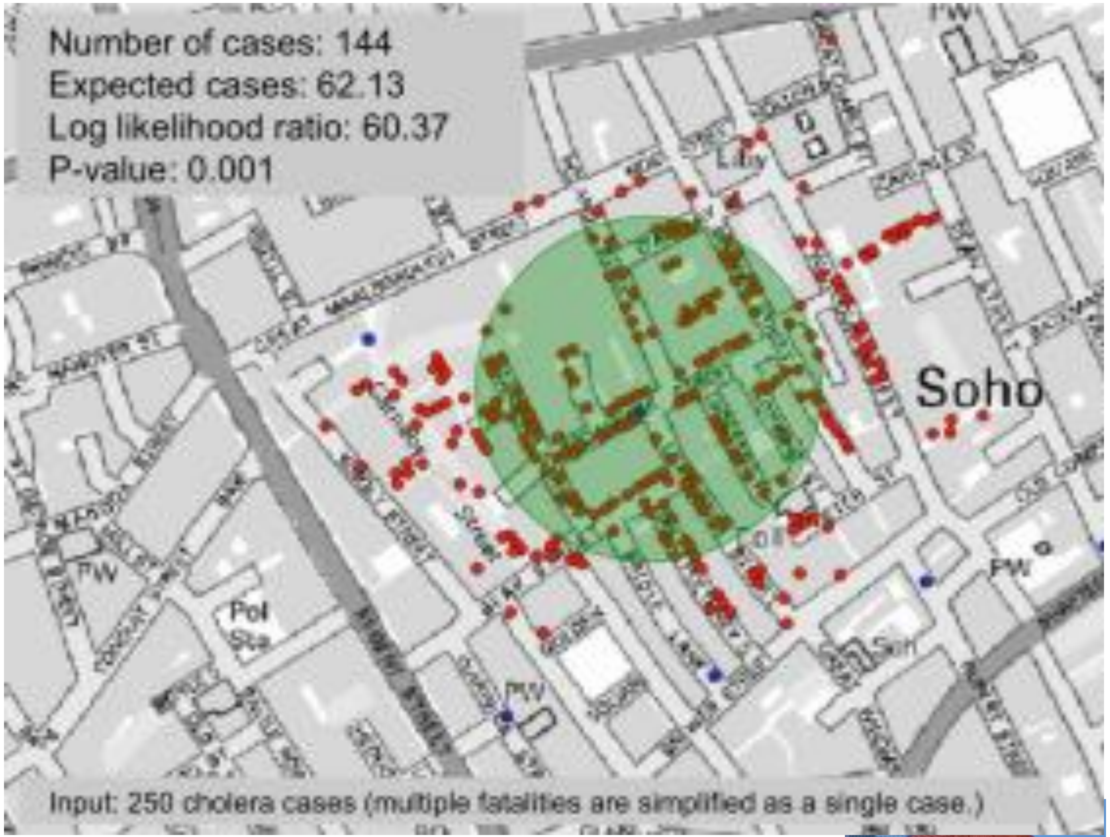
- Monitoring Tweets for disaster events & location

Even before cable news outlets began reporting the tornadoes that ripped through Texas on Tuesday, a **map** of the state **began blinking red** on a screen in the Red Cross' new social media monitoring center, alerting weather watchers that something was happening in the hard-hit area. (AP, April 16th, 2012).

Tactical Use: Hotspots

- The 1854 Asiatic Cholera in London
  - Near Broad St. water pump except a brewery





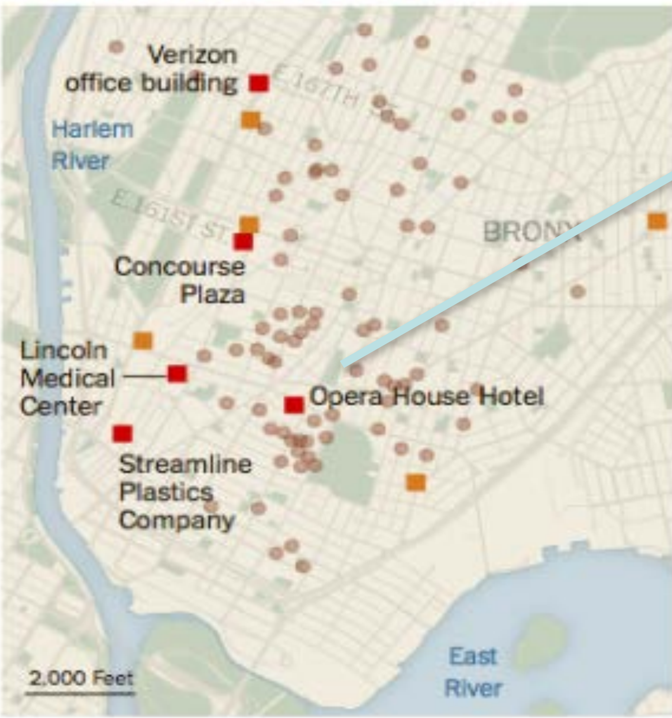
Hotel That Enlivened the Bronx Is Now a 'Hot Spot' for Legionnaires'

By WINNIE HU and NOAH REMNICK AUG. 10, 2015

Contaminated Cooling Towers

Five buildings have been identified as the potential source of the Legionnaires' disease outbreak in the South Bronx.

- Possible sources of Legionnaires' outbreak
- Additional sites found with legionella bacteria
- Locations of people with Legionnaires'

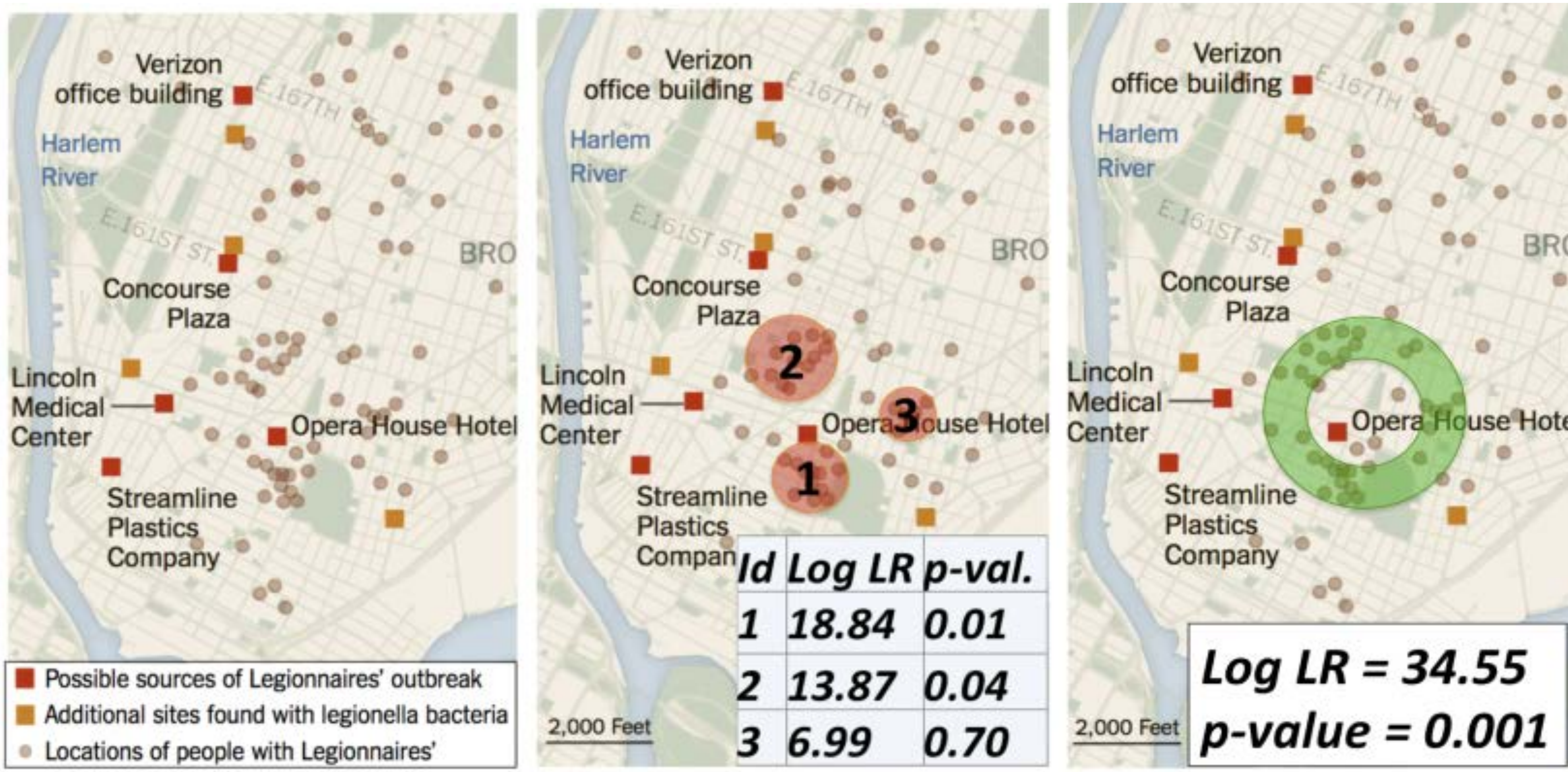


Source: New York Mayor's Office

By The New York Times

The Opera House Hotel is at the center of the outbreak. Edwin J. Torres for The New York Times

Legionnaires' Disease Outbreak in New York



(a) Legionnaire's in New York (2015)

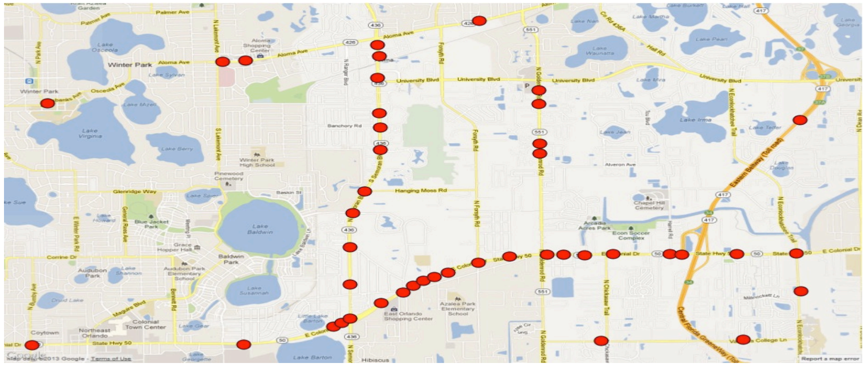
(b) Output of SaTScan

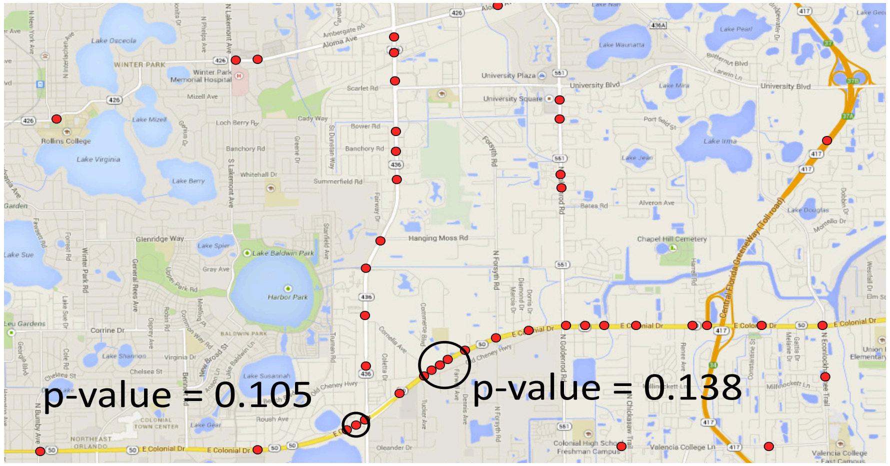
(c) Output of RHD

Details: Ring-Shaped Hotspot Detection, IEEE Trans. Know. & Data Eng., 28(12), 2016.
(A Summary in Proc. IEEE ICDM 2014) (w/ E. Eftelioglu et al.)

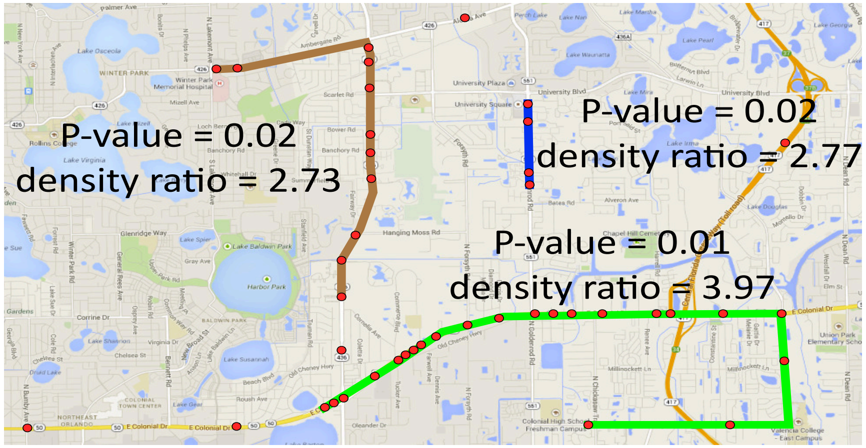
Tactical Use: Linear Hotspots

- Urban data, e.g., road accidents
- Ex. Pedestrian fatalities, Orlando, FL





Circular hotspots (SatScan)



Linear hotspots

Details: Significant Linear Hotspot Discovery, IEEE Transactions on Big Data, 3(2):140-153, 2017.
(Summary in Proc. Geographic Info. Sc., Springer LNCS 8728:284-300, 2014.

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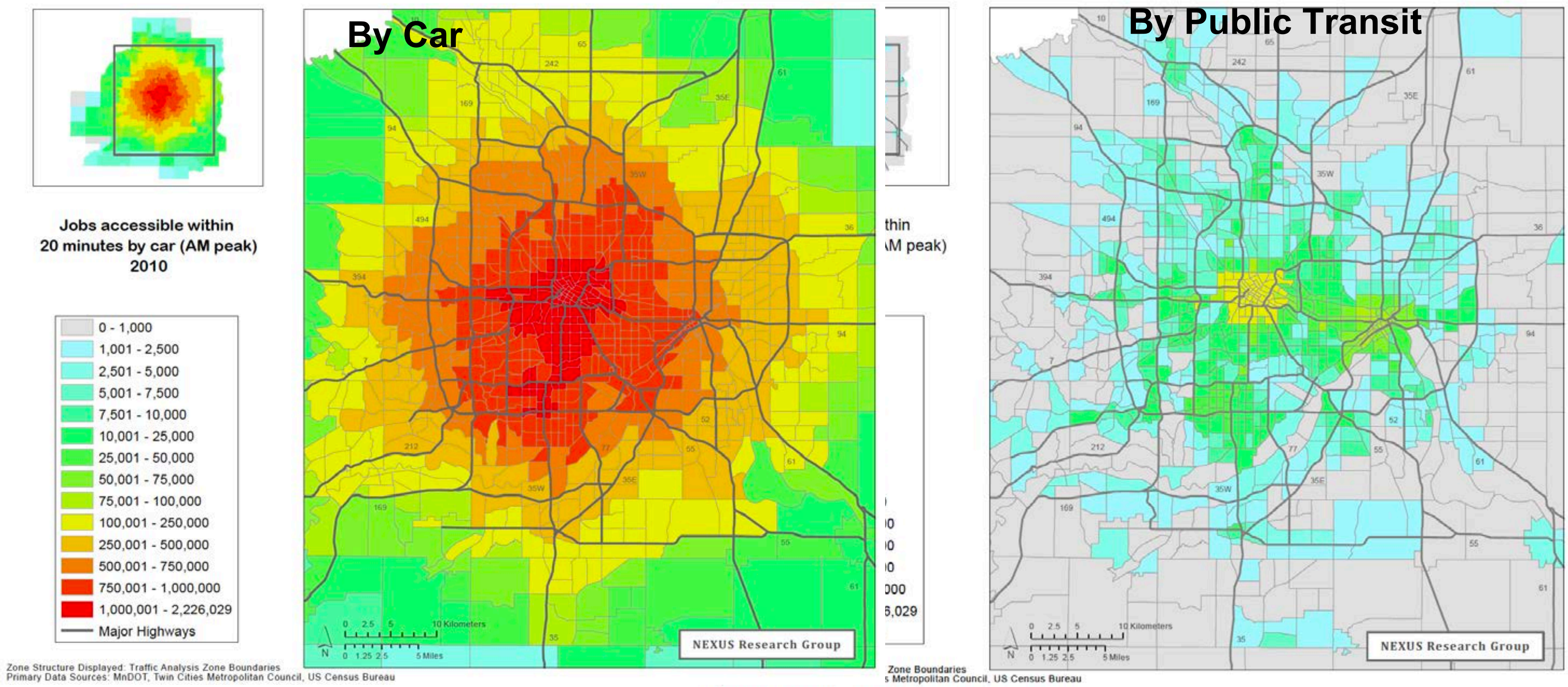
Driven t

Strategic Use: **Mapping Accessibility**

- Number of jobs Accessible in a 20-minute trip during AM rush hour 2010



- Source: A. Owens, D. Levinson, Access to Destination, UMN CTS Report MN/RC 2012-34.

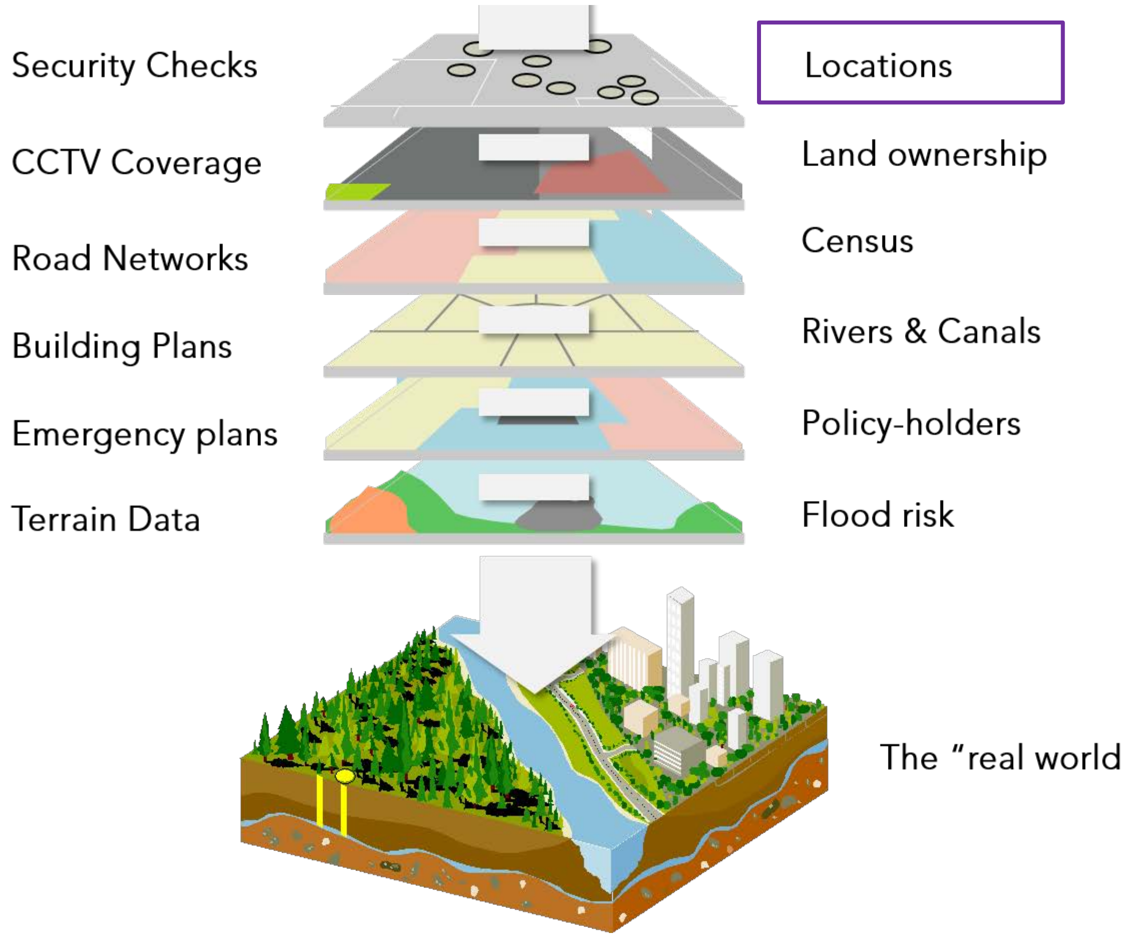
Strategic Use: Change Monitoring

- Google Timelapse:
  - Ex. MSP & Minneapolis 1984-2016
  - Global 29-frame video
  - 260,000 CPU core-hours
- Spatio-temporal Resolution
  - Planet Labs. : daily 1m (visual bands)




Spatial Computing in Modern Cities

- Operational
  - E-911, CMAS/PLAN
  - Early Warning
  - Situation awareness
  - Public Safety, e.g., Floods
- Tactical
  - Hotspot Detection
  - Property tax
  - Site selection
  - Asset tracking
- Strategic
  - Land-use change monitoring
  - Long-term planning



Source: https://www.cbronline.com/wp-content/uploads/2017/03/what-is-GIS.png

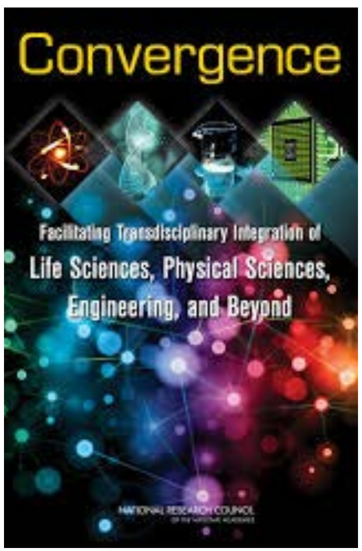
Outline

- Motivation
- Next: Knowledge Co-production (KC)
- KC Story 1: Evacuation Planning
- KC Story 2: A S&CC Project
- Conclusions

Source: The Sheffield Mental Health Guide, sheffieldflourish.co.uk, 5 Apr 2017.

Advancing Science Discovery to Application

- Convergence
  - Solve societal grand challenges
  - Harness Spatial Data Revolution, e.g., Cloud hosted satellite imagery, GPS trajectories,
  - Power AI, e.g., CNN, to map buildings, roads, trees, …



Collaborate with Stakeholders

- Convergence: Solve societal grand challenges via Transdisciplinary Research
- Knowledge **co-production** with stakeholders

Disciplinary research within academia

Interdisciplinary (multidisciplinary) research within academia

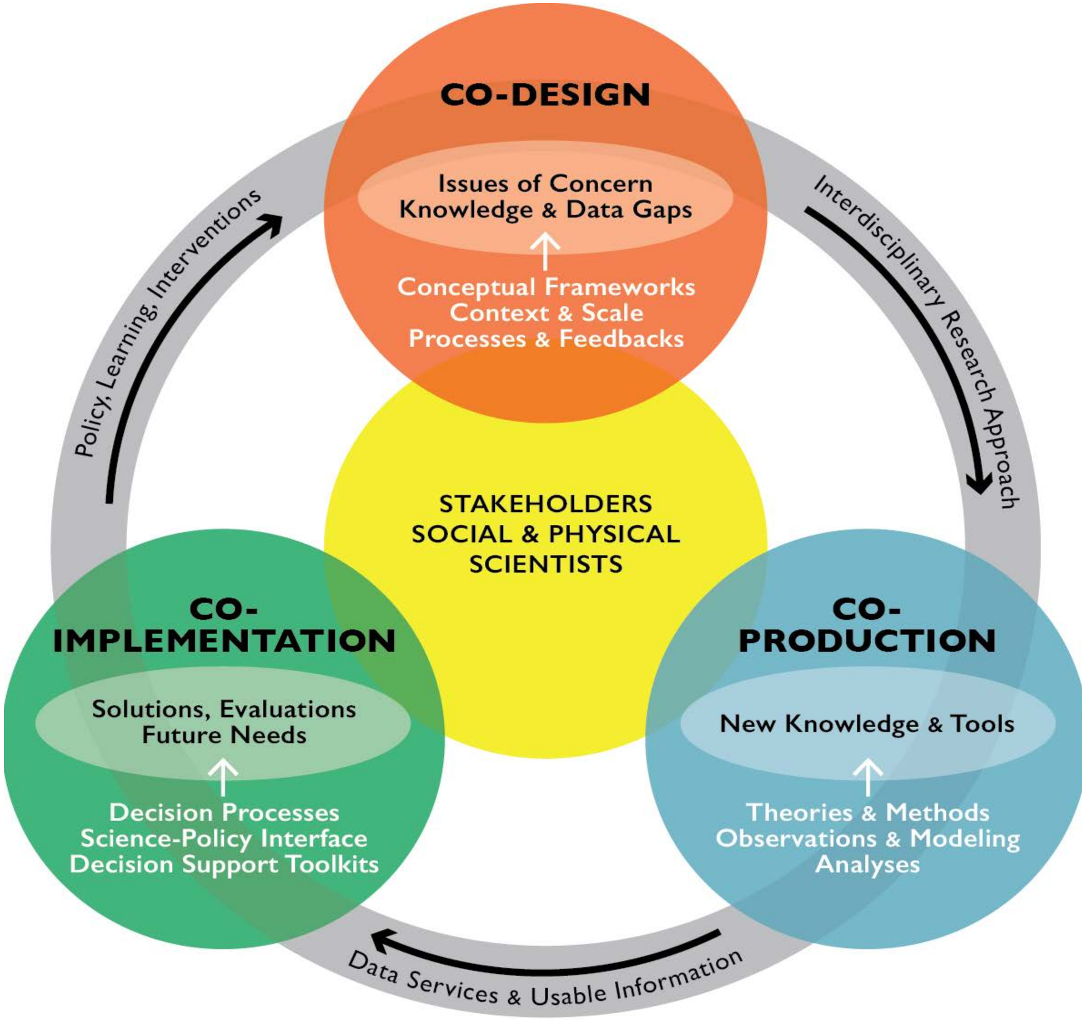
Transdisciplinary research goes beyond academia and involves stakeholders from policy, civil society etc.

Source: https://www.thearcticinstitute.org/future-of-arctic-research/

Knowledge Co-Production with Stakeholders

- Knowledge **co-production**
  - Co-Visioning
  - Co-define Problems
  - Co-select Science Questions
  - Co-Evaluate Discoveries

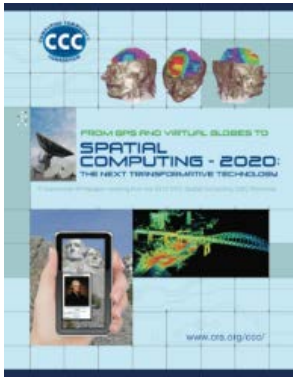
  - Ex. NCAR



Source: NCAR/UCAR 2016 Annual Report

Knowledge Co-Production

- **Co-production Initiatives**
  - CRA/CCC Visioning Workshops
  - (Midwest) Big Data Hubs & Spokes
  - NSF Sustainability Research Networks
  - NSF Smart & Connected Community



- **Co-Production Examples** in my work
  - 2005: Evacuation Planning: MN local governments
  - Current: NSF SCC Project: counties, cities in MN, FL

Outline

- Motivation
- Knowledge Co-production (KC)
- KC Story 1: Evacuation Planning
- KC Story 2: A S&CC Project
- Conclusions

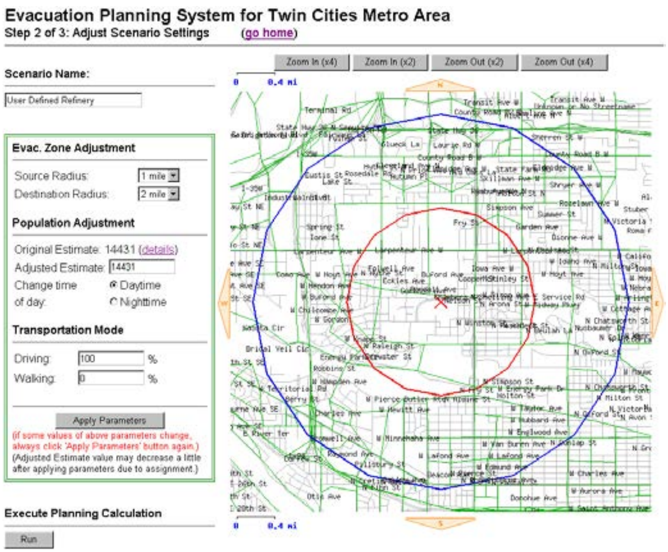
Knowledge Co-Production: Evacuation Planning (2005)

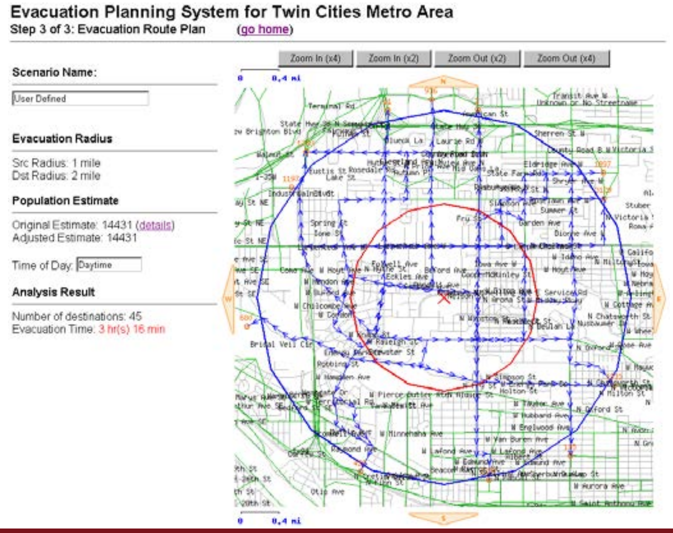
FoxTV newsclip (5-minutes), Disaster Area Evacuation Analytics Project
https://www.youtube.com/watch?v=PR9k72W8XK8

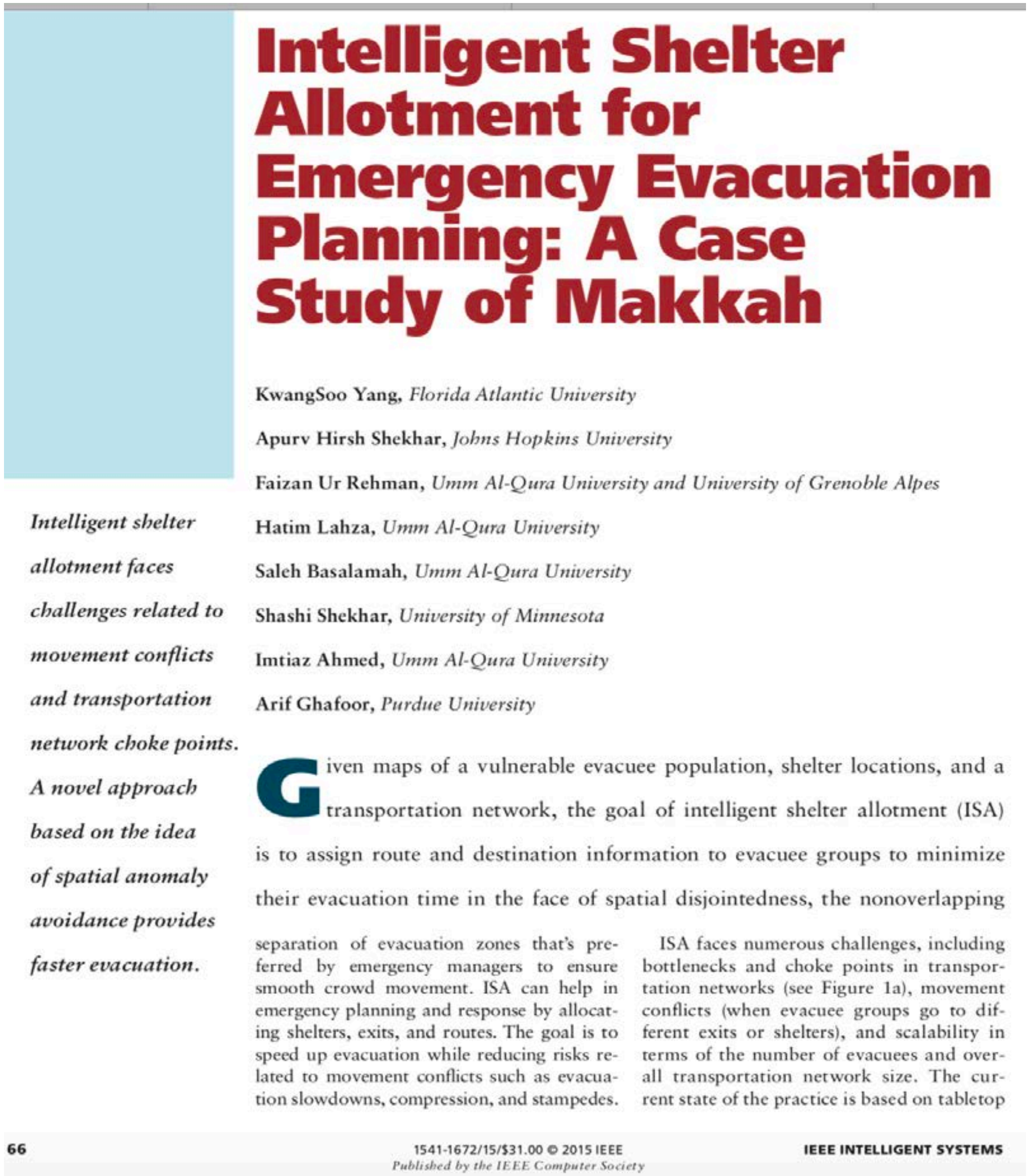
KC Story 1: Evacuation Planning (2005)

- **Team**: US DHS, MN Dept. of Transportation, URS Corp.
  - Emergency Mangers, Police, Fire Fighters, Natl. Guard
- Co-Visioning via monthly meetings
  - Challenges: evacuees & traffic maps
  - Police: focus on what can be done!
- Problem Co-Definition
  - 1-mile scenarios: 5 sites, work-day or night-time
- Co-Discovery
  - For 1st mile, walking faster than driving
- Co-Evaluation
  - Walk selected routes : avoid wooden bridge near E
  - Lock parking garages during evacuation ?

Scenario	Population	Vehicle	Walking
A	143,360	4:45	1:32
B	83,143	2:45	1:04
C	27,406	4:27	1:41
D	50,995	3:41	1:20
E	3,611	1:21	0:36







Intelligent Shelter Allotment for Emergency Evacuation Planning: A Case Study of Makkah

KwangSoo Yang, *Florida Atlantic University*

Apurv Hirsh Shekhar, *Johns Hopkins University*

Faizan Ur Rehman, *Umm Al-Qura University and University of Grenoble Alpes*

Hatim Lahza, *Umm Al-Qura University*

Saleh Basalamah, *Umm Al-Qura University*

Shashi Shekhar, *University of Minnesota*

Imtiaz Ahmed, *Umm Al-Qura University*

Arif Ghafoor, *Purdue University*

Intelligent shelter allotment faces challenges related to movement conflicts and transportation network choke points. A novel approach based on the idea of spatial anomaly avoidance provides faster evacuation.

Given maps of a vulnerable evacuee population, shelter locations, and a transportation network, the goal of intelligent shelter allotment (ISA) is to assign route and destination information to evacuee groups to minimize their evacuation time in the face of spatial disjointedness, the nonoverlapping separation of evacuation zones that's preferred by emergency managers to ensure smooth crowd movement. ISA can help in emergency planning and response by allocating shelters, exits, and routes. The goal is to speed up evacuation while reducing risks related to movement conflicts such as evacuation slowdowns, compression, and stampedes.

ISA faces numerous challenges, including bottlenecks and choke points in transportation networks (see Figure 1a), movement conflicts (when evacuee groups go to different exits or shelters), and scalability in terms of the number of evacuees and overall transportation network size. The current state of the practice is based on tabletop

1541-1672/15/$31.00 © 2015 IEEE
Published by the IEEE Computer Society

Intelligent Shelter Allotment for Emergency Evacuation Planning: A Case Study of Makkah, Intelligent Systems, IEEE, 30(5):66-76, Sept.-Oct., 2015.

Outline

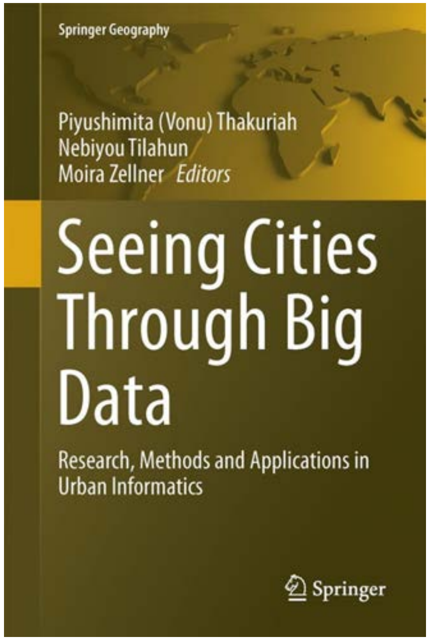
- Motivation
- Knowledge Co-production (KC)
- KC Story 1: Evacuation Planning
- KC Story 2: A S&CC Project (NSF Award #1737633)
  - NSF S&CC-IRG Track 1: Connecting the Smart-City Paradigm with a *Sustainable Urban Infrastructure Systems Framework* to Advance Equity in Communities
- Conclusions

KC Story 2: A NSF S&CC Project

- **NSF Workshops**
  - Big Data and Urban Informatics, U.I.C., 2014.

- **Academic History at UMN**
  - Humphrey center
  - Center for Urban & Regional Affairs
  - Hennepin University Partnership
  - Center for Transportation Studies Workshop on Smart Cities 2015

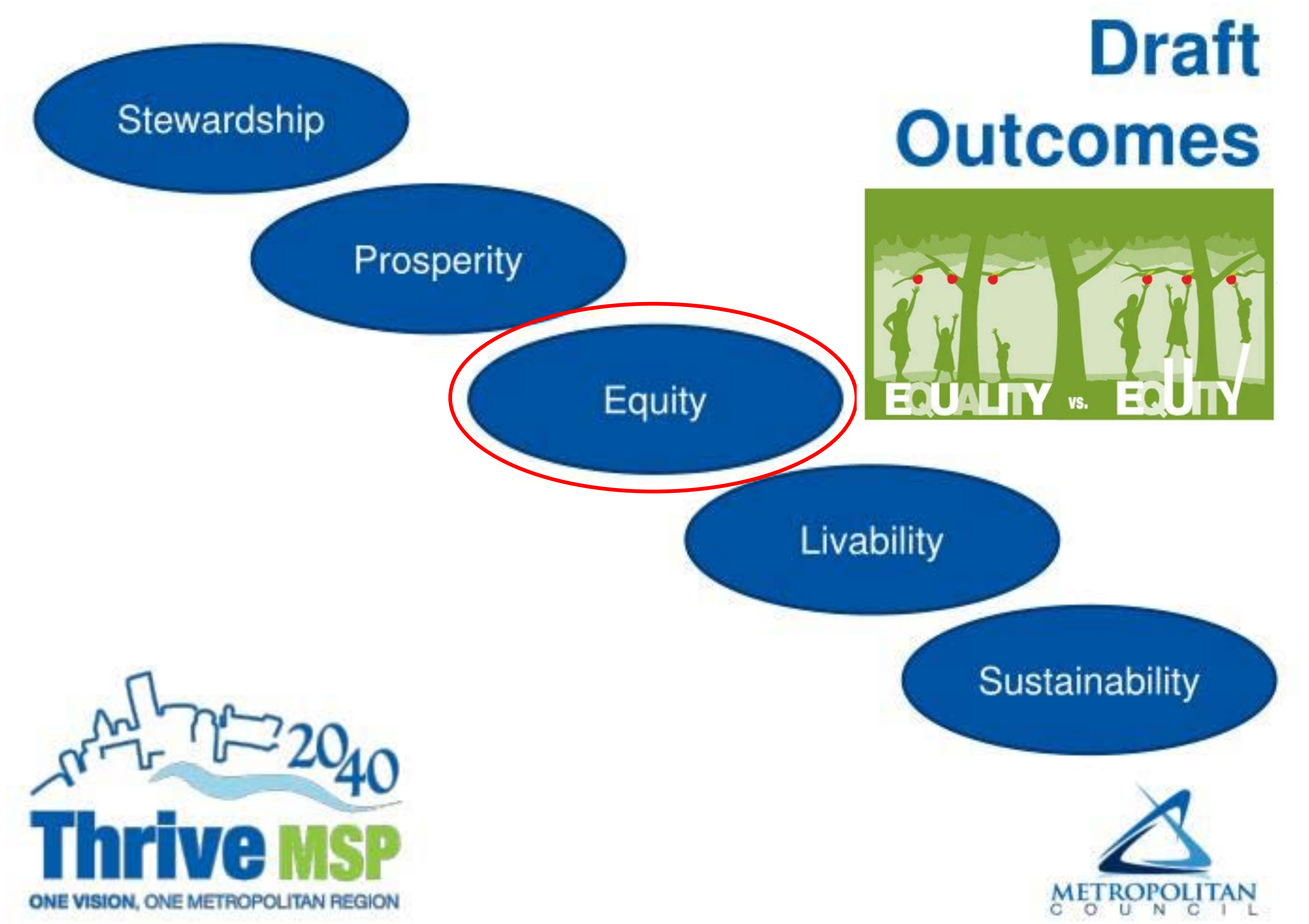
- **Local Government History**
  - 2010-2020: Regional 10-year planning cycle (Metropolitan Council)
  - 2013-14: Thrive MSP 2040
  - 2015: USDOT Smart Cities Challenge proposal by Minneapolis



Thrive MSP 2040


Local Plan Implementation and Plan Amendments
United States Census 2010
2013 - 2014
Regional Development Guide
2040 Thrive MSP
2014 - 2015
Regional System and Policy Plans:
Regional Parks
Water Resources
Transportation
Housing
Fall 2015
System Statements
Fall 2015
LOCAL PLANNING HANDBOOK
December 31, 2018
Comprehensive Plan Updates
METROPOLITAN COUNCIL
REGIONAL 10-YEAR PLANNING CYCLE

Source: https://metrocouncil.org/About-Us/why-we-matter/Equity.aspx



KC Story 2: S&CC – Co-visioning

- Co-visioning Meetings (Academics + Local Governments)
  - 2014: Smart City Workshop
  - 2015-16: NSF SRN Sustainable & Health Cities – Equity

- Co-Visioning
  - Infrastructure planning for driver-less, post-carbon future, climate change
  - Advance Environment, Health, Wellbeing & Equity via infrastructure refinement

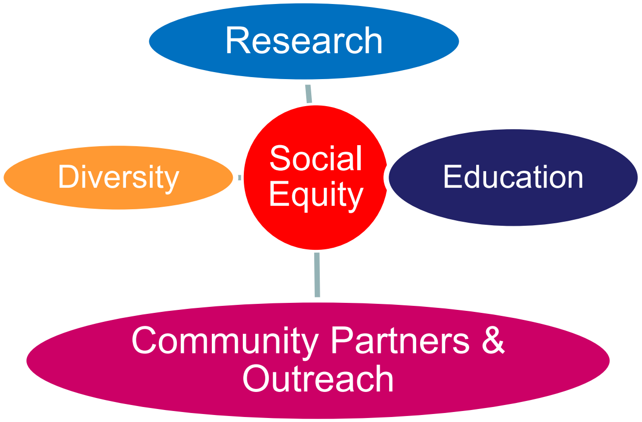
- Co-select Questions
  - Understand spatial equity in infrastructure & outcomes
    - wellbeing. health, environment
  - How does equity first approach differ from average-outcome based approaches ?

- Problem Co-Definition: How to measure spatial equity? Well-being?

KC Story 2: S&CC – Co-select Question

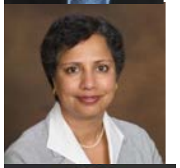
- Team: U of Minnesota, Purdue U, FL State U, U of WA
  - Schools, Counties (e.g., Hennepin), Cities (e.g., Minneapolis, St. Paul, Tallahassee);
  - MetroLab Network, National League of Cities, ICLEI-USA, Intl. City/County

- Co-Discovery:
- Co-Evaluation



Academic and Community Partnerships

- **Shashi Shekhar**; UMN; PI
  - Spatial data mining & spatial DB
- **Anu Ramaswami**; UMN; Co-PI
  - Env science/policy, sustainable urban sys.
- **Julian Marshall**; UW; Co-PI
  - Env eng., air pollution & public health
- **Venkatesh Merwade**; Purdue; Co-PI
  - Civil engineering, hydrologic modeling
- **Richard Feiock**; FSU; Co-PI
  - Political science & public affairs
- **Julie C. Brown**; UMN; SP
  - Education
- **Diana M. Dalbotten**; UMN; SP
  - Diversity
- **Robert Johns**; UMN; SP
  - Leadership; strategy; and management
- Jason Cao & Frank Douma UMN; SP
  - Urban planning
- Len Kne, UMN; SP
  - Cyberinfrastructure & U Spatial


City Partners:

- Brette Hjelle & Kathleen Mayell; Minneapolis
- Michael Olson; Tallahassee

Schools Partners:

- Charlene Ellingson; Minneapolis Public Schools
- Betsy Stretch; Minneapolis Public Schools

NSF Sustainable Research Network:

- Sustainable Health Cities (SHC)

Multi-Community Organizations/Other:

- Cooper Martin; National League of Cities
- Angie Fyfie; ICLEI-USA
- Tad McGalliard; Intl. City/County Management Association
- **Ben Levine**; MetroLab Network

Objectives & Challenges

- **Scope:**
  - **Cities**: multi-sector, multi-scalar Social-Ecological-Infrastructural Urban Systems (SEIUS).
  - **Infrastructures**: Food, Energy, Water, Buildings, Transportation, Sanitation, Public Spaces

- **Objectives**
  - Understand spatial equity (e) in the context of 7 basic infrastructure provisioning and related wellbeing (*W*), health (*H*), environment (*E*) and equity (e) outcomes in cities
  - Advance all four outcomes using smart spatial infrastructure planning in cities

- **Challenges:**
  1. Data Gaps: need intra-urban scale data on SEIU and EHW parameters (Theme 1)
  2. Knowledge Gaps (Themes 2, 3):
     - Data science to understand spatial interactions among SEIU-*WHEe parameters.*
     - All-infrastructure models of spatial futures in changing climate, with disruptive infrastructures (e.g., renewable energy) & technologies (e.g., CAVS)

Four Themes

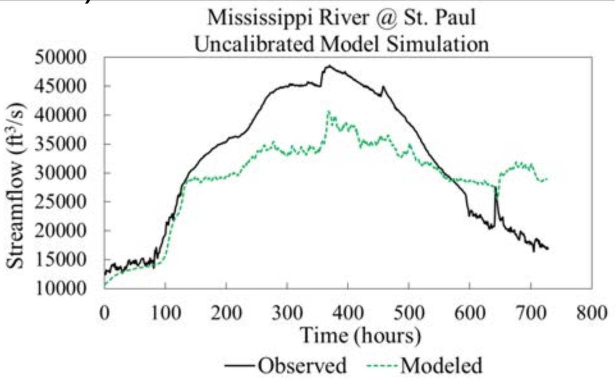
Theme 1: Develop comprehensive data sets on SEIS-EHW at intra-urban scales: • **Cyber infrastructure** for diverse and disparate data sets • **Novel citizen science, sensor and survey techniques** to characterize ○ air pollution ○ near-realtime flooding ○ subjective well-being (W)	**Theme 2**: Advance spatial data analysis to understand SEIU-*WHEe* relationships • Advanced **spatial computing algorithms** • Data and Discipline-inspired Hypotheses • Equity (e) as spatial dispersion & correlation of *WHE*-SEIU	**Theme 3**: Model and visualize spatial smart city futures for Equity-First Plan • **Multiple & connected spatial infrastructure futures** scenario modeling • Scenario **Visualization** • **Value of information** and policy-learning
Theme 4: Education and Workforce Development: Citizen science with middle & high-school students; Interdisciplinary Graduate Certificate; Professional education; Visualization for Policy Leadership;		

Project Update (1/2018- 4/2019)

- **New sociotechnical outcomes.**
- **Theme-1:**
- **Assessment of infrastructure & Well-being** (primary survey)
  - Streamlined survey and analysis techniques
  - On line survey developed (267 surveys completed).

- **Air pollution sensors**
  - Improved sensor design, tests in laboratory and in field.
  - Significance: Cheaper sensors for wider use

- **Citizen Science for near real-time urban flood simulations**
  - Hyper-resolution physical distributed flood modeling (Minneapolis).
  - Significance: urban flooding for extreme weather (e.g. Storms).



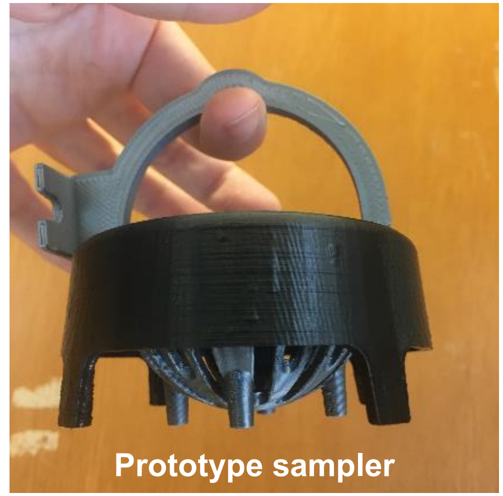
Developing an ultra low cost passive black carbon air pollution sampling approach for citizen science

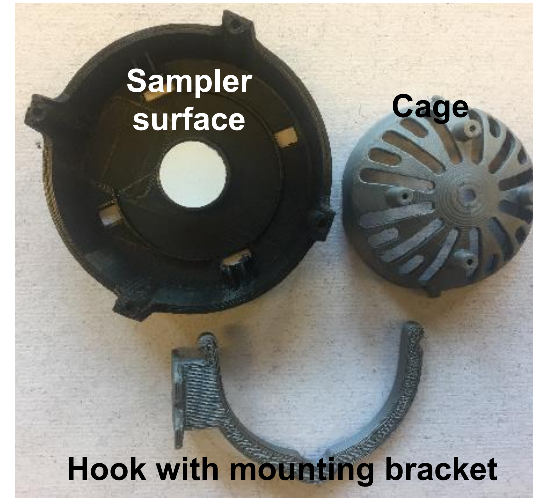
Updates:

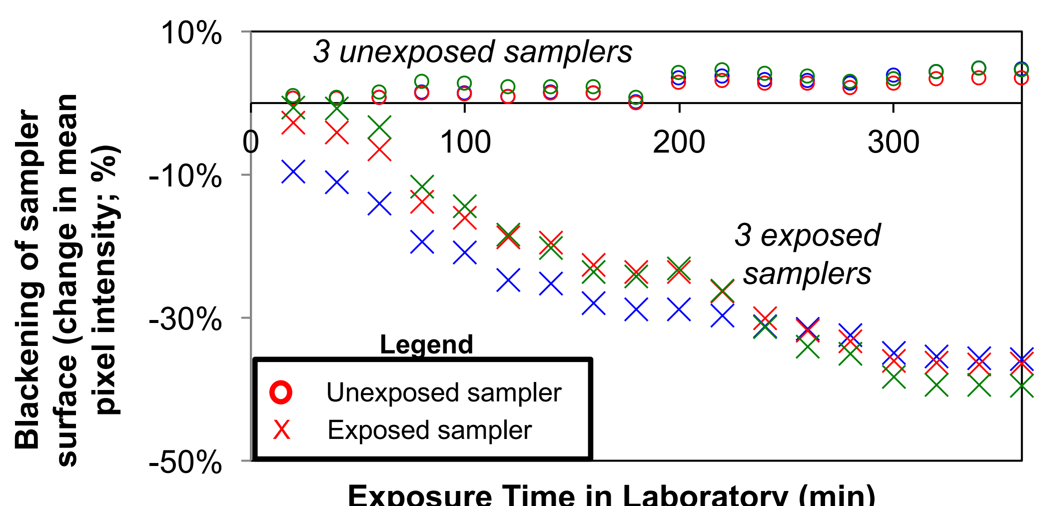
- Redesigned passive sampler prototype and sampling approach
- Tested prototype samplers in laboratory
- Tested prototype samplers in field
- Presented at Jt Annual Meeting of Intl. Society of Exposure Sc. and Intl. Society for Env. Epidemiology
- Being tested in India
  - Comparison with long-term.

Next steps:

- Develop a calibration curve using reference methods for black carbon concentration estimation







Task Lead: PI Marshall

University of Minnesota
Driven to Discover®

Household level Tallahassee database

Spatial equity in energy efficiency and programs adoptions across households and neighborhoods

- Sample of 3,000 homes to entire household population

- **Energy Consumption (2011-2018)**
  - 30 mins interval energy consumption of electricity and gas, monthly consumption of water for about 120,000 customers
- **Voter Registration (2005-2016) --** Yearly/monthly based voter affiliation, voter status, age
- **Tax Roll Record (1995-2016)** -- Property Tax data including house value, homestead exemption, housing features
- **Property Appraiser Data (2014-2015)** -- Property assessment information
- **Zillow (2018)** – Listed price, house characteristics, room type, appliances, heating/cooling system
- **Building Footprint Data (2015) --** LiDar (GIS) data of parcel area, shape
- **Tree Cover (2015) --** LiDar (GIS) data on tree cover percentage in 0.39 by 0.39 meter pixels.

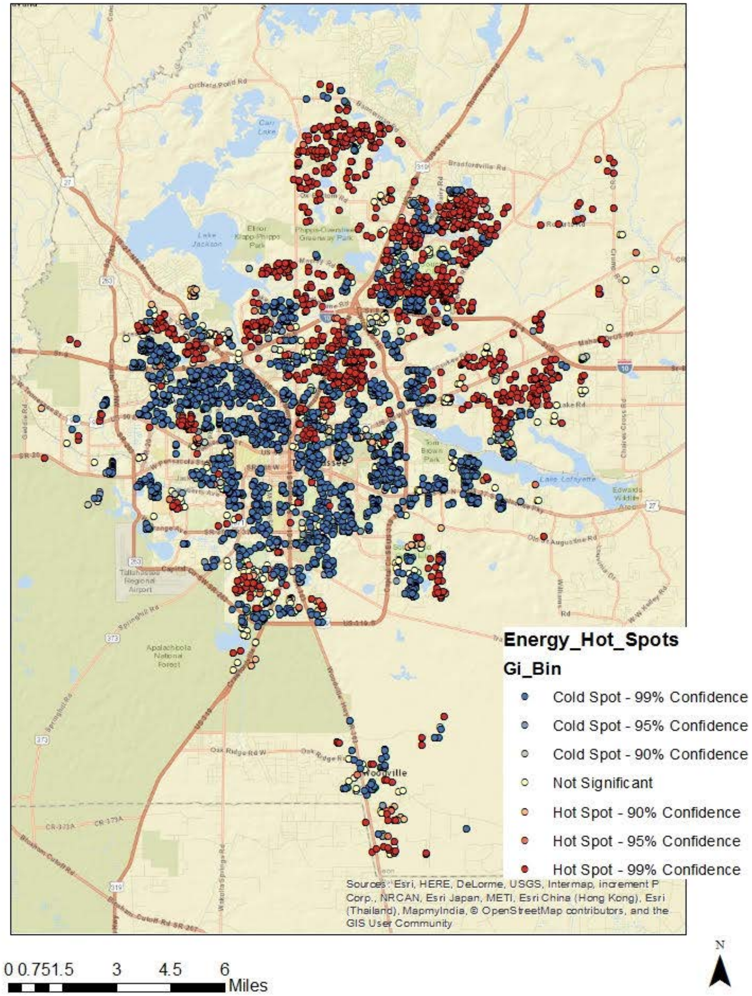
- **Energy Star Rebate Participation (2011-2017) --** Type of rebate program, participation date and rebate amount
- **Energy Star Rebate Participation (2011-2017) --** Type of loan program, participation date, loan time span, amount
- **Solar Farm Enrollment (2018) --** Percentage of electricity from solar, participation date.
- **Solar Panel Installation (2007-2018)** – Capacity, estimated generation, date of participation, and information on installer
- **Energy Audit Comments (2011-2017) --** Actual audit comment notes
- **eBill Registration (2012-2018) --** Date of eBilling Registration
- **Neighborhood Reach (2001-2017) --** Date of reach and house address, name neighborhood
- **Neighborhood and Homeowner associations (Current)** -- Demographic characteristics, Legal status, functional status, participation/interaction with city
- **Homeowner Association Covenants, Conditions, and Restrictions (Current)** – rules and regulations on solar panel adoption

Task Lead: PI Feiock

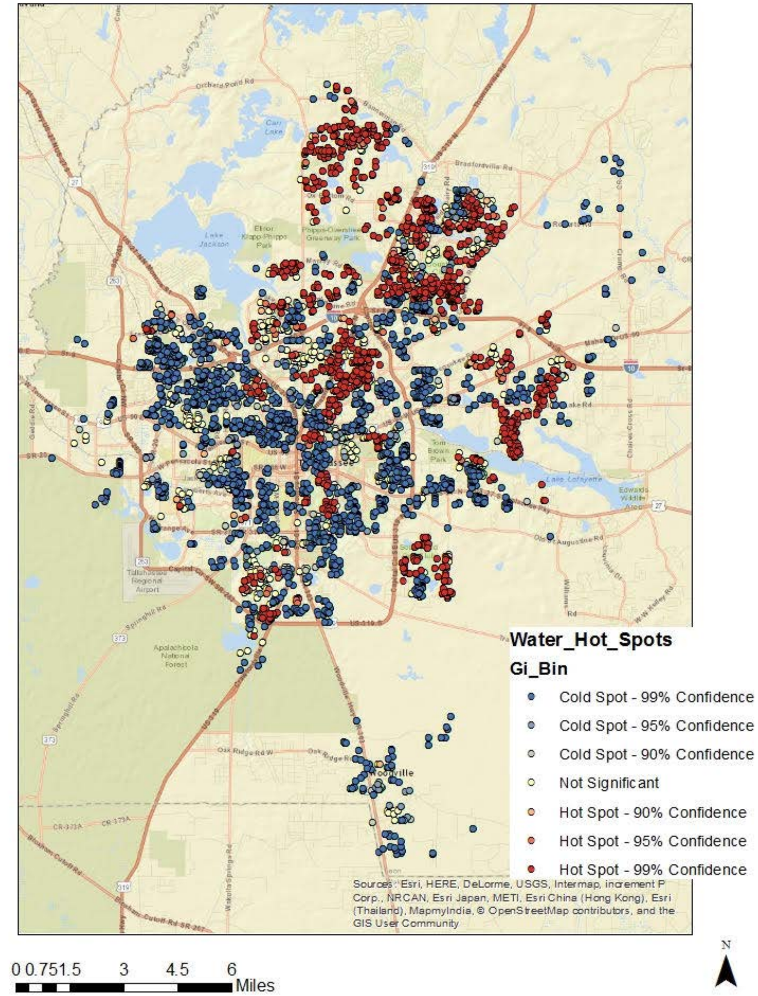
FLORIDA STATE UNIVERSITY

Comparing Consumption Hot Spots

Hot Spot Analysis of Tallahassee Energy Use



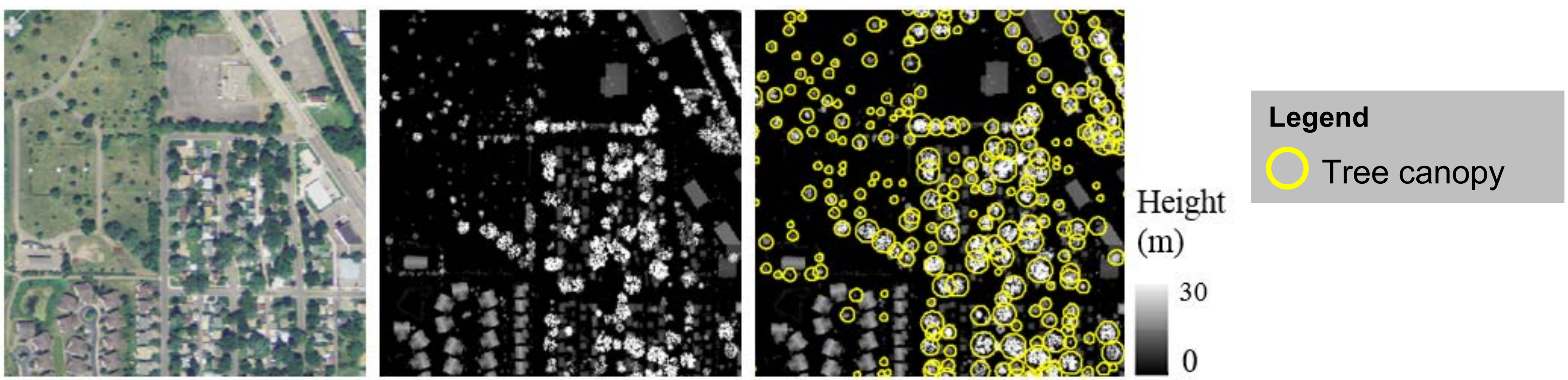
Hot Spot Analysis of Tallahassee Water Use



Task Lead: PI Feiock

Mapping Trees for Green Infrastructure Equity

- Theme 2: Advance spatial data analysis
- Task 2A: Algorithms for spatial patterns
- Accomplishments: individual tree detection for Ash Borer problem
  - A TIMBER (Tree Inference by Minimizing Bound-and-band ERrors)
    - Optimization to find tree locations and sizes
    - Deep learning to construct features to distinguish trees and non-trees
    - A CORE (Core Object REduction) to accelerate the detection process



Details: TIMBER: A Framework for Mining Inventories of Individual Trees in Urban Environments using Remote Sensing Datasets, IEEE Intl. Conf. on Data Mining (ICDM), 2018.

Mapping Ash Trees for Green Infrastructure Equity

- Work in progress: Tree species classification, including ash tree
  - Idea: Use tree shadows from high-resolution leaf-off imagery
  - Data collected
    - St. Paul road-side tree inventory with location and species (no canopy size), 2018 update.
    - Tree inventory on University of Minnesota campus (no canopy size).
    - High resolution leaf-off imagery (3’’ resolution) by Hennepin and Ramsey County
    - About 2500 training samples of tree shadows (i.e., profile geometry)
  - Next steps
    - Algorithms for tree shadow enhancement and clipping
    - Deep learning for tree species prediction

Task Lead: PI Shekhar

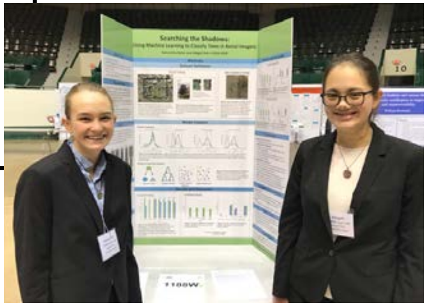
Project Update (1/18- 4/19): Community Outcomes

Major community outcomes

- Theme 1: Minneapolis PWD and Public Schools
  - Long term tracking of inequality in wellbeing and relationship to infrastructure.
  - Neighborhood associations, (Seward, Prospect Park)
  - Contacted all 87 Neighborhoods Associations (via Newsletters, Facebook)
  - Dissemination in 8 MSP schools

- Theme 2:
  - Shared Ash tree detection results with Hennepin county PWD

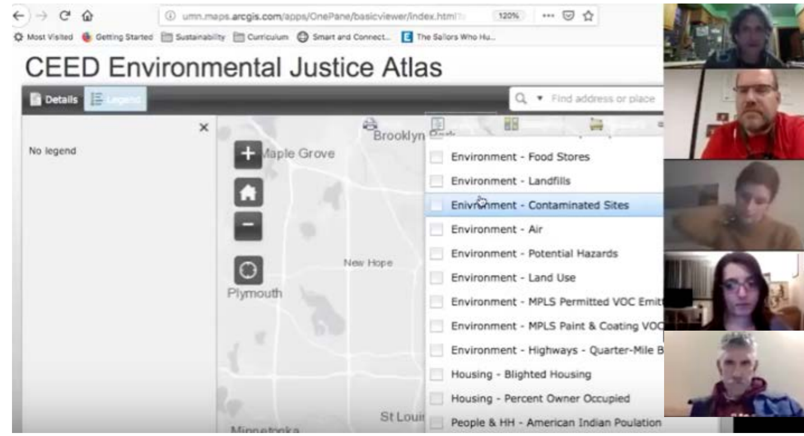
- **Theme 4:** Minneapolis School District:
  - Developed initial curriculum materials,
  - set up Air Pollution Monitors at all schools sites,
  - Professional Development of 13 high school teachers

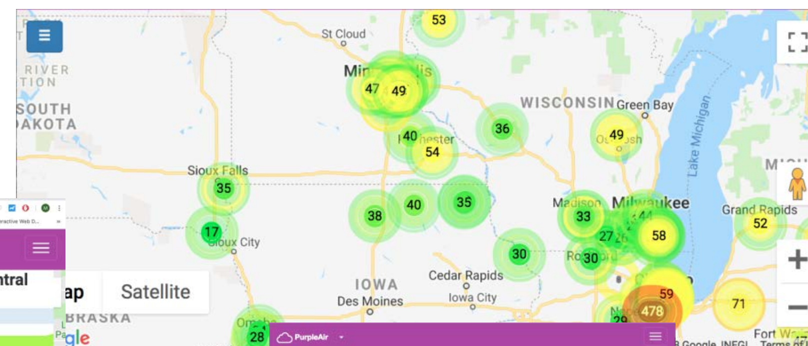


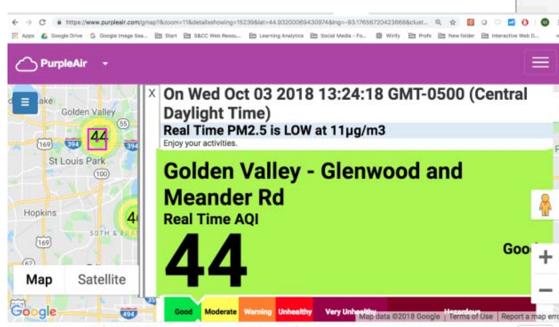
Teacher’s Workshop

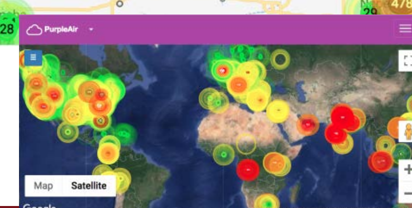
Updates

- August teacher workshop complete
- Monthly web-meetings to support teachers, provide updates, status checks and refine curriculum product
- Responsive Curriculum website set up for 8-12 classroom use
- Partial set up of Air Pollution Monitors at school locations
- Soft implementing of curriculum materials December through March









Task Lead: PI Upadhyay

Outline

- Motivation
- Knowledge Co-production (KC)
- KC Story 1: Evacuation Planning
- KC Story 2: Spatial Computing in Smart Cities
- Conclusions

CONCLUSIONS & NEXT STEPS

- Cities is societally important and facing challenges
  - Majority live in cities
  - Challenges: climate change, aging infrastructure, …
  - Opportunities: renewable energy, self-driving vehicles, …

- Spatial Computing has already transformed Cities
  - Sanitation, green spaces, E-911, public safety, …
- Many Transformative opportunities lie ahead
  - Ex. Spatial equity
- However, these will not material without
  - **Knowledge Co-production**: local governments, academics, businesses, …
  - **Basic Research**, e.g., spatial data science to overcome gerrymandering challenge