Transforming Smart Cities with Spatial Computing
Computer Sc. & Eng. Colloquium, University of Minnesota

Shashi Shekhar
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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 Framework to Advance Equity in Communities, NSF(Award 1737633), $2.5 M, 9/1/2017 - 8/31/2020.


- P.I., Identifying and Analyzing Patterns of Evasion (HM0210-13-1-0005), USDOD-NGA, $0.6M, 6/13-12/18.

New from CRA: Database of Candidates for Academic and Industrial/Government Laboratory Positions

In: November 2018, Vol. 30/No.10, Current Issue

CRA has started a new service intended to improve the recruiting process for academic and industrial/government laboratory research positions.

Candidates for these positions can upload their resumes, research and teaching statements, job objectives and other preferences, and a link to a presentation video. Recruiting officers with access are able to search this information and are encouraged to contact candidates.

The database can be accessed through https://cra.org/cv-database/. For further information, including an instructional video, visit: https://cra.org/cv-database/#Info.
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
- Conclusions
History of Transforming Cities with Spatial Computing

1854: What causes Cholera?

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
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:
## The Changing World of Spatial Computing

<table>
<thead>
<tr>
<th></th>
<th>Last Century</th>
<th>Last Decade</th>
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</thead>
<tbody>
<tr>
<td><strong>Map User</strong></td>
<td>Well-trained few</td>
<td>Billions</td>
</tr>
<tr>
<td></td>
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<tr>
<td><strong>Mappers</strong></td>
<td>Well-trained few</td>
<td>Billions</td>
</tr>
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</tr>
<tr>
<td><strong>Software, Hardware</strong></td>
<td>Few layers, e.g., Applications: Arc/GIS,</td>
<td>Almost all layers</td>
</tr>
<tr>
<td></td>
<td>Databases: SQL3/OGIS</td>
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<td></td>
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<tr>
<td><strong>User Expectations &amp; Risks</strong></td>
<td>Modest</td>
<td>Many use-case &amp; Geo-privacy concerns</td>
</tr>
</tbody>
</table>
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

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

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 satellite imagery to map crops, water, buildings, roads, …

<table>
<thead>
<tr>
<th>Google Earth Engines</th>
<th>NEX</th>
<th>AWS Earth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation, Landsat, LOCA, MODIS, NAIP</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>NOAA</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>AVHRR, FIA, GIMMM, GlobCover, NARR, TRIMM, Sentinel-1</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>IARPA, GDELT, MOGREPS, OpenStreetMap, Sentinel-2, SpaceNet (building/road labels for ML)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CHIRPS, GeoScience Australia, GSMap, NASS, Oxford Map, PSDI, WHRC, WorldClim, WorldPop, WWF, BCCA, FLUXNET</td>
<td>x</td>
<td></td>
</tr>
</tbody>
</table>
Global Agriculture Monitoring
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 data² 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 crops³ for early warnings and planning to avoid food shortages.

Summer 2018
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:
Bringing the Geospatial Perspective to Data Science Degrees and Curricula

University Consortium for Geographic Information Science

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 methods such as spatially-explicit models, spatial statistics, geo-statistics, geographic data mining, spatial databases, etc.

6 H. Miller and J. Han, Geographic Data Mining and Knowledge Discovery, CRC Press, 2009 (2nd Ed.).

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Summer 2018
Spatial Partitioning: Gerrymandering

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

<table>
<thead>
<tr>
<th>Election Results</th>
<th>0 - 5</th>
<th>2 - 3</th>
<th>3 - 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gini-Index</td>
<td>0.47</td>
<td>0.47</td>
<td>0</td>
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</table>

<table>
<thead>
<tr>
<th>Partition Based Pearson’s Correlation</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>0</td>
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<tr>
<td>-</td>
<td>1</td>
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</tbody>
</table>

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.
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### Spatial Computing in Modern Cities

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

Operational Use: Emergency Services

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

Sources: www.ci.minneapolis.mn.us/police/statistics, communitycrimemap.com
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’
Legionnaires’ Disease Outbreak in New York

(a) Legionnaire’s in New York (2015)

(b) Output of SaTScan

(c) Output of RHD

(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

Strategic Use: Mapping Accessibility

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

---

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

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

Source: [https://www.thearcticinstitute.org/future-of-arctic-research/](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
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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 Managers, 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?

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Population</th>
<th>Vehicle</th>
<th>Walking</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>143,360</td>
<td>4:45</td>
<td>1:32</td>
</tr>
<tr>
<td>B</td>
<td>83,143</td>
<td>2:45</td>
<td>1:04</td>
</tr>
<tr>
<td>C</td>
<td>27,406</td>
<td>4:27</td>
<td>1:41</td>
</tr>
<tr>
<td>D</td>
<td>50,995</td>
<td>3:41</td>
<td>1:20</td>
</tr>
<tr>
<td>E</td>
<td>3,611</td>
<td>1:21</td>
<td>0:36</td>
</tr>
</tbody>
</table>

Details: [FoxTV newsclip], Shashi Shekhar Disaster Area Evacuation Analytics, https://www.youtube.com/watch?v=PR9k72W8XXK
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

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 are 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

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KC Story 2: A NSF S&CC Project

- NSF Workshops
  - Big Data and Urban Informatics, 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
Broader Motivation

3) Good Health and Well-Being
9) Industry, Innovation, and Infrastructure
10) Reduced Inequalities
11) Sustainable Cities and Communities
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

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

- **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
- **Brette Hjelle & Kathleen Mayell**: Minneapolis
- **Michael Olson**: Tallahassee
- **Charlene Ellingson**: Minneapolis Public Schools
- **Betsy Stretch**: Minneapolis Public Schools
- **Sustainable Health Cities (SHC)**
- **Cooper Martin**: National League of Cities
- **Angie Fyfie**: ICLEI-USA
- **Tad McGalliard**: Intl. City/County Management Association
- **Ben Levine**: MetroLab Network
Objectives & Challenges

• Scope:
  • 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)
<table>
<thead>
<tr>
<th>Theme 1: Develop comprehensive data sets on SEIS-EHW at intra-urban scales:</th>
</tr>
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<tbody>
<tr>
<td>- Cyber infrastructure for diverse and disparate data sets</td>
</tr>
<tr>
<td>- Novel citizen science, sensor and survey techniques to characterize</td>
</tr>
<tr>
<td>- air pollution</td>
</tr>
<tr>
<td>- near-realtime flooding</td>
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<tr>
<td>- subjective well-being (W)</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Theme 2: Advance spatial data analysis to understand SEIU-WHEε relationships</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Advanced spatial computing algorithms</td>
</tr>
<tr>
<td>- Data and Discipline-inspired Hypotheses</td>
</tr>
<tr>
<td>- Equity (ε) as spatial dispersion &amp; correlation of WHE-SEIU</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Theme 3: Model and visualize spatial smart city futures for Equity-First Plan</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Multiple &amp; connected spatial infrastructure futures scenario modeling</td>
</tr>
<tr>
<td>- Scenario Visualization</td>
</tr>
<tr>
<td>- Value of information and policy-learning</td>
</tr>
</tbody>
</table>

| Theme 4: Education and Workforce Development: Citizen science with middle & high-school students; Interdisciplinary Graduate Certificate; Professional education; Visualization for Policy Leadership: |
Community Partners

- Regular meetings with
- Cities of Minneapolis, St. Paul, and Tallahassee
- The county of Hennepin.
Research Objective

To address the key gaps in science, data and knowledge, we propose 3 broad research themes that are closely aligned with Education:

Task Lead: PI Ramaswami

**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)

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**Theme 4:** Education and Workforce Development: Citizen science with middle & high-school students; Interdisciplinary Graduate Certificate; Professional education; Visualization for Policy Leadership;
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
Comparing Consumption Hot Spots

Hot Spot Analysis of Tallahassee Energy Use

Hot Spot Analysis of Tallahassee Water Use
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

![Prototype sampler](image1)
![Hook with mounting bracket](image2)

![Graph](image3)

Legend:
- Unexposed sampler
- Exposed sampler

Exposure Time in Laboratory (min)
Blackening of sampler surface (change in mean pixel intensity; %)

3 unexposed samplers
3 exposed samplers

Task Lead: PI Marshall
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**Task Lead: PI Shashi Shekhar**

---

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- Multiple & connected spatial infrastructure futures scenario modeling
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- 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;
Mapping Trees for Green Infrastructure Equity

- Theme 2: Advance spatial data analysis
- Task 2A: Algorithms for spatial patterns
- Recent accomplishments: individual tree detection
  - 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
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
Urban Garden Detection using Aerial Imagery

<table>
<thead>
<tr>
<th>City/County</th>
<th>Resolution</th>
<th>Marked Garden</th>
<th>Accuracy</th>
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<tr>
<td>Hennepin County</td>
<td>7.5 cm</td>
<td>1163</td>
<td>70%</td>
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<tr>
<td>Ramsey County</td>
<td>5 cm</td>
<td>532</td>
<td>NA</td>
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Types of Urban garden

- Community Garden
- Backyard Garden (Hennepin County)
- Backyard Garden (Detroit)

Image Annotation sequence

Impact of imagery resolution

- Low Resolution
- High Resolution

- Will the same approach work in other urban areas (e.g., Atlanta)

Acknowledgement.
- Data Source: PI Ramaswami, Hennepin County, Ramsey County

Task Lead: PI Shekhar
Task 2B: Discover co-location and teleconnection patterns

- Challenge: Traditional statistical methods miss spatial interactions
- Prelim. Results: Co-location and teleconnection reveal spatial interaction
  - between variables for point data types
- Proposed: address data with multiple levels of aggregation, e.g., areal summary

(a) a map of 3 features
(b) Spatial Partitions
(c) Neighbor graph

<table>
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<tr>
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<th>Pearson’s Correlation</th>
<th>Support</th>
<th>Ripley’s cross-K</th>
<th>Participation Index (colocation)</th>
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<td><img src="#" alt="Ripley’s cross-K" /></td>
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</table>

University of Minnesota
Driven to Discover®
Data-Intensive Science of S&CC in 21st Century

SEIU EHW

Collect, & Curate
Big Data

Volume, Variety

Spatial Patterns,
Hypothesis Generation

Hotspots of infrastructure
deprivation, consumption, pollution,
investment, disease & well-being.
Correlates?

Test Hypothesis
(Policy Intervention)

Equity first
policies

Role of policies
& urban forms

S&CC
Theory

Data-driven and
Discipline-inspired
hypothesis generation

The
FOURTH
PARADIGM
Data-Intensive Scientific Discovery
EDITED BY TONY NEY, STEWART TANSLEY, AND KRISTIN TOLLE

nature

BIG DATA

SCIENCE IN THE PETABYTE ERA
Research Objective

To address the key gaps in science, data and knowledge, we propose 3 broad research themes that are closely aligned with Education:

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;

Task Lead: PI Upadhyay
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
Theme 4: Next Steps

- Complete set up Air Pollution Monitors at all schools sites
- Finalize school implementation and teacher observation schedules
- Continued monthly web-meetings
- Begin implementation of curriculum modules and lessons
- Continued refinement to curriculum materials, supports for individual school contexts ie: Grade level, course or program
- Maintain updates on website

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