Towards a Smart… *Er* City

What the City of Philadelphia does with Asset Knowledge

AND

Why Constant Progress and Evaluation
is more important
than hard and fast goals

What do we mean by Smart***er*** City

- Too often, we aim for “Smart City” …
  without agreement on what it means
- What is SmartEr?
  - Knowledge of what assets (land, capital, human) you have
  - A clear vision of what you want to do
  - A concrete method of getting to that vision
  - A backup plan if things don’t go as planned.
  - Hint: They never go as planned.

- Integrated Workplace Asset Management System (IWAMS)
  - Knowing Where Property Is
  - Knowing Who Is Responsible for Property
  - Being able to query on important building / site characteristics:

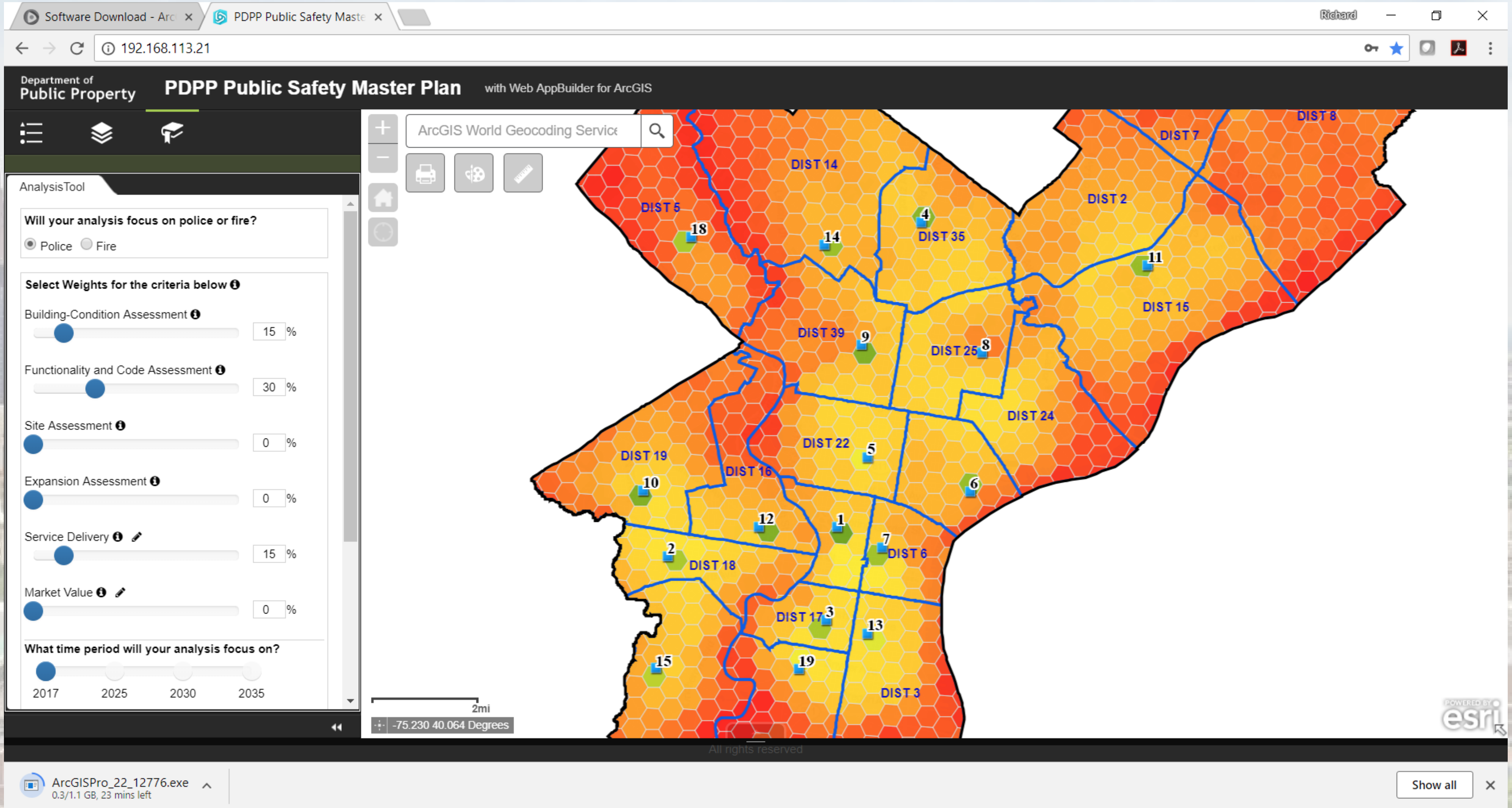
- Unified Platform for Information Delivery
  - Single key ID for Asset identification
  - Foreign tables can key off of this for easy exchange of information
  - Single Repositories of information that can be accessed by multiple departments reduces silos and increases sharing capacity

- Empower Decisions
  - Know where the politics are
  - Know where the city spends the most

InVision – Space Allocation Software

- Understanding what the internal and external built environments are
- Assigning people and costs to spaces
- Creating a better understanding of the value of owned space and lease

Public Safety Master Facilities Plan: GIS-based Decision Support Tool



In Conclusion

- Knowing what you have is more important than anything else
- There’s always more that you don’t know
- Therefore, the key is continuous improvement and having tools that contribute to an environment of learning and asset knowledge

Any Questions?

- Richard D. Quodomine
- Richard.Quodomine@phila.gov
- Twitter: @RDQ_Geography

What Kind of Place is a Smart City?

IREG | 06.13.2018

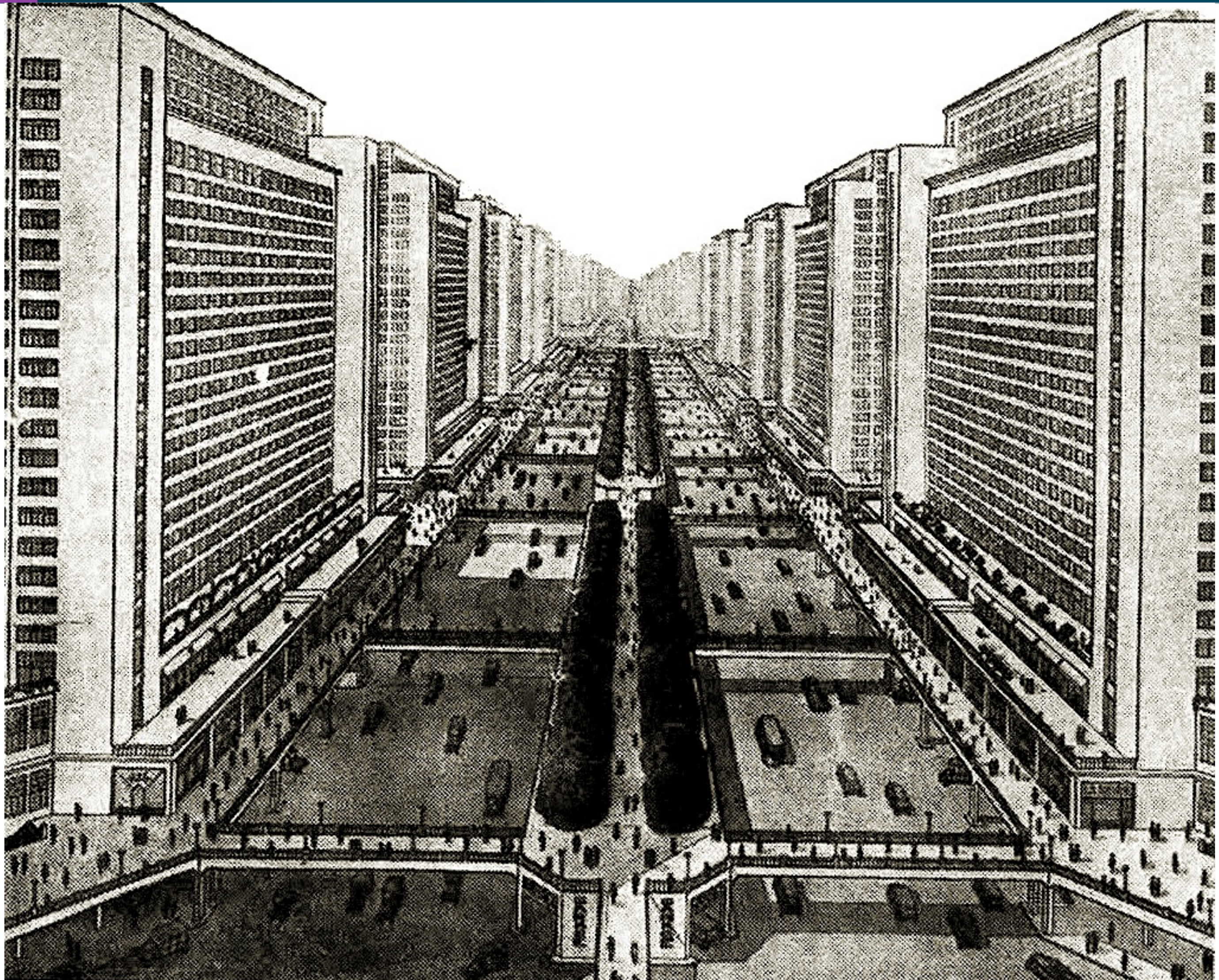
CONNECTIONS 2045

DELAWARE VALLEY dvrpc REGIONAL PLANNING COMMISSION

The Industrial Revolution

Source: Wellcome Collection

Modernist Planning



Source: http://thecharnelhouse.org/2010/09/17/exact-air/ from Radiant City by Le Corbusier

Cybernetic Systems (1960s-1970s)

Source: http://lispmeister.com/images/Cybersyn-Opsroom.JPG.

= modern-classical planning model.

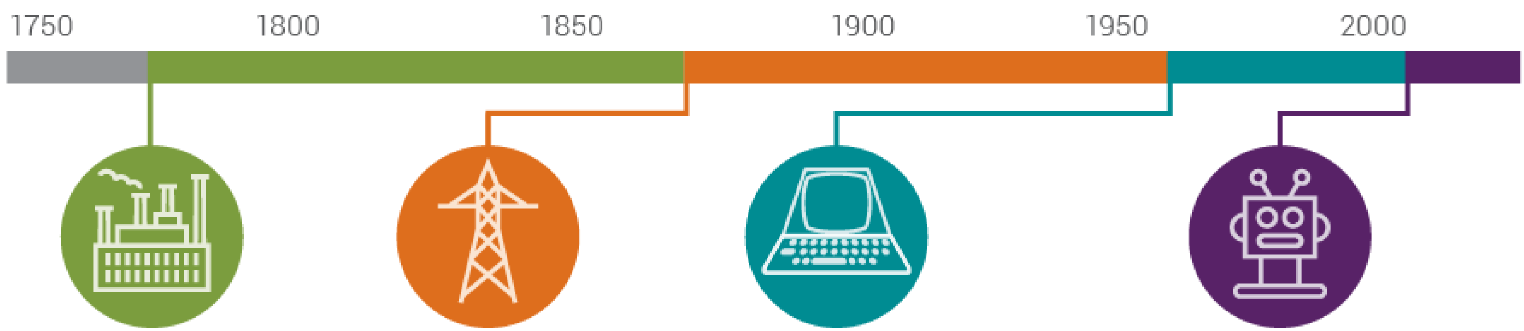
Use systematic procedures to:

1. Continuously identify goals and problems;
2. Forecast uncontrollable contextual changes;
3. Invent alternative strategies, tactics, and time-sequenced actions;
4. Stimulate alternative and plausible action sets and their consequences;
5. Evaluate alternatively forecasted outcomes; statistically monitor conditions; and
6. Feed information into simulation and decision-making channels.

"And yet we all know that such a planning system is unattainable … It is even questionable whether such a planning system is desirable."

- Horst J. Rittel and Melvin M. Webber, *Dilemmas in a General Theory of Planning* (1973)

Four Industrial Revolutions



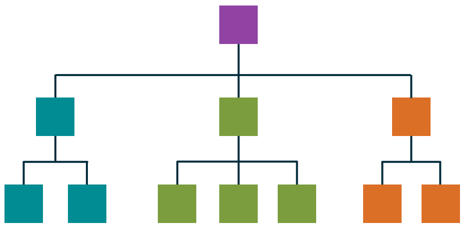
	FIRST (1770s)	SECOND (1870s)	THIRD (1960s)	FOURTH (2010s)
PRIMARY TECHNOLOGIES	Steam Power Mechanical Production	Electricity & Lighting Mass Production	Computers, IT, & Internet Automated Production	Robotics & AI Digital Fabrication
ECONOMIC GROWTH AREAS	Cities and Towns	Big Cities / Streetcar Suburbs	Regions / Auto-Oriented Suburbs	Megaregions / Innovation Hubs
URBAN FORM	Factories	Separation of Uses Skyscrapers & Elevators	Globalization/Deindustrialization e-Commerce	Smart Cities / IoT Augmented Reality
TRANSPORTATION	Canals Railroads	Subways & Trolleys Cars, Buses, Trucks Airplanes	Intelligent Transportation Systems Real-Time Transportation	Connected Vehicles Automated Vehicles UASs (Drones)
			THE DIGITAL REVOLUTION	

Source: DVRPC, 2017. Adapted from World Economic Forum.

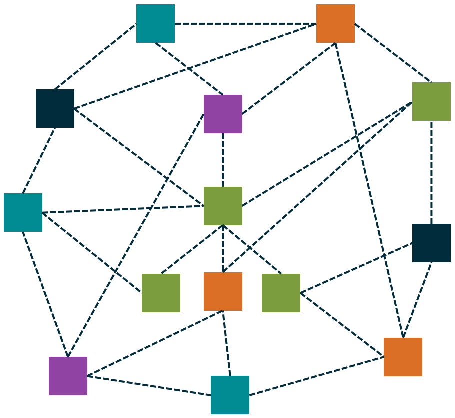
Networks

A **network** is a group of interconnected people and things.

A **network effect** occurs when a good or service becomes exponentially more valuable as more people use it.



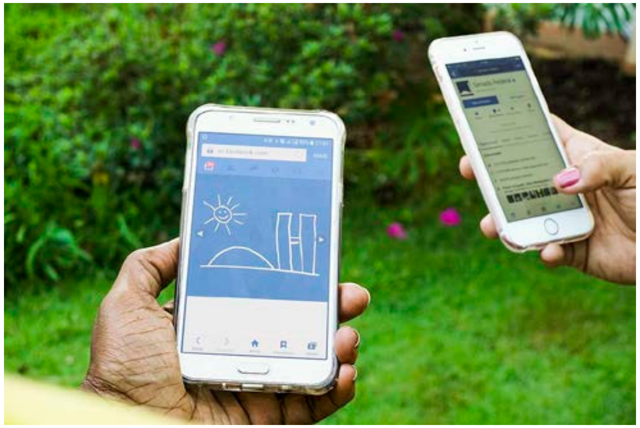
Hierarchy



Network

Internet of Things

The Quantified Self



Source: Fotos produzidas pelo Senado via Wikimedia Commons

Source: MorePix via Wikimedia Commons

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Internet of Things

The Quantified Self

The Smart Home

Source: MorePix via Wikimedia Commons

Source: David Berkowitz via Wikimedia Commons

Source: Amazon

dvrpc

Internet of Things

The Quantified Self

The Smart Home

The Smart City

- Instrumentation
- Urban Informatics
- Urban Information Architecture

Songdo, South Korea

Source: Cisco

Songdo, South Korea

Source: Gale International

Source: Piotrus via Wikipedia

Source: Gale International

Source: Ken Eckert via Wikipedia

Source: Gale International

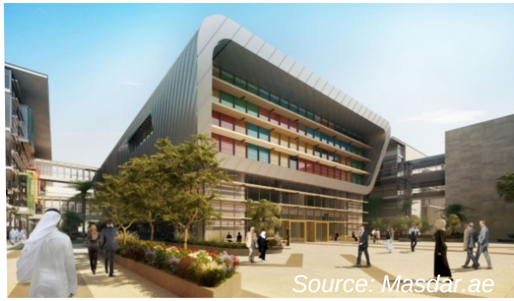
Source: Gale International

Masdar City, UAE

Source: Iain Masterton/incamerastock/Corbis

Source: Masdar.ae

Source: Masdar.ae



Source: Masdar.ae

Source: Masdar.ae

Hudson Yards, NYC

Pedestrians outside the Hudson Yards subway station? Or automatons in a behavioral experiment?

Rio Intelligence Operations Center

Source: Cisco

Smart Signals

Other Smart City Efforts

Columbus, Ohio (FHWA Smart Cities Challenge)

The Array of Things, Chicago

Belmont, Arizona (Bill Gates City of the Future)

Quayside, Toronto (Alphabet’s Sidewalk Labs)

Smart Cities Mission in India (100+ Smart Cities)

Yinchaun, China (+193 more Smart City Pilots)

“Neom,” Saudi Arabia ($500 billion megaproject)

Big Data

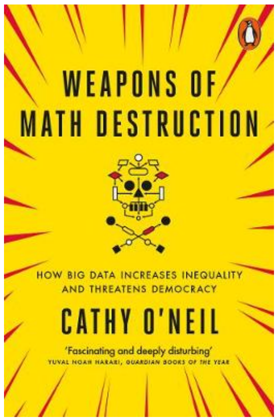
The Economist

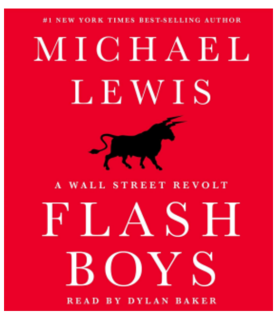
Regulating the internet giants

The world's most valuable resource is no longer oil, but data

The data economy demands a new approach to antitrust rules

Algorithmic Control





Intelligent Machines

Algorithms are making American inequality worse

In a new book, political scientist Virginia Eubanks says using computers to decide who gets social services hurts the poor.

by Jackie Snow   January 26, 2018

SADAF RASSOUL CAMERON

William Gibson wrote that the future is here, just not evenly distributed. The phrase is usually used to point out how the rich have more access to technology, but what happens when the poor are disproportionately subject to it?

Intelligent Machines

Biased Algorithms Are Everywhere, and No One Seems to Care

The big companies developing them show no interest in fixing the problem.

by Will Knight   July 12, 2017

Kate Crawford, speaking at the AI Now conference at MIT this week.
JOHN MAEDA (@JOHNMAEDA)

Opaque and potentially biased mathematical models are remaking our lives—and neither the companies responsible for developing them nor the government is interested in addressing the problem.

dvrpc

Smart City Observations

1. The Smart City Builds off Modernist Design Principles

New development is easier / Hard to retrofit existing cities.

Too focused on optimization and efficiency?

Lack of urbanity

2. Smart Cities Could Undermine Democracy & the Public Good

Proprietary systems.

Have data, need public outreach?

End of privacy?

Creeping privatization.

What are the implications for equity?

How do we prevent repressive uses?

3. The Smart City Adds a Layer of Complexity on top of Complex Urban Areas

Technological overspecification and obsolescence.

Smart technologies are buggy, brittle, and bugged.

Seamless, hidden Intervention

4. The Smart City is Likely to Have Unintended Consequences

Drive change or reinforce the status quo?

Jevons Paradox (rebound effect).

Advertising-as-a-business model . . . will it ruin cities?

When we measure something we change it.

Key Questions for Urban Planning

1. What kind of world / society / community do we want to build?

2. How can we build it?

Occupy Sandy

Source: Lala via www.sandystoryline.com

Using Technology to Build Better Communities

- Design for the here and now
- Open source software and open data, maintain public ownership
- Recognize inherent bias and limitations
- Use tech to harness residents' knowledge & give them a voice
- Improve community understanding of the challenges, risks, and opportunities it faces, and use this to guide decision-making
- Respond to concerns about power, privilege, and justice
- Smart City oversight board / Gov. Compliance Team
- Team up technologists and urban planners & designers
- Connect everyone
- Use urban science to ask tough questions
- Use data to understand trade-offs and generate behavior change
- Build 'Privacy-by-Design' & 'right-to-use the city' into technologies
- Civic education on smart cities, and how to manage the use of their data

CONNECTIONS 2045

Thank You!
bfusco@dvrpc.org

www.dvrpc.org/connections2045

DELAWARE VALLEY dvrpc REGIONAL PLANNING COMMISSION

CONNECT WITH US
www.dvrpc.org

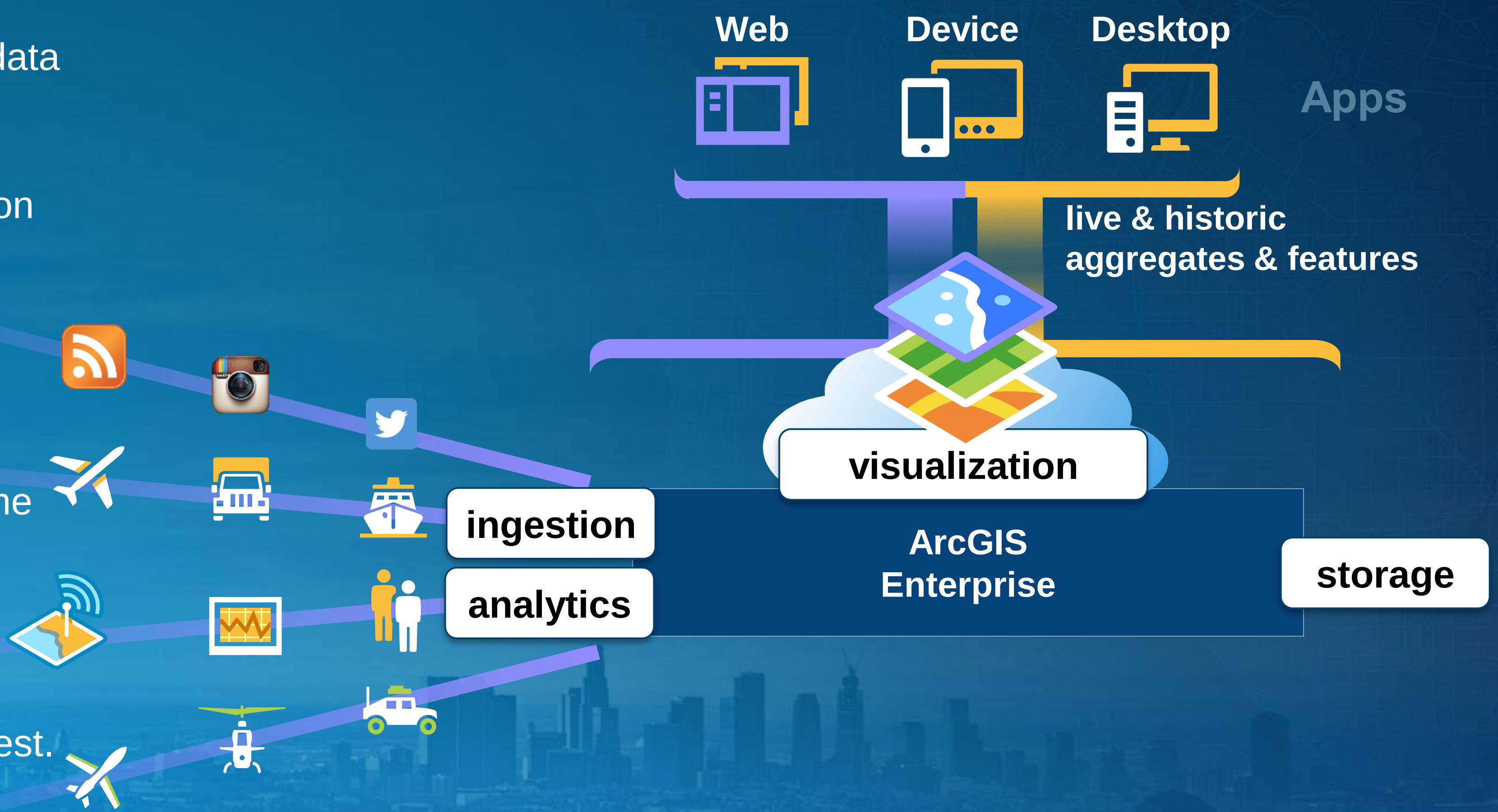
Applying Real-Time Data and Analytics with Waze and ArcGIS

Daniel Wickens – Esri Solution Engineer

ArcGIS Enterprise

with real-time capabilities

- Ingest high velocity real-time data into ArcGIS.
- Perform continuous analytics on events as they are received.
- Store observations in a spatiotemporal big data store.
- Visualize high velocity & volume data:
  - as an aggregation
  - or as discrete features.
- Notify about patterns of interest.



Commercial

- Financial Services
- Insurance
- Logistics / Trucking
- Manufacturing
- Media & Entertainment
- Real Estate
- Retail

Defense & Intelligence

- Intelligence
- Military Operations

Public Safety

- Emergency / Disaster Management
- Fire, Rescue, EMS
- Homeland Security
- National Security
- Law Enforcement
- Special Events

Natural Resources

- Agriculture
- Forestry
- Mining
- Oil & Gas
- Pipeline

1,316

Organizations

88

Countries

Health & Human Services

- Hospital & Health Systems
- Pharmaceuticals
- Public Health

Transportation

- Aviation
- DOT
- Railways
- Maritime & Ports
- Public Transit

Government

- National
- State
- Local

Utilities

- Electric & Gas
- Telco / Cable
- Public Works

Water

- Water resources
- Water / wastewater / stormwater

Professional Services

- AEC
- Environmental Management
- GIS & IT

Nonprofits & Education

- Conservation
- Humanitarian
- Sustainable Development
- Higher Ed
- Research/Science Institutions

Real-Time GIS usage as of December 2017

Internet of Things (IoT)

enabling geospatial insights with your IoT

Environment
noise co2 nitrates
gases temperature humidity
atmospheric pressure radiation
pesticides electromagnetic feedback
rain gauges water level gauges
water quality air quality

Weather
warnings earthquakes
precipitation icy conditions

Airports
flight status queues
plane location runway status

Connected Cars
autonomous driving traffic conditions holes
parking meters road conditions slippery areas
network improvements

Transit
buses taxis rail
trains crowds

People
health monitoring
social activity

Public Health
hospitals ambulances

Public Safety
police fire
surveillance

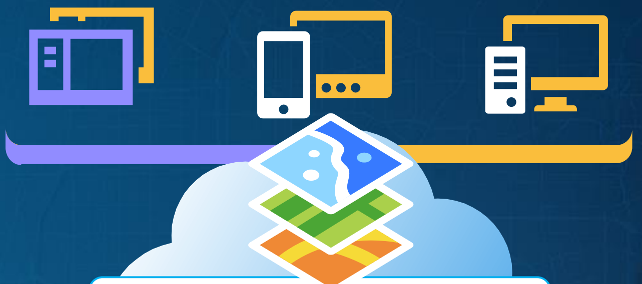
Buildings
lighting hvac
occupancy counts

Energy Usage
electricity gas smart meters

City Workers
sanitation snow plows

Telecommunications
cell phone signals dropped calls

Web Device Desktop



ArcGIS Enterprise

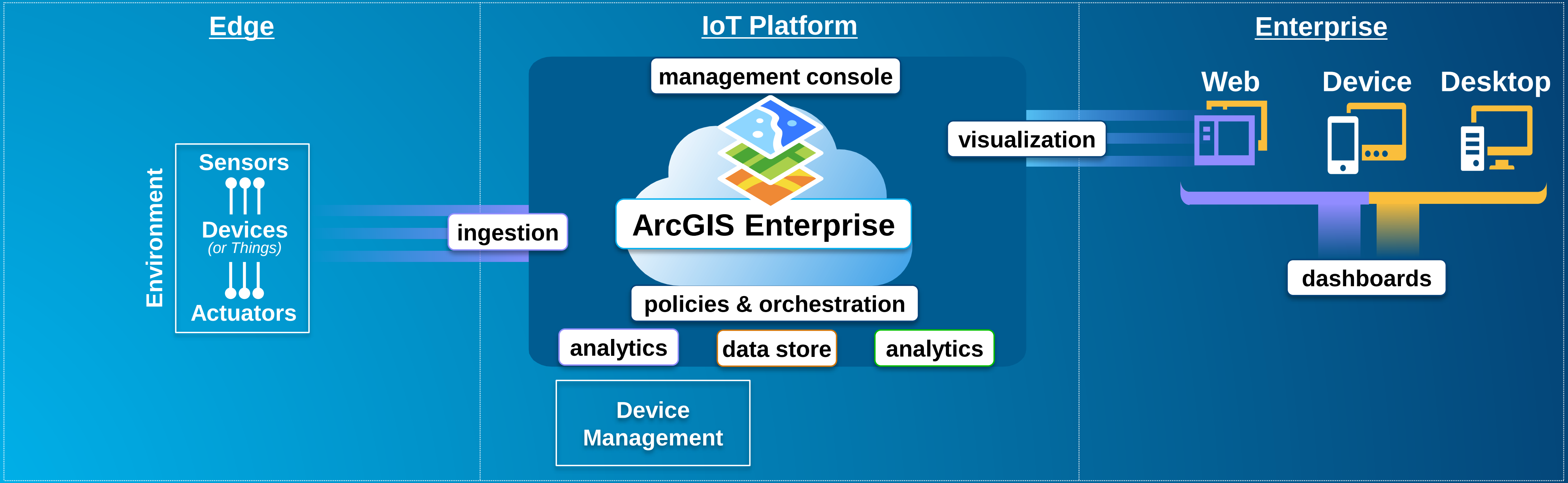
with real-time & big data capabilities

ingest, store, analyze, visualize

Internet of Things (IoT)

blueprint for IoT solutions

- An IoT Platform & Enterprise consists of the following capabilities:
  - Ingestion
  - Streaming Analytics & Policies
  - Actions (including Actuation)
  - Data Store
  - Device Management
  - Batch Analytics
  - Management Console
  - Visualization
  - Dashboards



Collecting your own big data

Clinton J Andrews

Edward J. Bloustein School of Planning & Public Policy

Rutgers University

RUTGERS
THE STATE UNIVERSITY
OF NEW JERSEY

Collecting your own big data (housing examples)

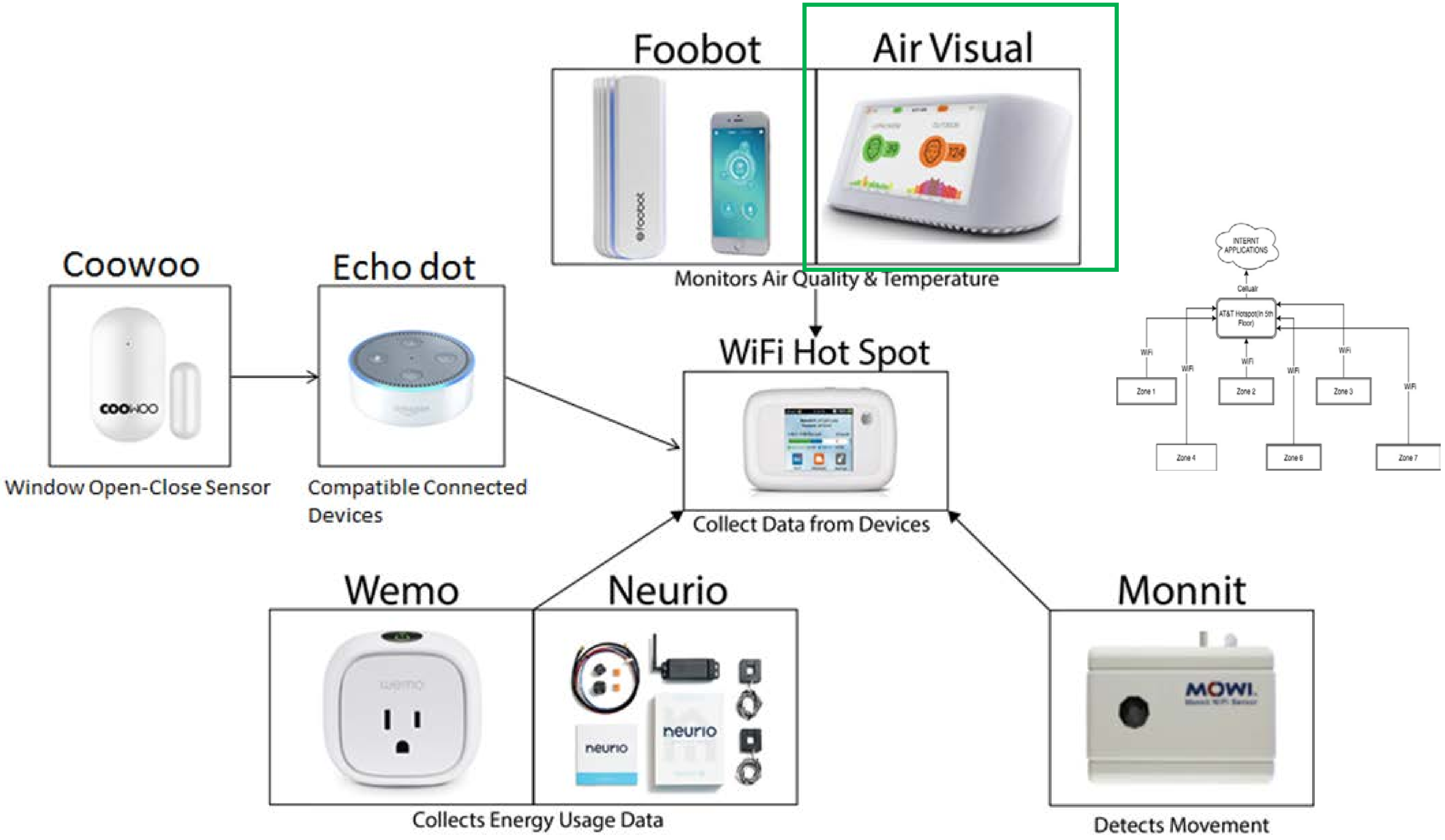
- Occupant behavior during heat waves
- Cost-effective detection of defects in affordable housing structures

Coping with Heat Waves in Public Housing

Funding from NSF Grant AGS-1645786

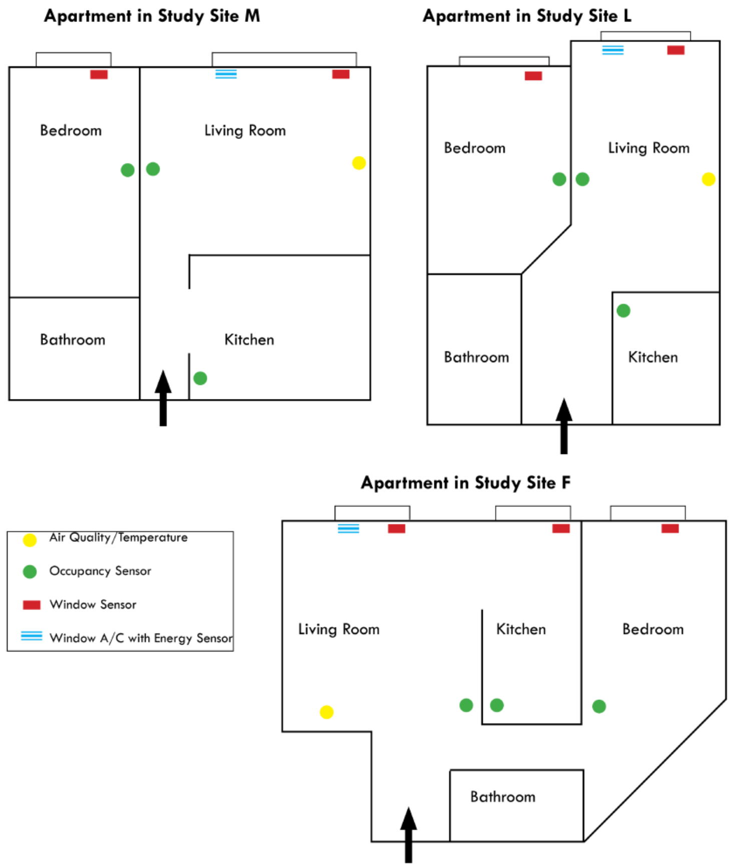
- What do seniors living in public housing do during heat waves?
- High risk of heat stroke, dehydration, asthma, falls
- No central air conditioning, can’t afford to run window AC units
- Cool drinks, wet clothes, open windows, fan, leave apartment?
- Field study in Elizabeth, NJ of 24 households (interviews, sensors)

Consumer-grade sensors in apartments



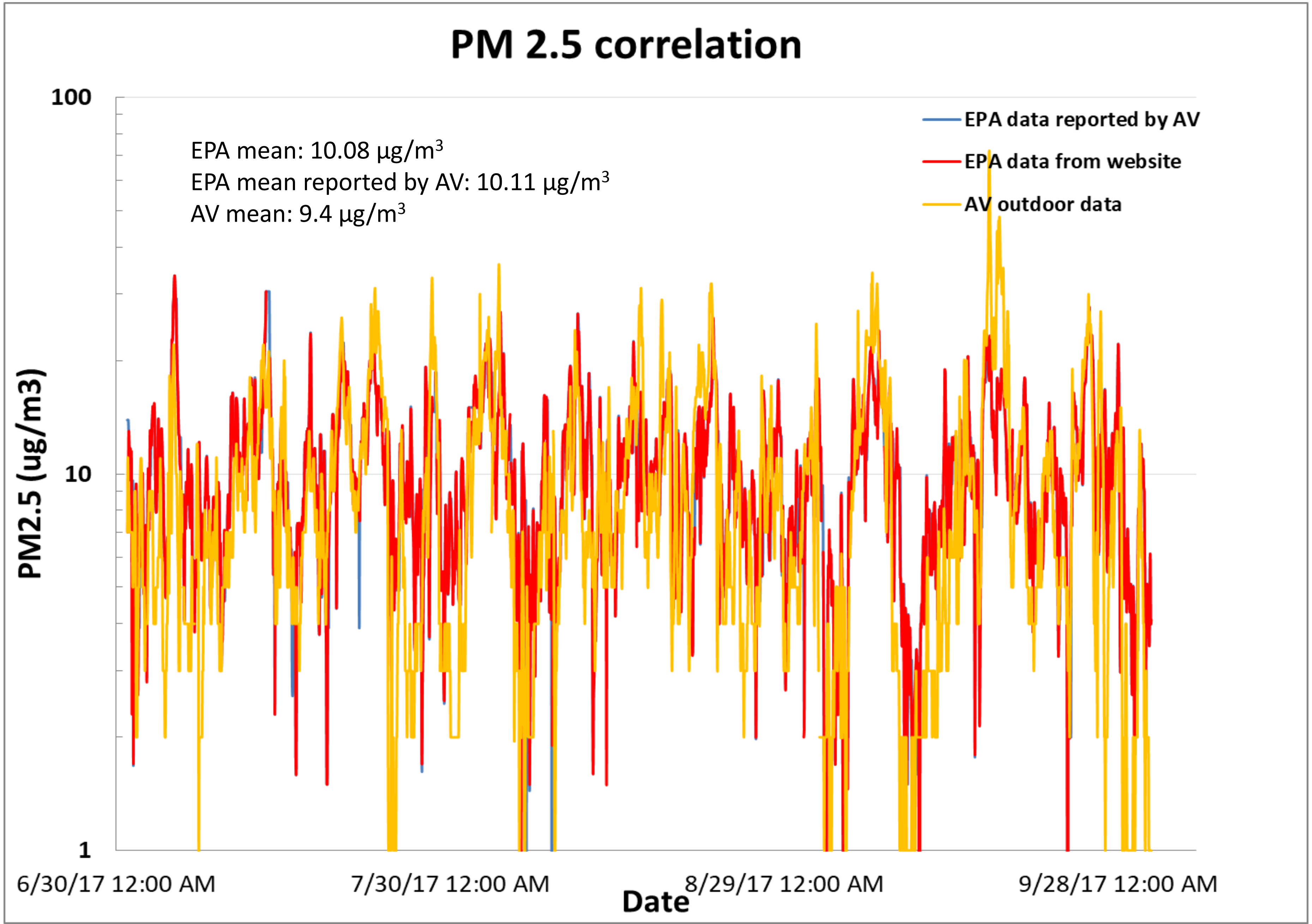
PM measurements. Outdoor site

Apartment Plans and Sensor Locations

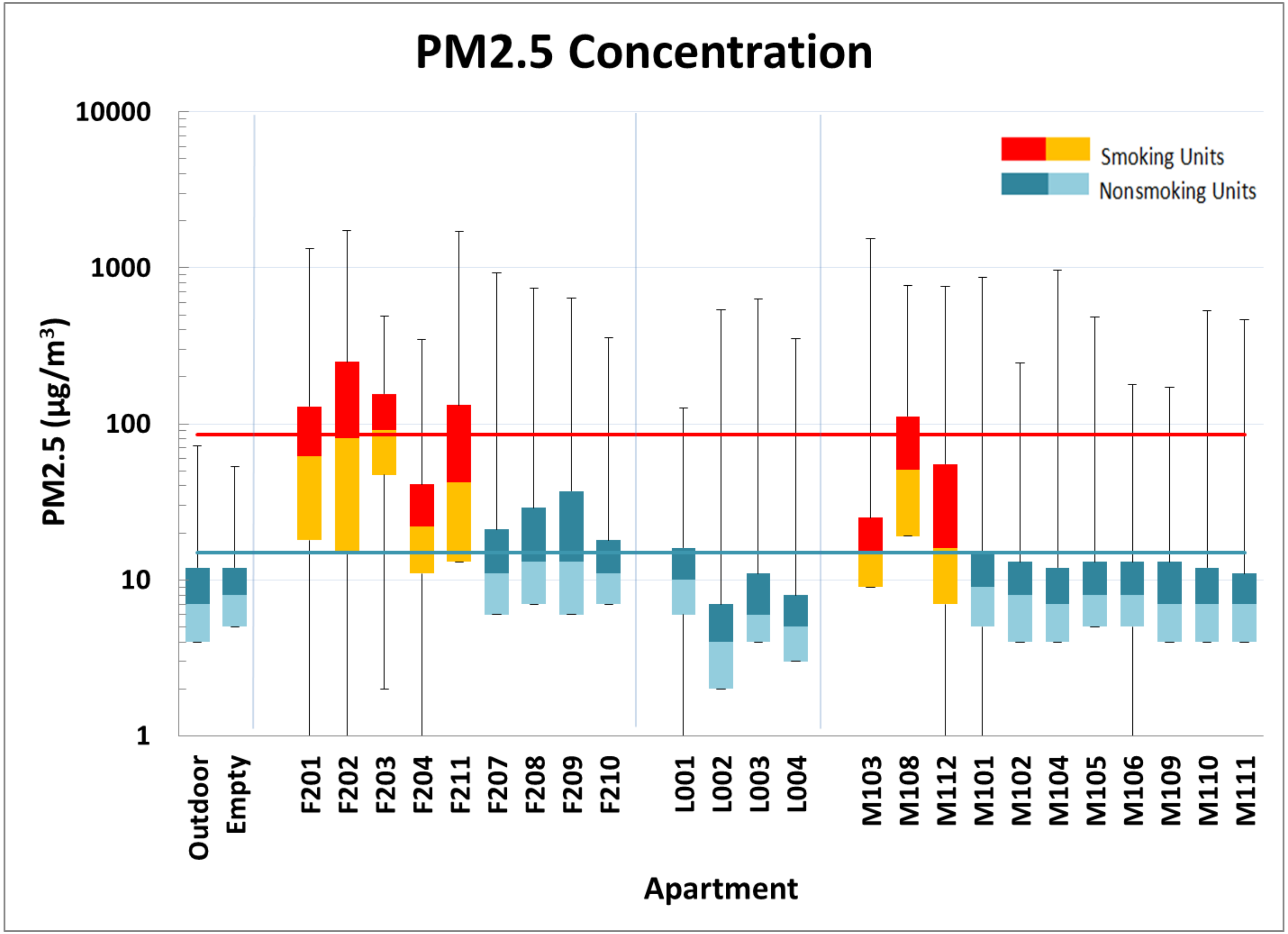


Name	Status	AQI	PM2.5 In	PM2.5 Out	CO_2	Temp	Hum
empty	OFF	AQI 12 Good	3 µg/m³	6.9 µg/m³	408 ppm	77 °F	66 %
f201	OFF	AQI 110 Unhealthy for SG	39 µg/m³	6.9 µg/m³	415 ppm	77 °F	66 %
f202	ON	AQI 274 Very Unhealthy	224 µg/m³	6.9 µg/m³	524 ppm	82.4 °F	59 %
f203	OFF	AQI 55 Moderate	14 µg/m³	6.9 µg/m³	422 ppm	78.8 °F	65 %
f204	OFF	AQI 50 Good	12 µg/m³	6.9 µg/m³	497 ppm	78.8 °F	62 %
f207	OFF	AQI 74 Moderate	23 µg/m³	6.9 µg/m³	461 ppm	78.8 °F	66 %
f207 check ...	OFF	AQI 76 Moderate	24 µg/m³	6.9 µg/m³	451 ppm	78.8 °F	67 %
f208	ON	AQI 409 Hazardous	363 µg/m³	6.9 µg/m³	797 ppm	80.6 °F	72 %
f209	Offline	AQI 29 Good	7 µg/m³	6.3 µg/m³	613 ppm	75.2 °F	54 %
f210	OFF	AQI 29 Good	7 µg/m³	6.9 µg/m³	474 ppm	77 °F	68 %
f211	OFF	AQI 175 Unhealthy	102 µg/m³	6.9 µg/m³	418 ppm	75.2 °F	57 %
l001	ON	AQI 37 Good	9 µg/m³	6.9 µg/m³	601 ppm	77 °F	59 %
l002	OFF	AQI 25 Good	6 µg/m³	6.9 µg/m³	427 ppm	78.8 °F	61 %
l003	OFF	AQI 25 Good	6 µg/m³	6.9 µg/m³	462 ppm	80.6 °F	63 %
l003 check ...	OFF	AQI 29 Good	7 µg/m³	6.9 µg/m³	459 ppm	80.6 °F	60 %
l004	ON	AQI 17 Good	4 µg/m³	6.9 µg/m³	482 ppm	78.8 °F	65 %
m101	ON	AQI 21 Good	5 µg/m³	6.9 µg/m³	709 ppm	75.2 °F	68 %
m102	ON	AQI 21 Good	5 µg/m³	6.9 µg/m³	445 ppm	78.8 °F	65 %
m103	OFF	AQI 21 Good	5 µg/m³	6.9 µg/m³	464 ppm	78.8 °F	63 %
m104	ON	AQI 21 Good	5 µg/m³	6.9 µg/m³	974 ppm	73.4 °F	55 %
m105	ON	AQI 17 Good	4 µg/m³	6.9 µg/m³	450 ppm	80.6 °F	62 %
m106	ON	AQI 12 Good	3 µg/m³	6.9 µg/m³	428 ppm	77 °F	66 %
m108	OFF	AQI 110 Unhealthy for SG	39 µg/m³	6.9 µg/m³	438 ppm	80.6 °F	61 %
m109	OFF	AQI 12 Good	3 µg/m³	6.9 µg/m³	460 ppm	78.8 °F	62 %
m109 chec...	OFF	AQI 17 Good	4 µg/m³	6.9 µg/m³	465 ppm	80.6 °F	63 %
m110	OFF	AQI 17 Good	4 µg/m³	6.9 µg/m³	414 ppm	77 °F	67 %
m111	OFF	AQI 17 Good	4 µg/m³	6.9 µg/m³	567 ppm	80.6 °F	60 %
m112	ON	AQI 21 Good	5 µg/m³	6.9 µg/m³	400 ppm	78.8 °F	62 %
outdoor	OFF	AQI 21 Good	5 µg/m³	6.9 µg/m³	415 ppm	78.8 °F	64 %

- Example of AV website
- All data presented here are based on 1-hr averages

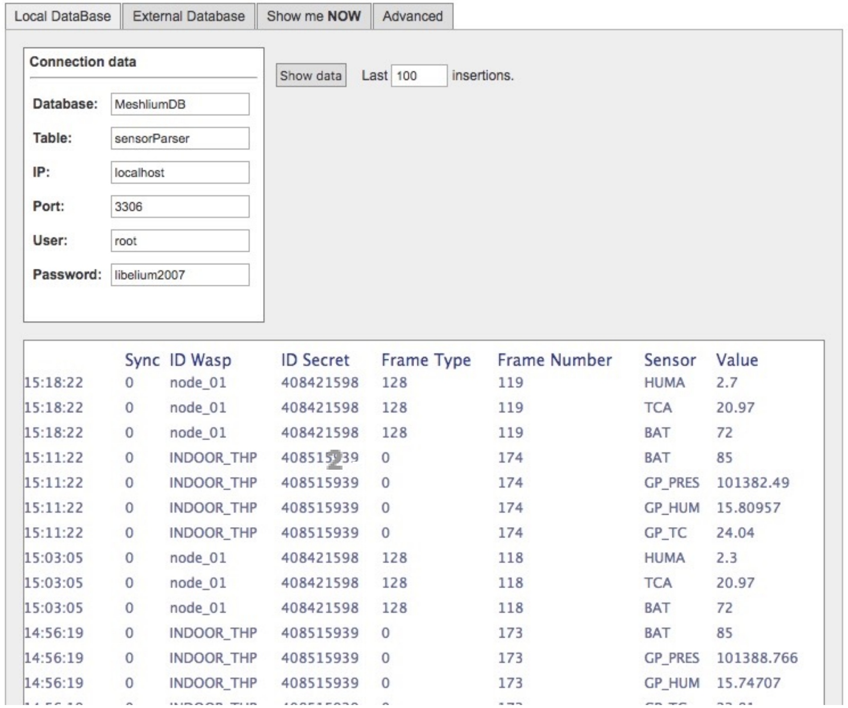


PM 2.5 correlation
EPA mean: 10.08 μg/m3
EPA mean reported by AV: 10.11 μg/m3
AV mean: 9.4 μg/m3
EPA data reported by AV
EPA data from website
AV outdoor data
PM2.5 (ug/m3)
100
10
1
6/30/17 12:00 AM
7/30/17 12:00 AM
8/29/17 12:00 AM
9/28/17 12:00 AM
Date



PM2.5 Concentration
PM2.5 (µg/m3)
10000
1000
100
10
1
Smoking Units
Nonsmoking Units
Outdoor
Empty
F201
F202
F203
F204
F211
F207
F208
F209
F210
L001
L002
L003
L004
M103
M108
M112
M101
M102
M104
M105
M106
M109
M110
M111
Apartment

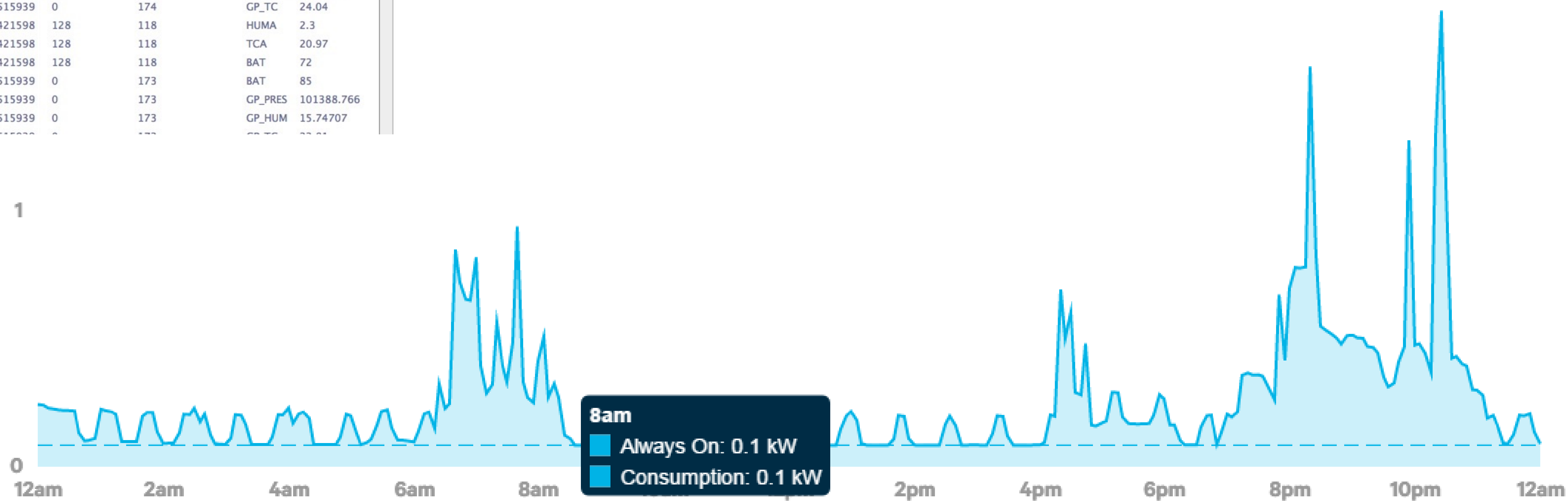
Retrieve data from cloud



	Sync	ID Wasp	ID Secret	Frame Type	Frame Number	Sensor	Value
15:18:22	0	node_01	408421598	128	119	HUMA	2.7
15:18:22	0	node_01	408421598	128	119	TCA	20.97
15:18:22	0	node_01	408421598	128	119	BAT	72
15:11:22	0	INDOOR_THP	408515939	0	174	BAT	85
15:11:22	0	INDOOR_THP	408515939	0	174	GP_PRES	101382.49
15:11:22	0	INDOOR_THP	408515939	0	174	GP_HUM	15.80957
15:11:22	0	INDOOR_THP	408515939	0	174	GP_TC	24.04
15:03:05	0	node_01	408421598	128	118	HUMA	2.3
15:03:05	0	node_01	408421598	128	118	TCA	20.97
15:03:05	0	node_01	408421598	128	118	BAT	72
14:56:19	0	INDOOR_THP	408515939	0	173	BAT	85
14:56:19	0	INDOOR_THP	408515939	0	173	GP_PRES	101388.766
14:56:19	0	INDOOR_THP	408515939	0	173	GP_HUM	15.74707

Lessons

- Do-it-yourself big data projects are feasible
- Consumer-grade equipment is often adequate and cost-effective
- Partner with technologists on sensors & wireless data retrieval
- Data analytics are an increasingly important part of the story



Cost-effective detection of defects in affordable housing structures

- Two low-income, high-rise apartment buildings in Bronx, NY
- Developed & owned by local non-profit organization
- Many households had been homeless or lived in temporary housing prior to moving into buildings
- Diversity of African-American and Hispanic or Latino residents

HUD Healthy Housing Technical Studies Grant # NJHHU0019-13

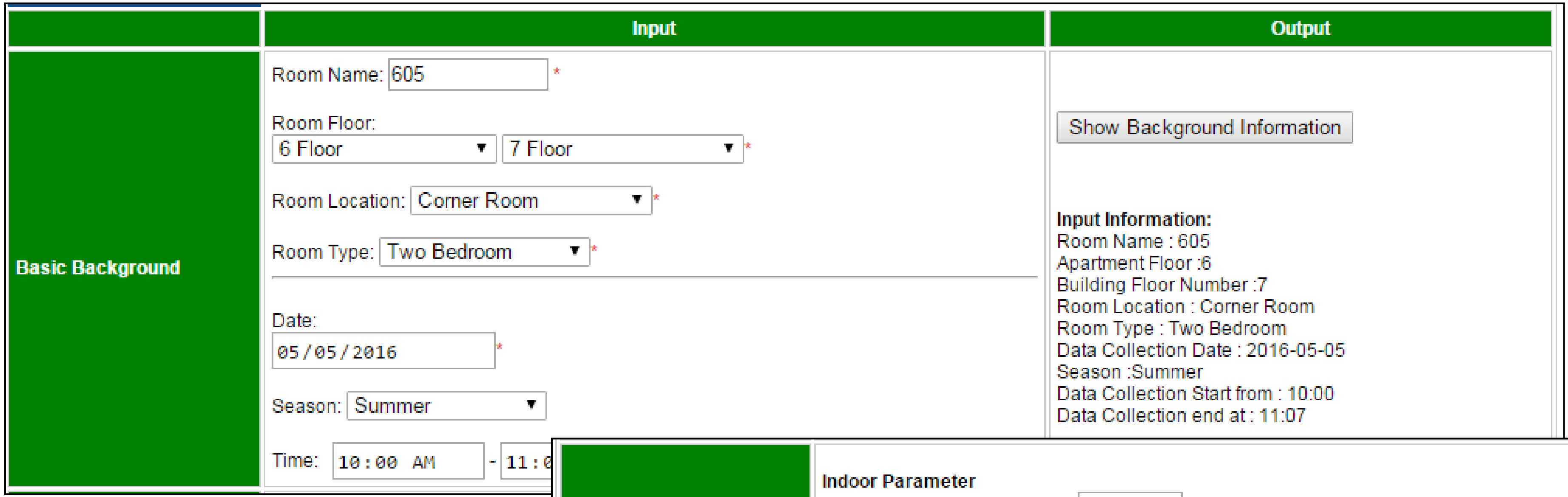
Bldg. 1: 1920's construction, retrofit 2006, contains family health center, commercial kitchen incubator, among other community services (132 apts.)

Bldg. 2: 2009 new construction, Energy Star certified, low VOC materials, with roof-top garden (127 apts.)

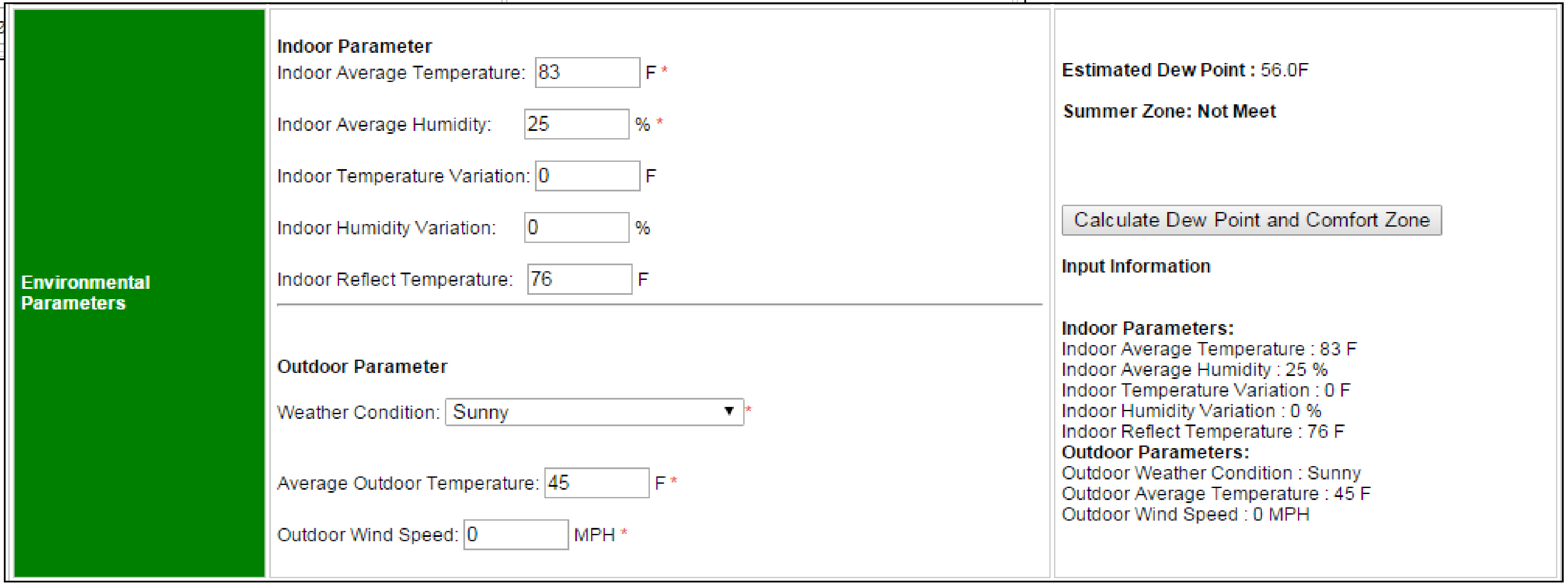
Building Inspection with the Spatially Resolved Infrared Thermography Approach

- Step 1. Collection of Basic Background Information
- Step 2. Collection of Environmental Parameters
- Step 3. Collection of Laser & Infrared Scan Data
- Step 4. Generation of Spatially Resolved Infrared Thermography Data
- Step 5. Visualization & Processing of Data
  - Room Envelope Information
  - Defect Detection and Quantification

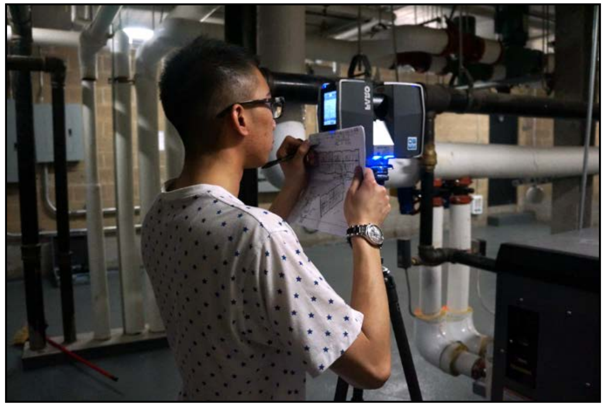
Step 1. Collection of Basic Background Information



Step 2. Collection of Environmental Parameters



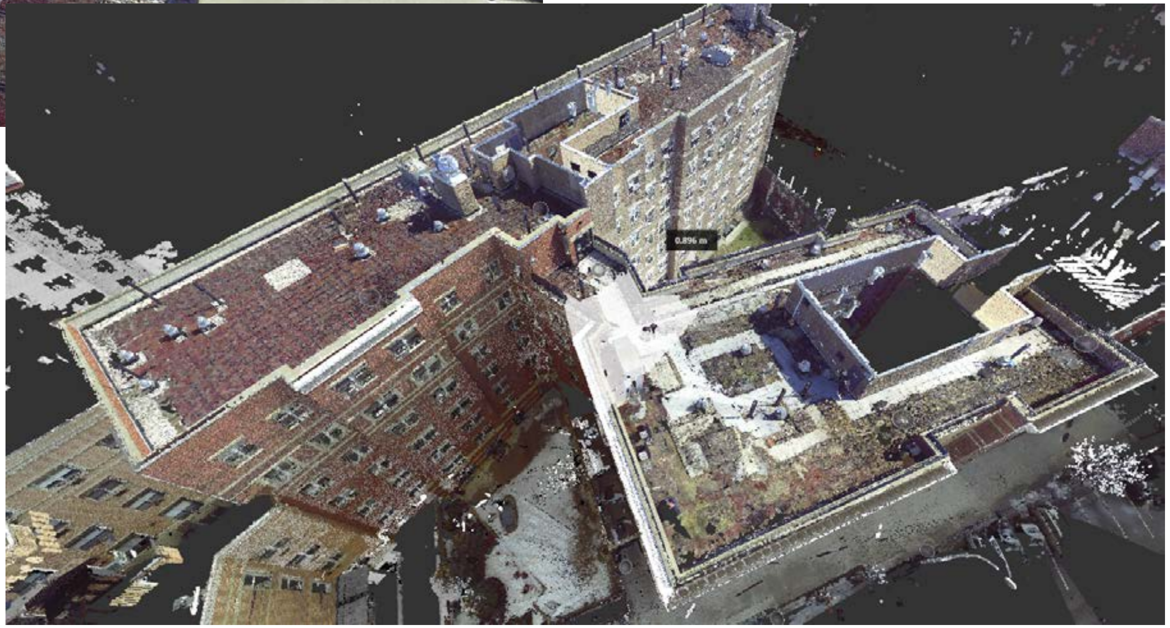
Step 3. Collection of Laser & Infrared Scan Data



- Laser scanner: FARO Focus^{3D}
- Infrared thermal imaging camera: FLIR T650sc

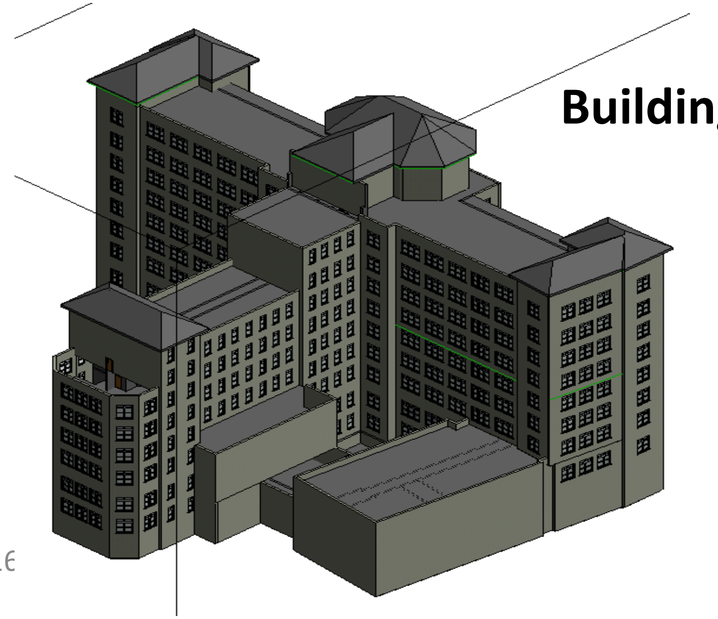
Step 3 (cont.). Sample Laser Scan Data

Panoramic Photo



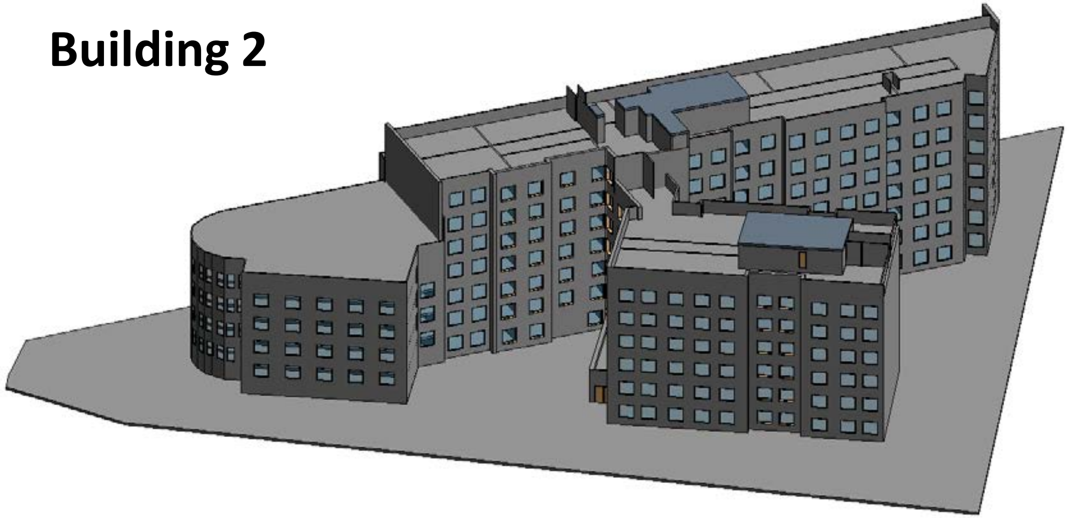
3D Scan Data

Step 3 (cont.). Laser scan data →building information model

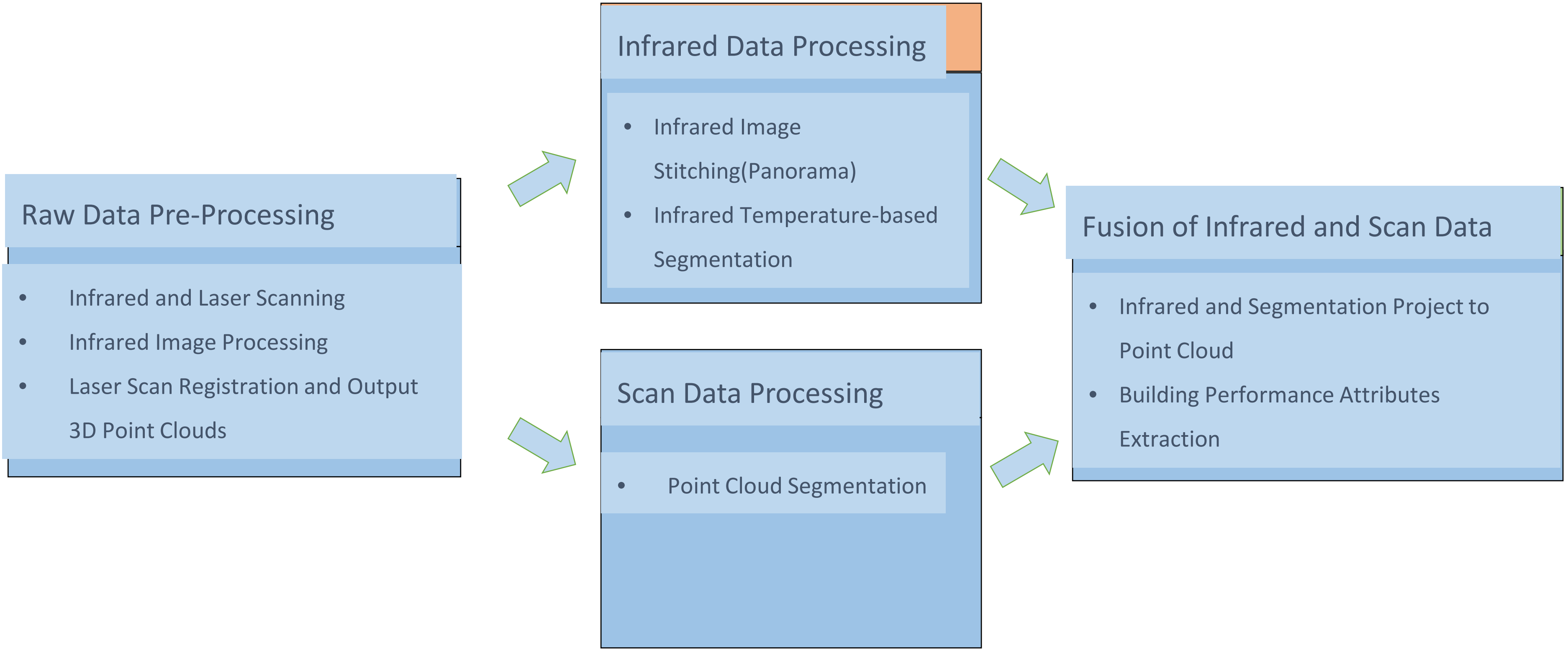


Building 1

Building 2

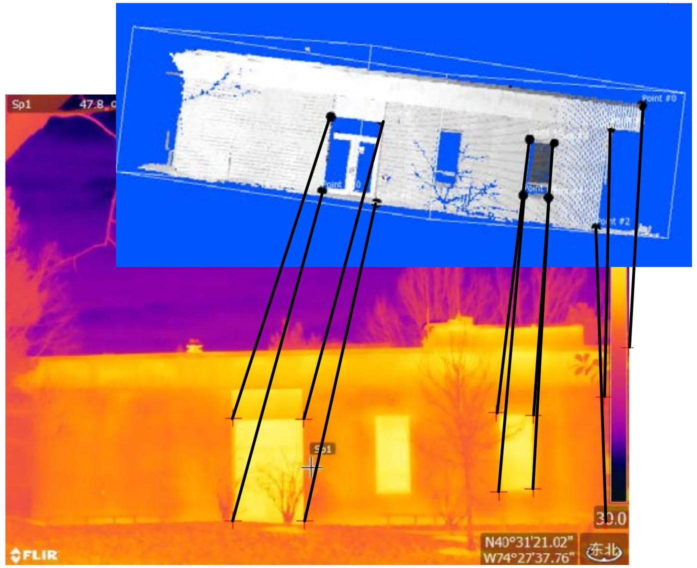


Step 4. Generation of Spatially Resolved Infrared Thermography

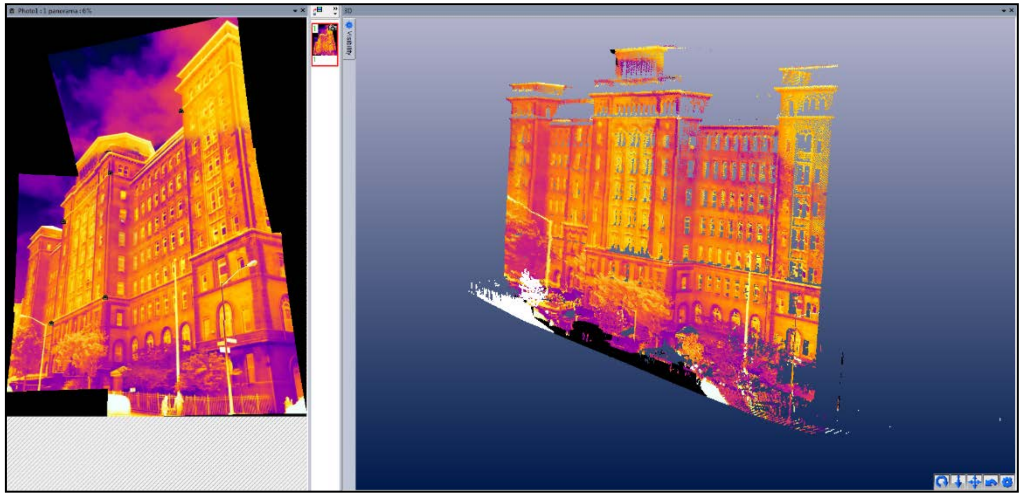


Generation of Spatially Resolved Infrared Thermography Data

Step 4. Generation of Spatially Resolved Infrared Thermography



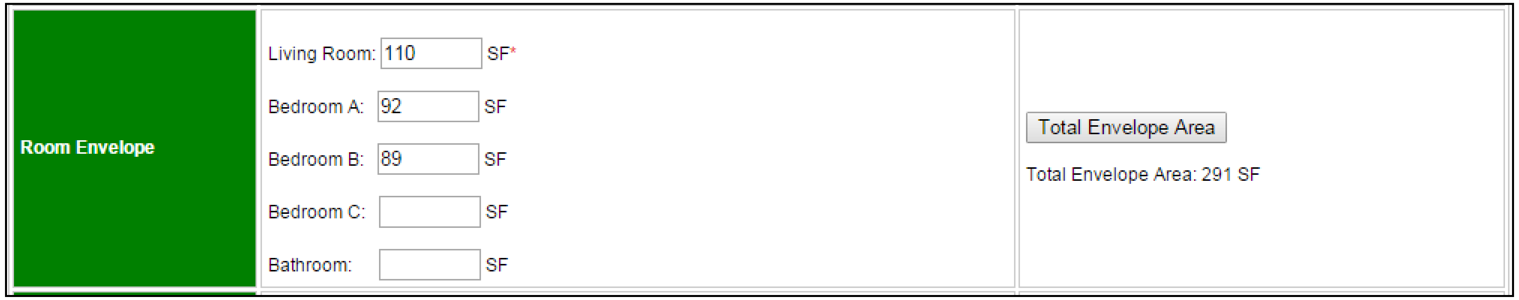
Common Point Detection → Identifying Mapping between Laser Scan Data and Infrared Data



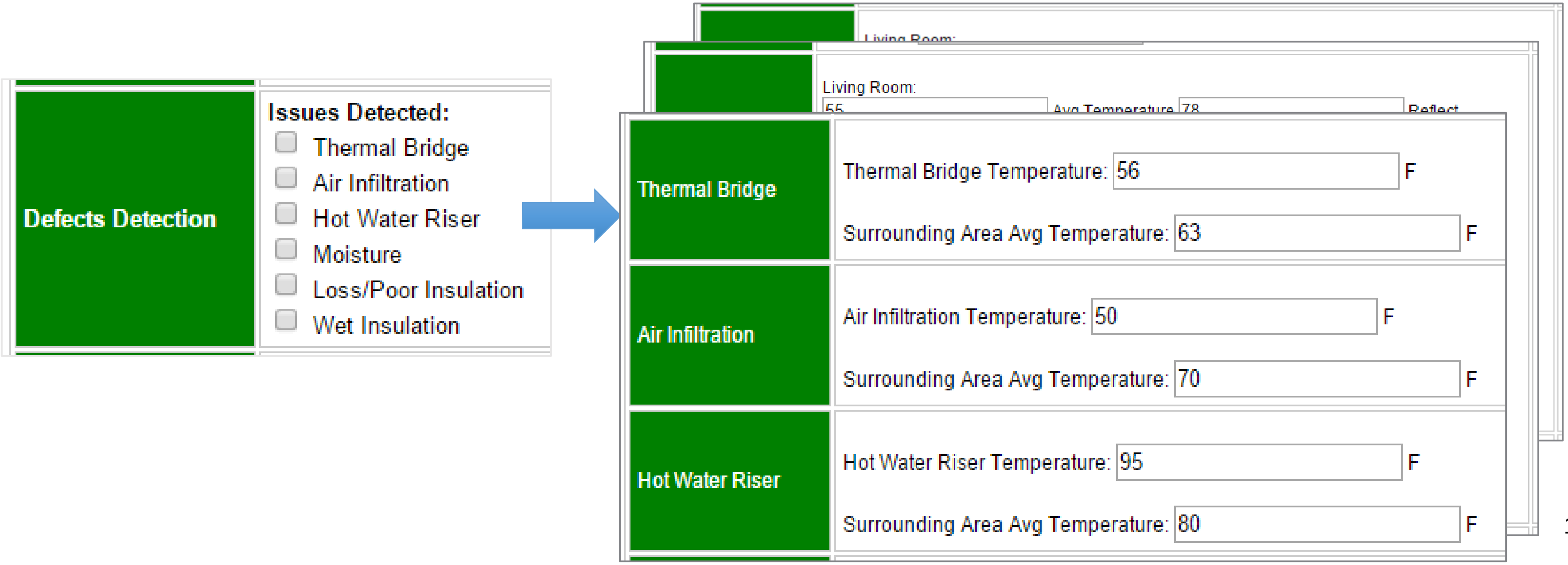
Spatially Resolved Infrared Data from Building 1 Exteriors

Step 5. Visualization and Processing of Data

Room Envelope Information



Defects Detection and Quantification



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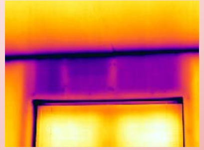
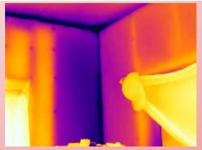
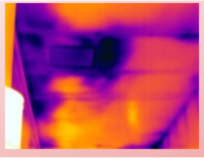
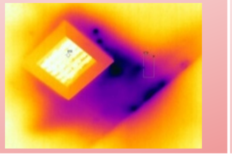
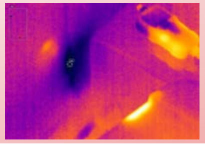
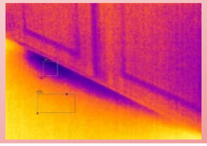
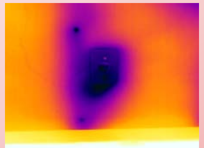
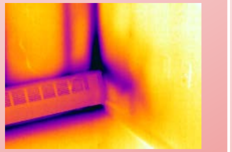
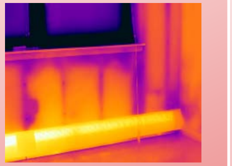
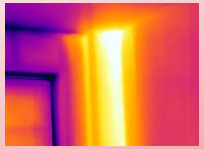
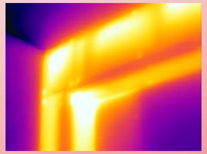
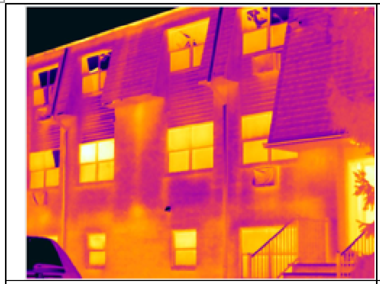
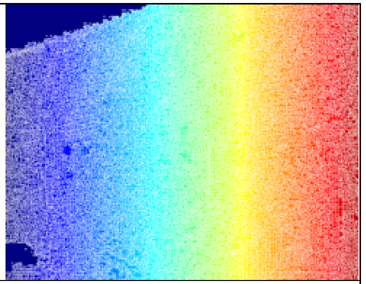
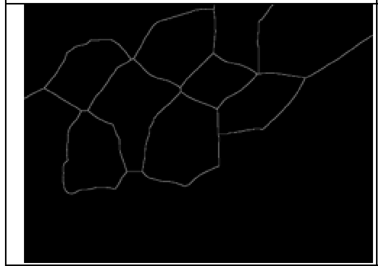
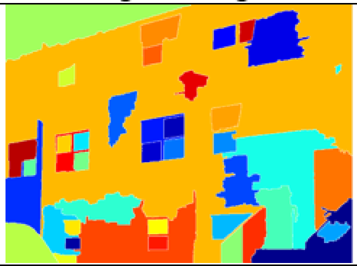
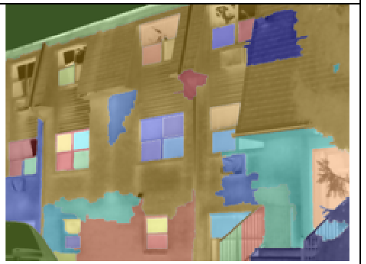
Detectable Building Defects by Infrared Thermography

Defect Types	Description	Infrared Image	Quantification
Poor/ missing insulation	Missing or poor insulation areas appear as light/dark colored patches with distinct edges outlining the problematic areas.	 	1. Poor or missing insulation area (sf) 2. Percentage of missing insulation (%)
Wet insulation	Wet insulation is often temporary and usually appears as areas without distinct edges.	 	1. Wet insulation area (sf) 2. Percentage of wet insulation area (%)
Moisture	Moisture areas usually appear as dark/cool areas without distinct edges.	 	1. Moisture issue area (sf)
Air leakage / Air infiltration	Air leakage usually appears as light/dark areas in building corners or near structural joints.	 	1. Temperature factor (f_{Rsi})
Thermal bridge	Thermal bridges usually appear as light/dark areas with linear features as they are often related to structural components that penetrate the insulation layers.		1. Temperature factor (f_{Rsi})
Hot water Riser	Components of HVAC systems are not well insulated, causing elevated temperature in part of wall surfaces.	 	1. Hot water riser surface area (sf) 2. Hot water riser surface temperature (°F)

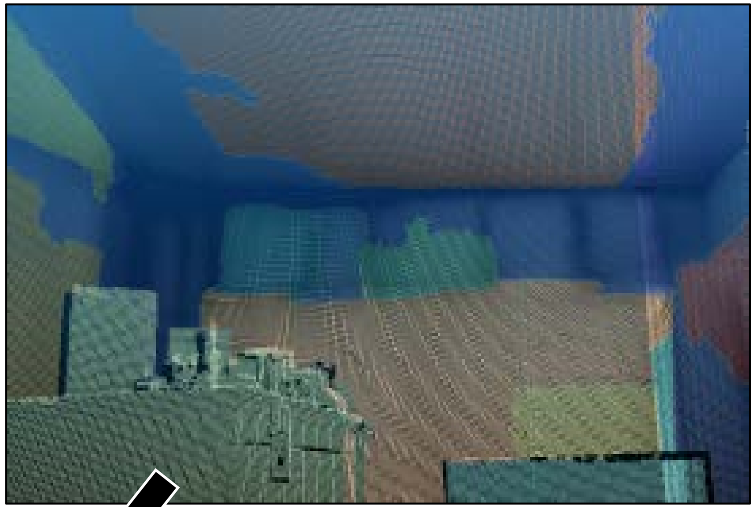
Temperature based Image Segmentation for Defect Detection

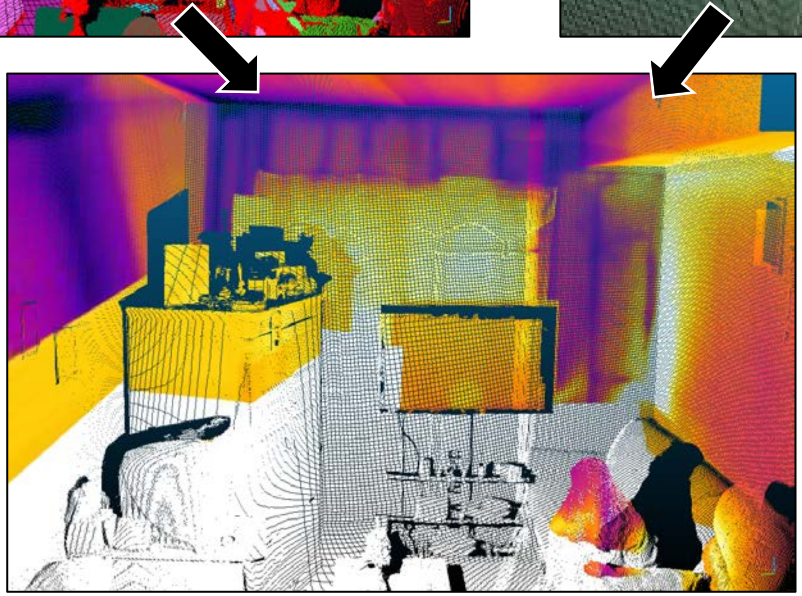
			
(A)Original IR image	(B)Gray-scale image	(C)Gradient magnitude by Sobel-operator	(D)Classical watershed segmentation algorithm showing oversegmentation
			
(E)Opening-closing by reconstruction	(F)Region maxima superimposed on original image	(G)Modified regional maxima superimposed on original image	(H)Thresholded opening-closing by reconstruction
			
(I)Watershed lines	(J)Markers and object boundaries superimposed on original image	(K)Colored watershed label matrix	(L)Colored watershed label matrix superimpose on the gray-scale image

Data Included with 3D Thermography Models

Point Cloud Segmentation

Infrared Image Segmentation





- Reasoning of Type of Detects
- Quantification of Defects

Summary of Performance Attributes for Bldg 1 and Bldg 2

Attribute (Median value)	Good Insulation(n = 4)	Fair Insulation (n = 12)	Poor Insulation (n = 4)
Thermal Bridge Temperature	70.55	71.15	65.75
Thermal Bridge Temperature Factor	0.78	0.87	0.63
Air Leakage Temperature	65.85	65.15	58.70
Air Leakage Temperature Factor	0.69	0.74	0.55
Missing Insulation Area (sf)	0.68	3.91	24.82
Missing Insulation Area (%)	0.22%	1.53%	10.59%
R-value	0.89	1.37	0.63

Apartment with Good Insulation Condition (Missing Insulation Area < 0.5%)
Apartment with Fair Insulation Condition (Missing Insulation Area < 5%)
Apartment with Poor Insulation Condition (Missing Insulation Area > 5%)

Lessons

- Do-it-yourself big data projects are feasible
- Technology getting cheaper
- Partner with technologists
- Data analytics are key

Correlations (winter)

Missing Insulation (Area in sq. ft) ↑

- **Particle concentration** ↑
- **Temperature and relative humidity** ↓
- **Bioaerosols, endotoxins and allergens** ↓
- **Apartment location on top floor & corners** ↑

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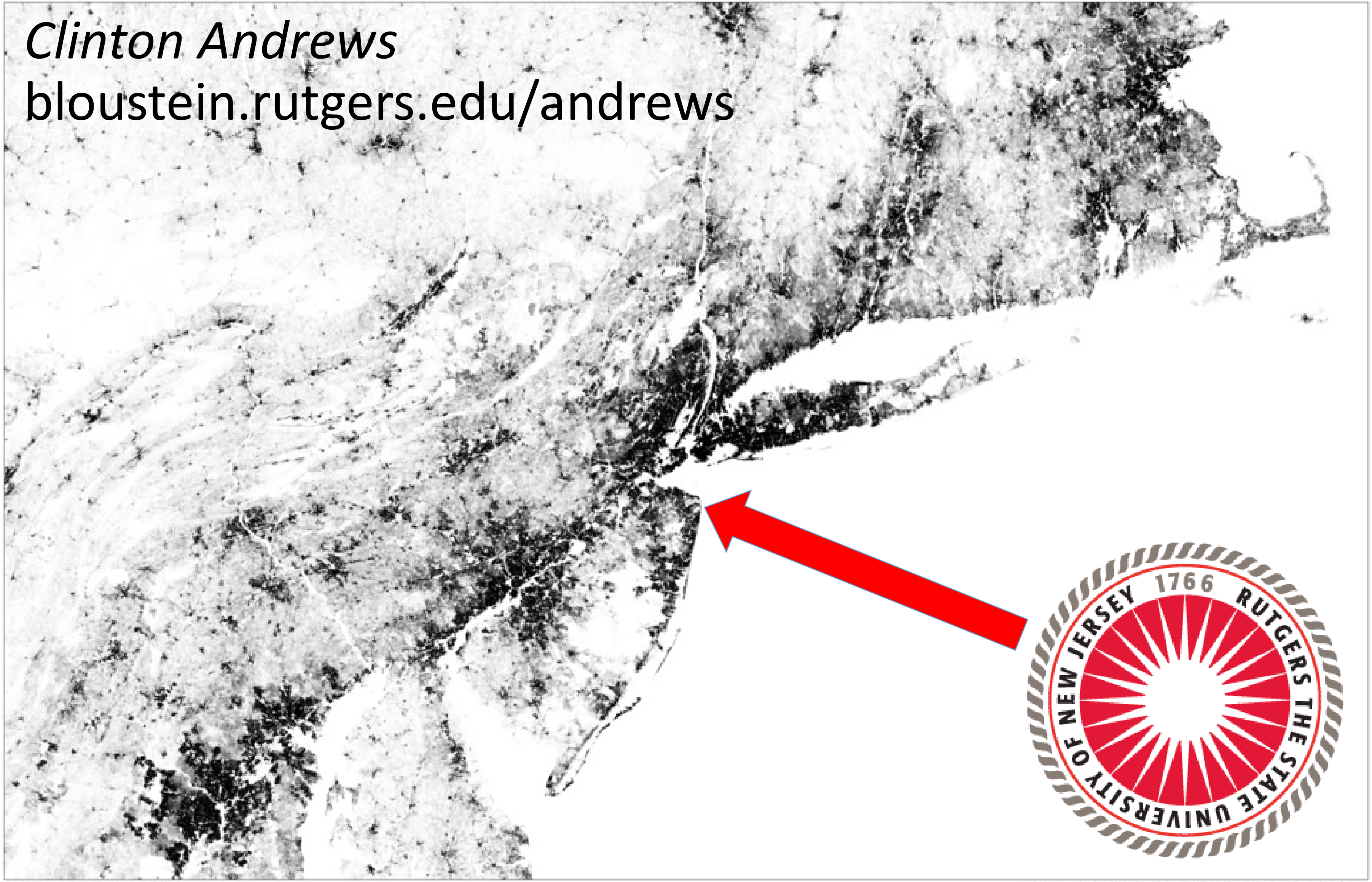
bloustein.rutgers.edu/andrews



https://c1.staticflickr.com/9/8352/8413200469_70fe75511d_b.jpg