Using Sensors to Assess Environmental Exposures

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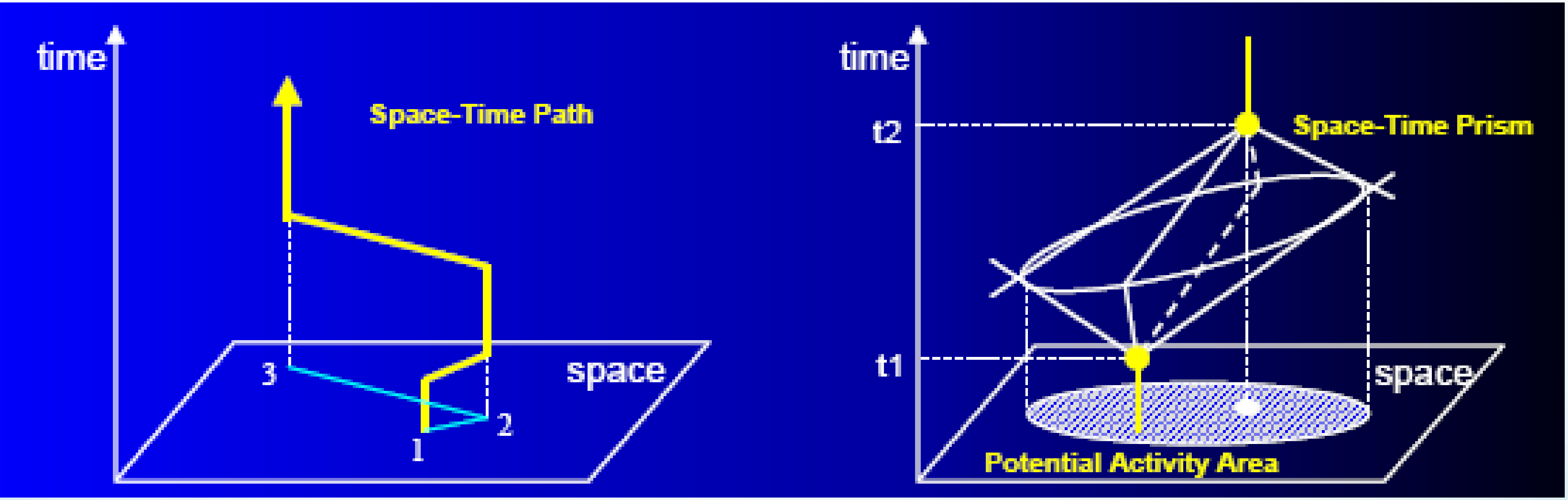
Map of the Talk

- Time Geographies and the lifeline of exposures
- Ubiquitous sensing in a Ubicomp World
- Applied examples with air pollution, built environments and physical activity
  - Smart phone sensors
  - Stand alone micro-sensors
  - Embedded sensor networks
  - Some key issues and future directions

Time Geographies of Exposure

- Physical space-time paths are the dominant determinants of environmental exposures
- Torsten Hägerstrand's "Time Geography" a critical geographic concept for the exposure
- Exposure can be viewed as summation of travel through "hazard fields" in space over time

Space-Time Prism:
What Exposures and Activity Levels?



Source: Shaw (2005)

Lifelines of Exposures

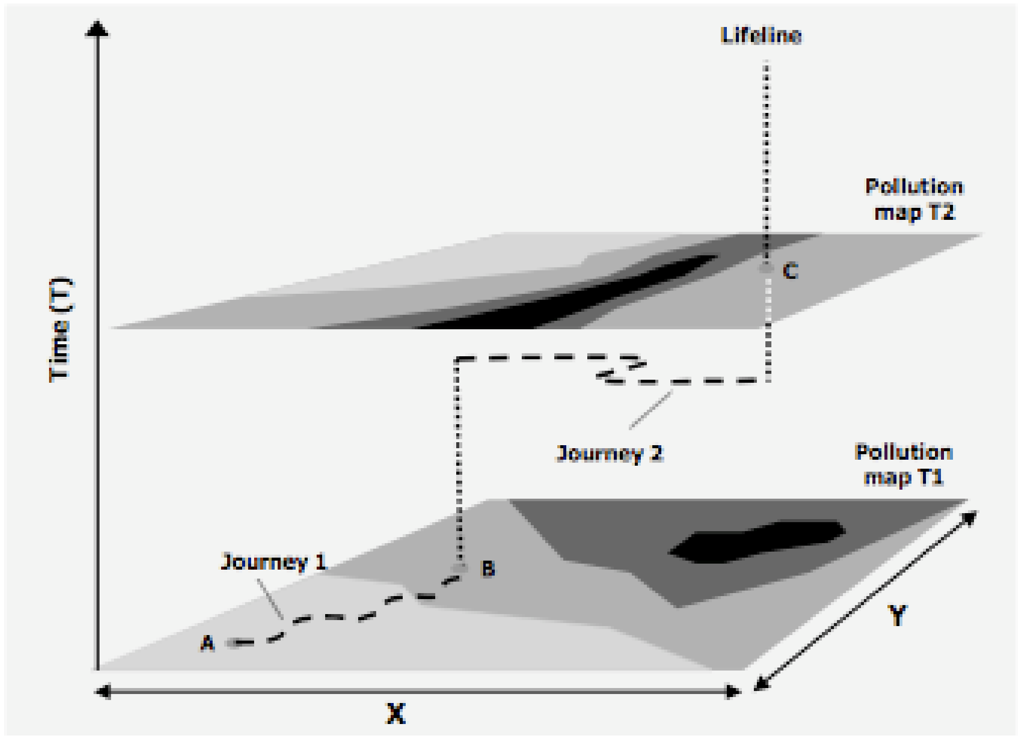


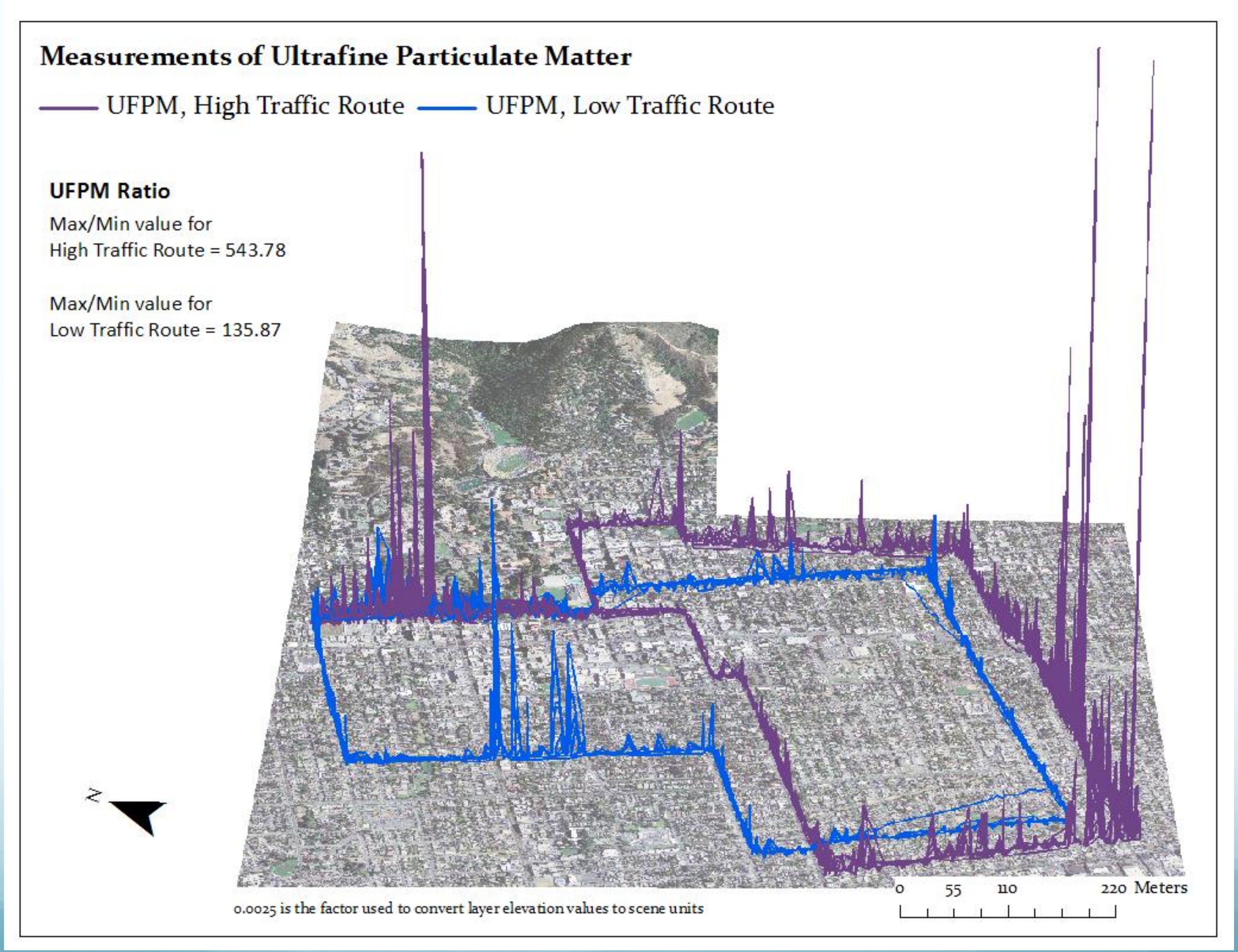
FIGURE 1. Lifelines and pollution fields.

- What is the activity level, activity type and physiology at the moment of contact?

Source: Briggs and Gulliver (2005)

What is the Activity Level in the Exposure Field?

Air Pollutant Concentrations on Bike Routes in 3-D



Source: Jarjour et al. (2013)

Inhalations During Exercise by Mode of Transport

MODE	Mean concentrations by travel mode and urban fixed site monitor (London, UK)			Typical inhalation rate (L/min)*	Typical journey duration for a 4km trip (minutes)**
	PM2.5 (ug/m3)		**CO** (ppm)		
Bus	39	35	0.8	4.5	20
Car	36	38	1.3	4.5	12
Bicycle	29	34	1.1	37	17
Walking		35	0.9	23	48
Subway	202			10	16
Fixed site monitor	14	10	0.3		
Reference	(Adams et al. 2001)	(Kaur et al. 2005)			

Source: de Nazelle et al. 2011

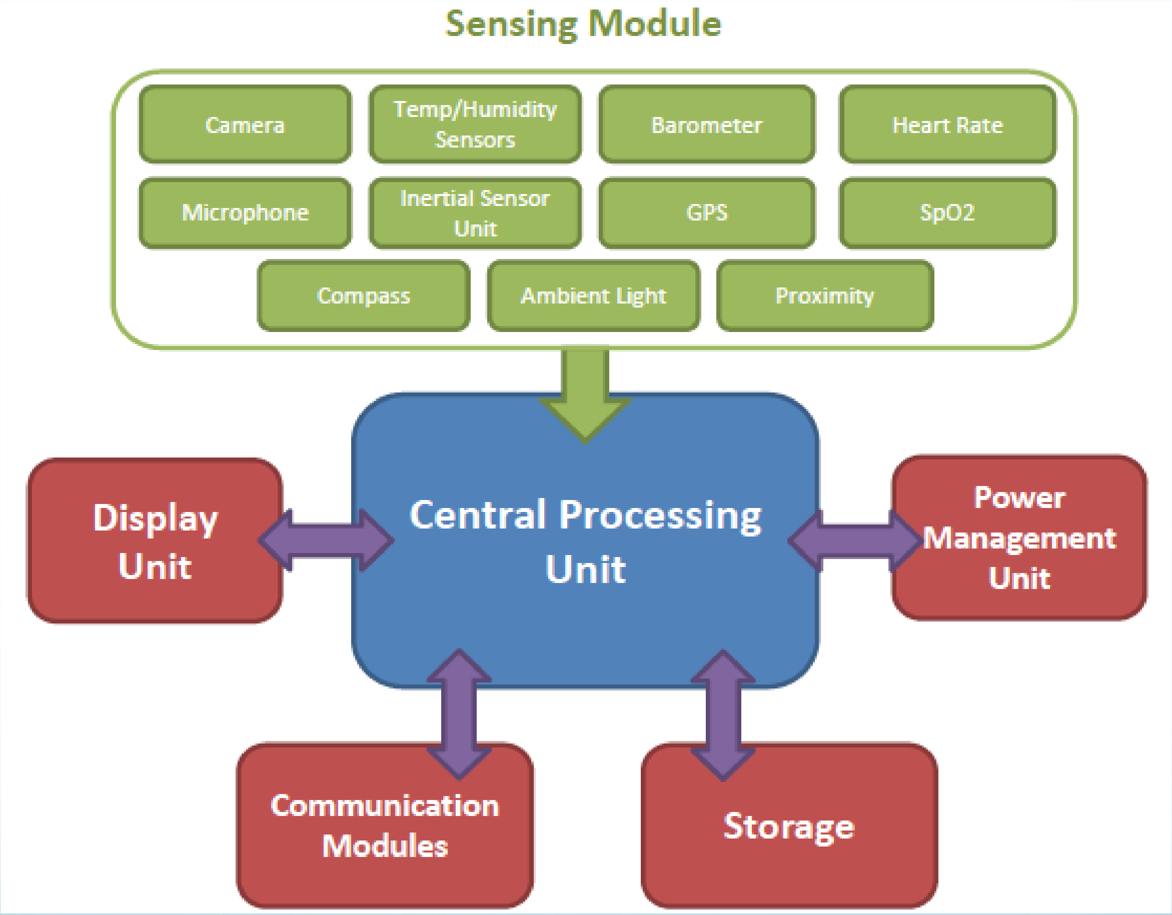
Time Geographies

- Important conceptually, but have remained more theoretical construct than empirical reality
- Or attempts to develop them have had to rely on simulation models which often have had weak data support
- New technologies offer the first realistic possibility of direct measurements on large numbers of subjects
- Opportunity to understand "micro-geographies" of *personal* exposure – which can be used in epidemiological studies and everyday life

Time Geographies of Exposure in a Ubicomp World

- Following the vision of Mark Weiser (1991) – ubiquitous computing or "Ubicomp" world
- The complete embedding of computational technology into our everyday lives
- Being driven by health care sector (e.g., field of telemedicine) and other commercial applications related to mobile phones (now 7 billion cell phones globally, more than 1.5 billion smart phones)
- Huge potential to sense many aspects affecting environmental exposures and health

Components of Cellular Smart Phone



Higher Burden

Type of Sensor / Type of Sensing	Opportunistic Personal Sensing	Participatory Personal Sensing
On Cell Phone	Location with GPS, Physical Activity, Trip Mode (e.g., walk, bike, drive, public transit), proximity to others	Ecological Momentary Assessment of Mood and Affect, Gait and position, Noise, UV Exposure, Blood Oxygen, Heart Rate, Dietary Assessment
Connected to Cell Phone, but Requiring External Device	None	Air Pollution, Water Pollution, Noise, Ultraviolet Exposure, Blood Pressure, Sleep
Stand Alone Sensors	None	Physical Activity, Location, Noise, Air Pollution, Chemical Exposures, Numerous Biological Functions

Review of 25 Sm Phone Models

Key Points:

All smart phones measure location, proximity, orientation physical activity

Large variation in types and quality of sensors on smart phones

COMPLICATES the collection of comparable data from large populations

Source:
Nameti, Batteate Jerrett (2017)

Smartphone Model	Accelerometer	Barometer	Color spectrum	Fingerprint	Gesture	Gyroscope	Heart rate	Humidity	Iris scanner	Magnetometer	Proximity	Sensor core	SpO2	Temperature	UV
	Embedded sensors on-board phone														
Samsung Galaxy Note 4	•	•		•	•	•	•			•	•		•		•
Samsung Galaxy Note7*	•	•		•		•	•		•	•	•		•		
Samsung Galaxy Note5 & Duos	•	•		•		•	•			•	•		•		
Samsung Galaxy S6 & edge	•	•		•		•	•			•	•		•		
Samsung Galaxy S7, active & edge	•	•		•		•	•			•	•		•		
Samsung Galaxy S8	•	•		•		•	•			•	•		•		
Samsung I9500/5 Galaxy S4	•	•			•	•		•		•	•			•	
LG G5 & SE	•	•	•	•		•				•	•				
Microsoft Lumia 950 & XL	•	•				•			•	•	•	•			
Apple iPhone 6, 6s & plus	•	•		•		•				•	•				
Apple iPhone 7	•	•		•		•				•	•				
Huawei Mate 9	•	•		•		•				•	•				
Huawei Nexus 6P	•	•		•		•				•	•				
Motorola Moto X & 2nd Gen X	•	•				•				•	•			•	
Samsung Galaxy S6 active	•	•				•	•			•	•				
Sony Xperia X & Performance	•	•		•		•				•	•				
Sony Xperia Z5 Premium & Dual	•	•		•		•				•	•				
Amazon Fire Phone	•	•				•				•	•				
HTC One (E8)	•	•				•				•	•				
Motorola Nexus 6	•	•				•				•	•				
Sony Xperia Z5 Dual	•	•				•				•	•				
Sony Xperia Z3+	•					•				•	•				

* recalled by manufacturer due to a battery safety issue

Smart phone study: Location, activity patterns and air pollution

Aim: *Test novel opportunistic and participatory sensing technology to assess activity patterns and air pollution exposure*

Methods:
36 volunteers equipped with 3 activity measurement devices including novel smart phone technology CalFit and reporting daily travel activity during 5 days

Contents lists available at SciVerse ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

ELSEVIER

Improving estimates of air pollution exposure through ubiquitous sensing technologies

Audrey de Nazelle [a,b,c,d,*,1], Edmund Seto [e], David Donaire-Gonzalez [b,c,d,f], Michelle Mendez [b,c,d,g], Jaume Matamala [b,c,d], Mark J. Nieuwenhuijsen [b,c,d], Michael Jerrett [e]

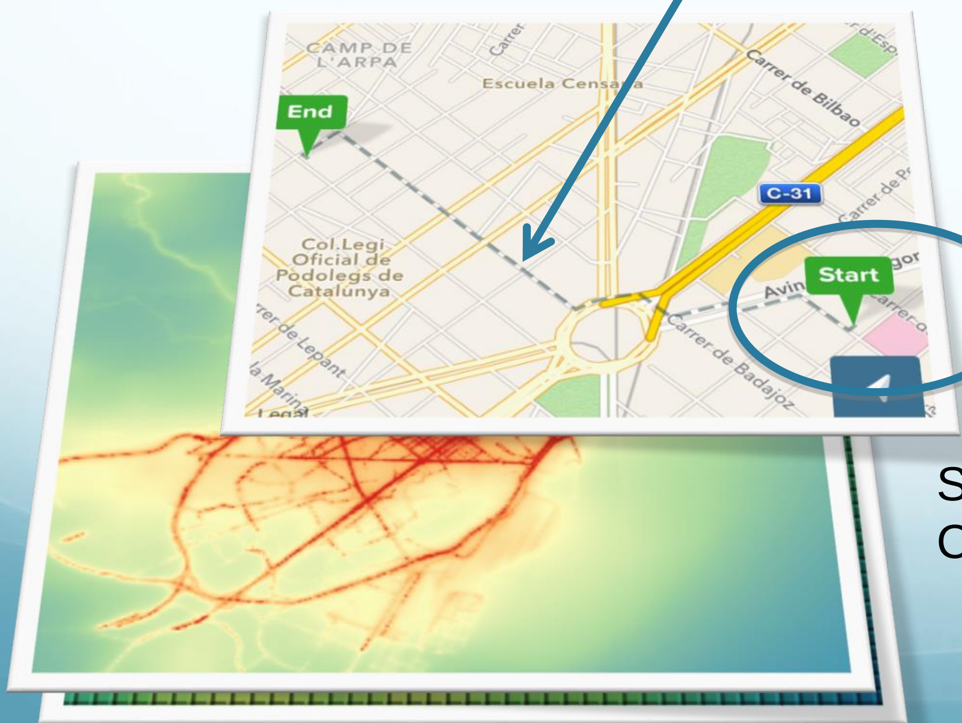
A. Methods

Hour and day specific ratio using background station

Mode correction factor: Bicycle, car, walking, bus, train (...)

Indoor/Outdoor Ratio

Personal exposure to air pollution

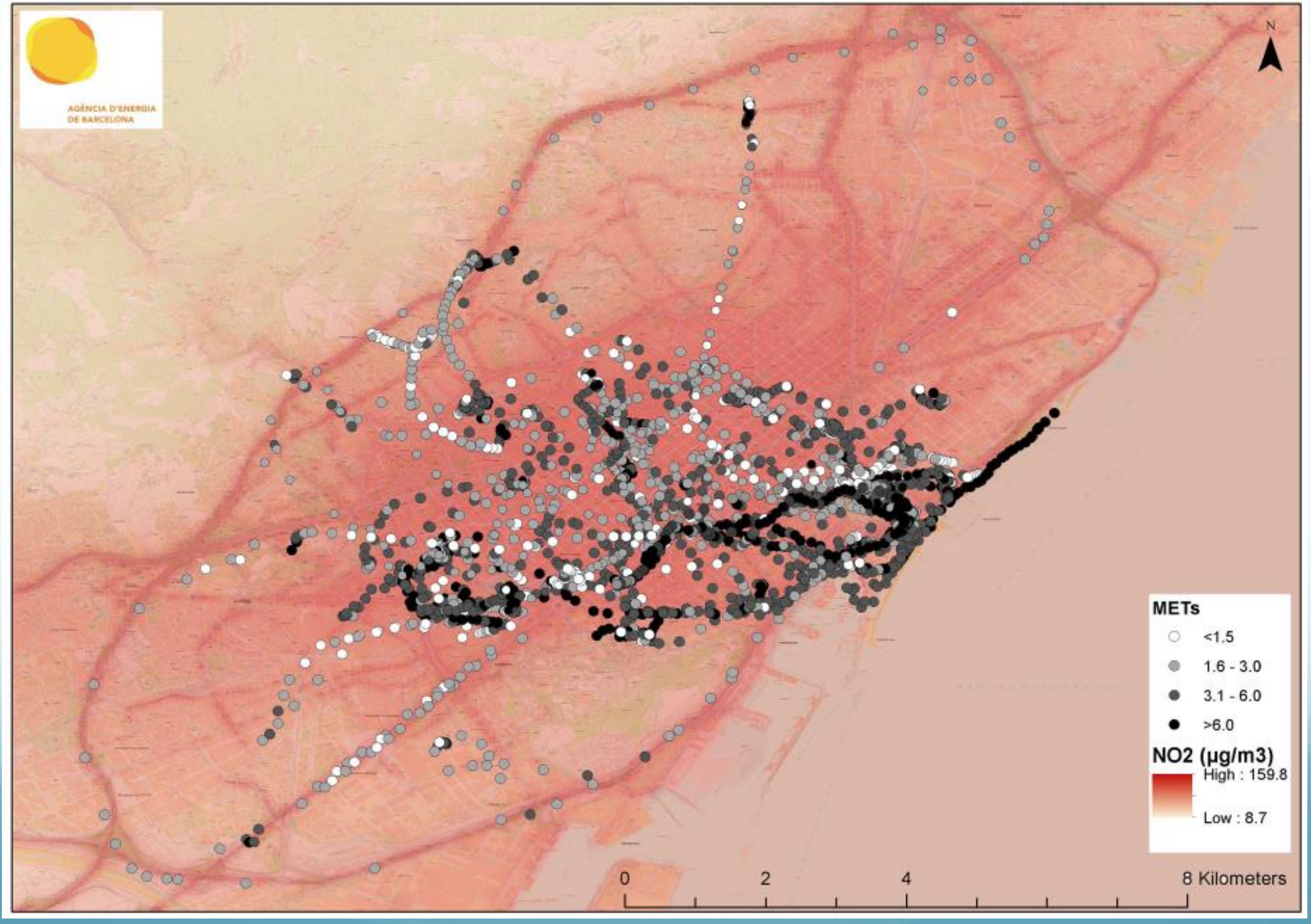


Energy expenditure from accelerometer data

Source: Courtesy of A. de Nazelle

Air pollution inhalation

volunteer
+ air pollution map (NO2)



Travel microenvironments, air pollution, and health

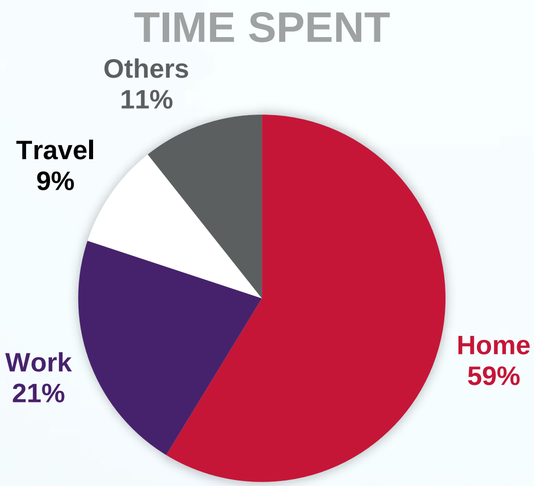
- **Travel microenvironments**
- (Barcelona sample, de Nazelle et al. 2013):

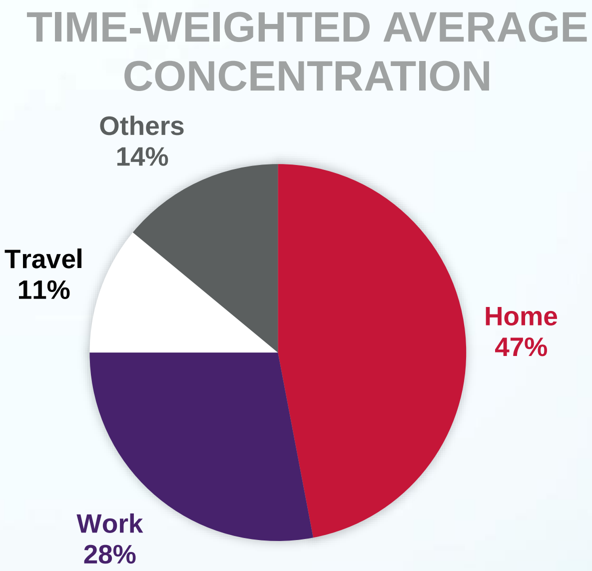
6% Time

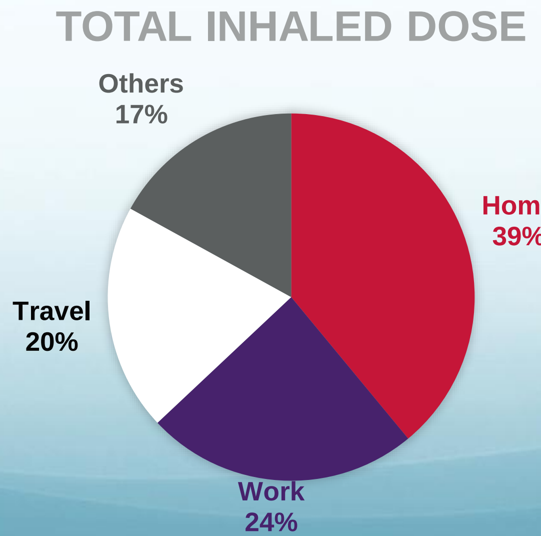
11% NO_2 exposure

24% NO_2 inhalation

Next step: 174 participants







Source: Juan Pablo-Orjuela's MSc thesis 2014

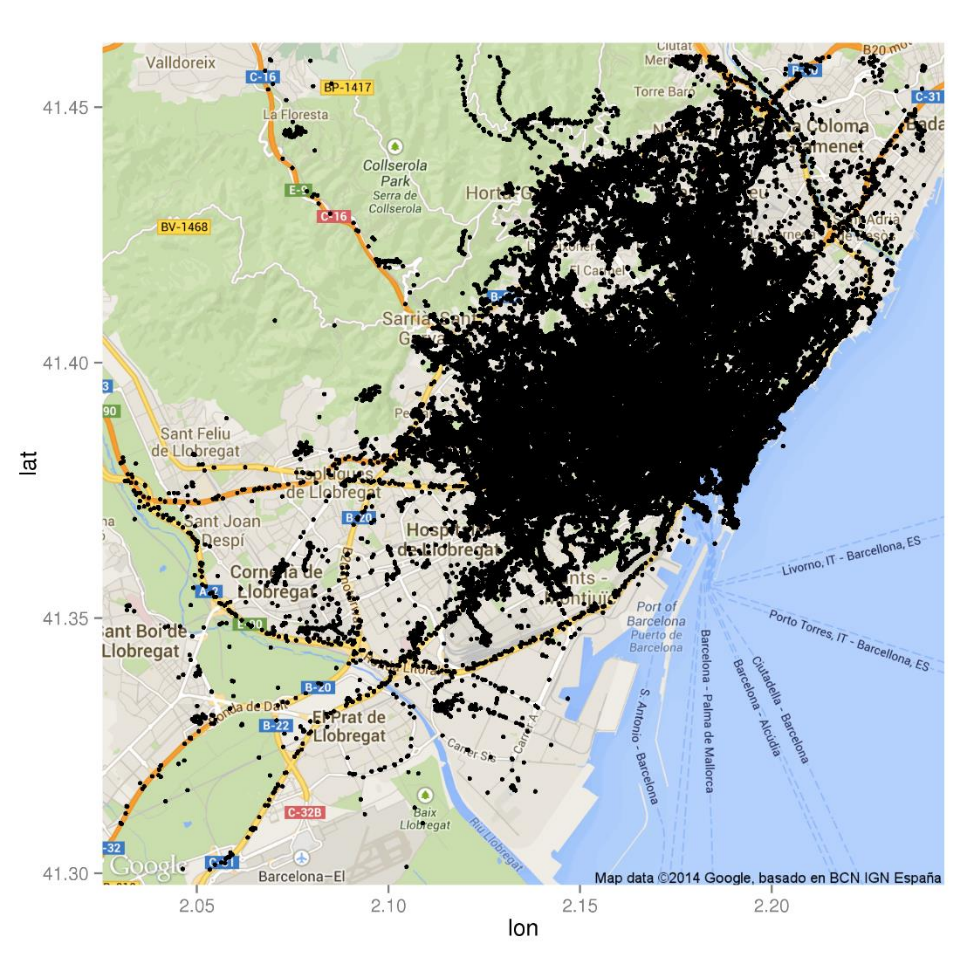
activity (i.e. phone) –based exposure assignment

	NO_2 (μgm^{-3})	$PM_{2.5}$ (μgm^{-3})
Home-based exposure	56.5	24.6
	+20%	+22%
Activity-based exposure	67.8	30

GPS Traces from 174 Subjects: Big Data Fast!

Some 10,886,400 observations per week for just 2 sensors on CalFit Phone

If cohort is 1,000,000 people 60,480,000,000!



Lessons

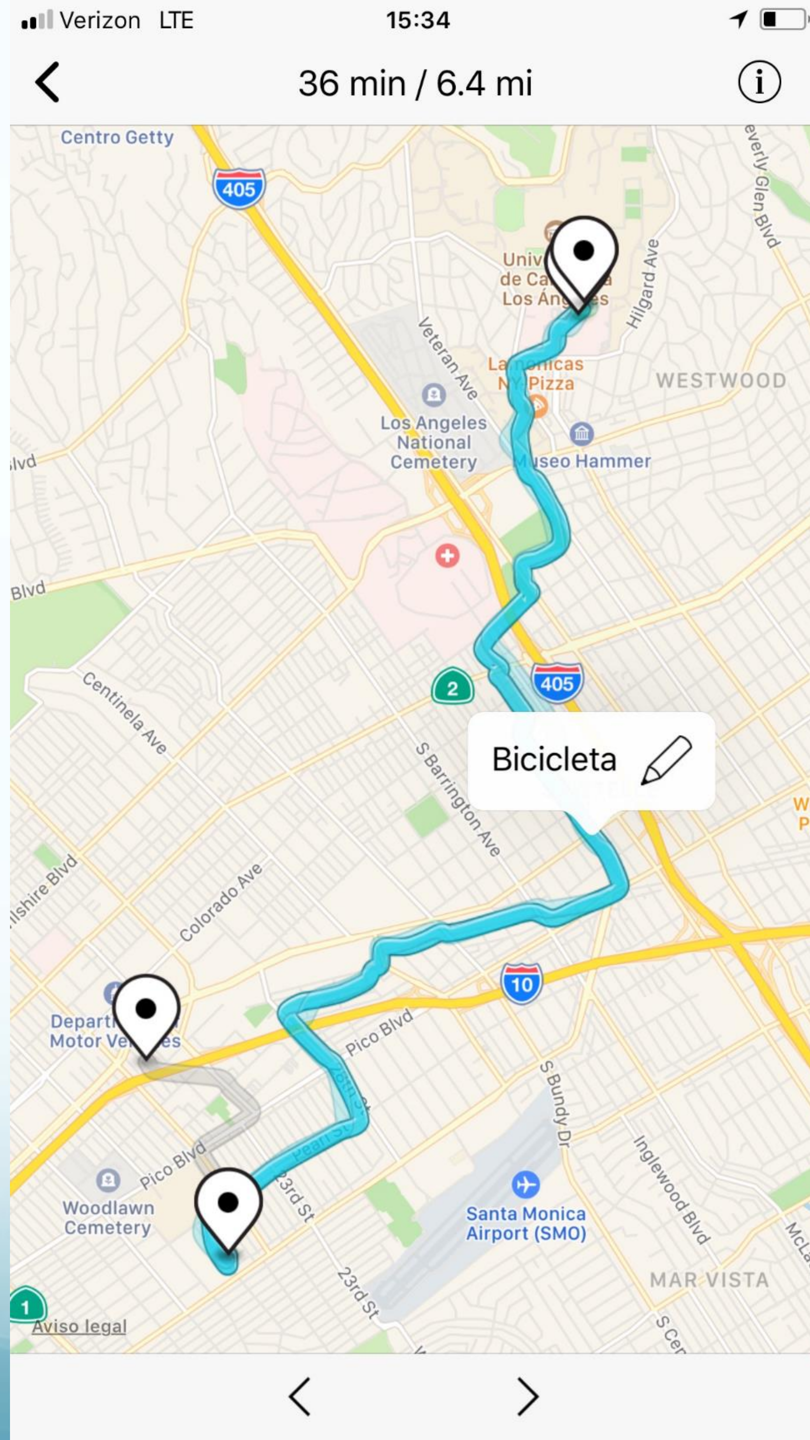
- Location and physical activity can be linked to exposure surfaces to derive “lifelines” of exposure
- This information can significantly improve estimates when fused with models
- Data are very big, messy and a lot of work to deal with
- Sustainability of the applications and distribution to mass populations limited

Activity Tracking with Commercial Cell Phone Applications: MOVES

Please follow the steps below to download and install the MOVES App on your phone!

Choose a phone:

Android iPhone



Verizon LTE
15:34
36 min / 6.4 mi
Centro Getty
405
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Hilgard Ave
WESTWOOD
Los Angeles
National
Cemetery
Centinela Ave
2
405
Bicicleta
S Barrington Ave
Colorado Ave
Pico Blvd
10
S Bundy Dr
Inglewood Blvd
Woodlawn
Cemetery
Pico Blvd
23rd St
Santa Monica
Airport (SMO)
MAR VISTA
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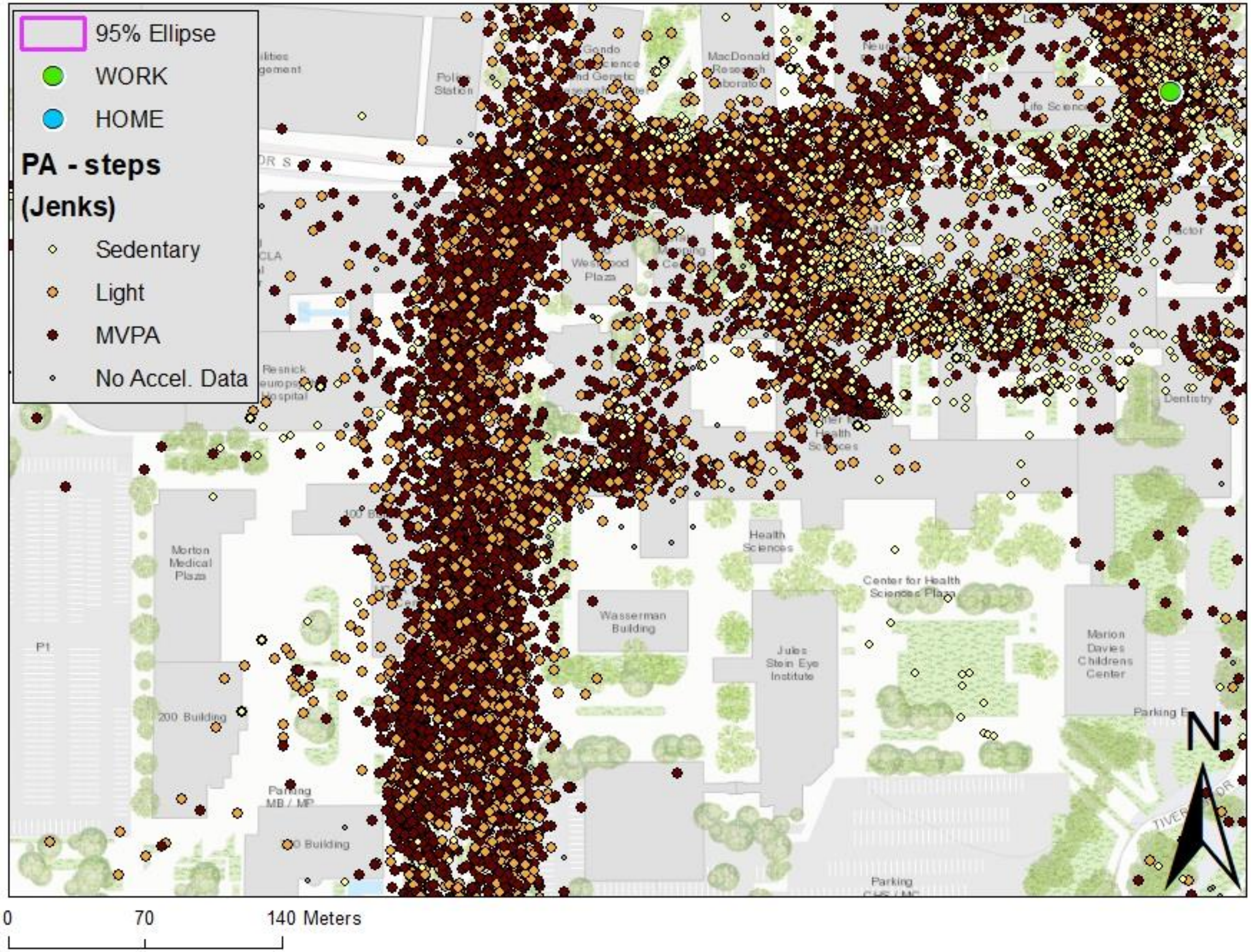
Aviso legal


95% Ellipse
WORK
HOME
PA - steps (Jenks)
Sedentary
Light
MVPA
No Accel. Data
0
70
140 Meters
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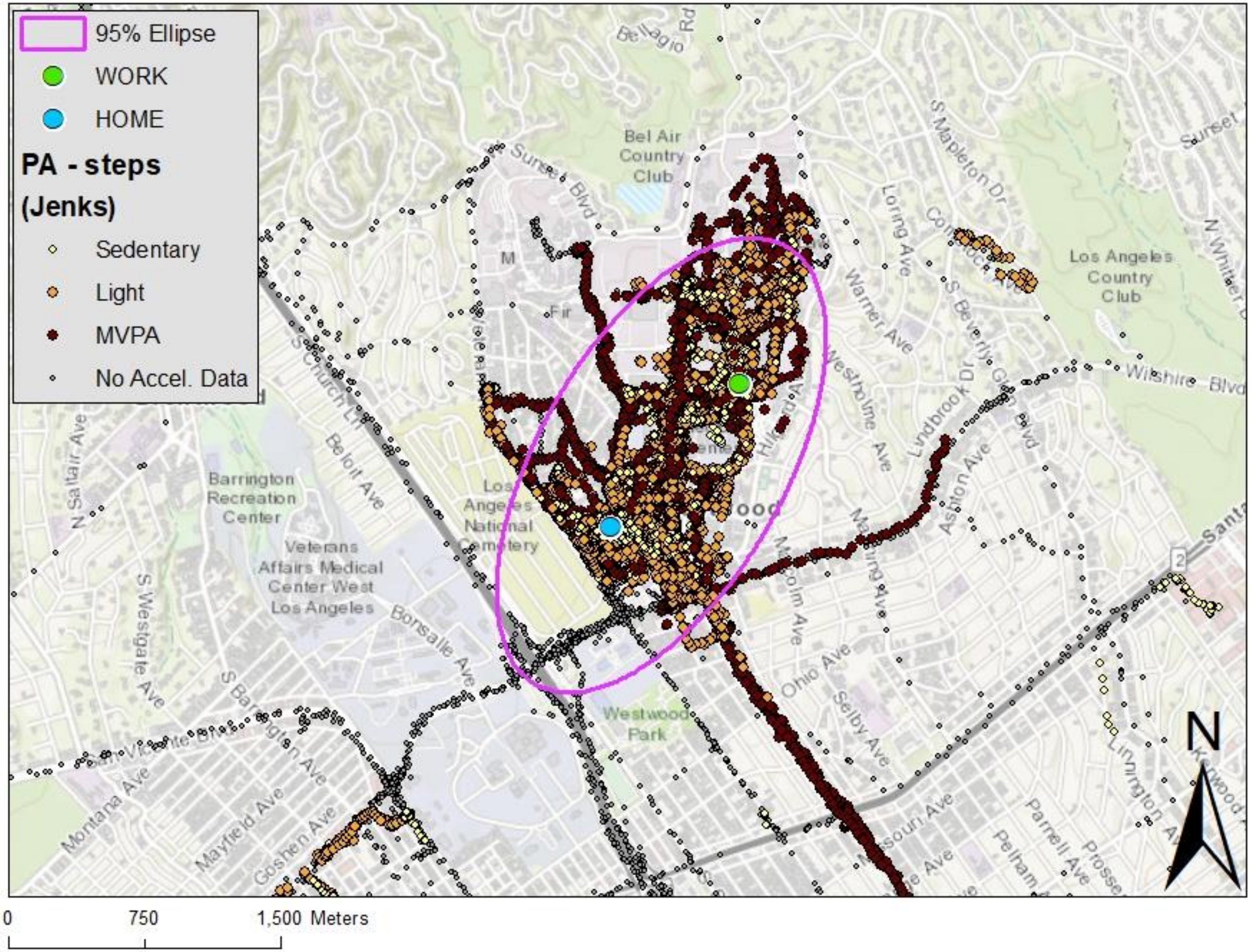
Morton Medical Plaza
200 Building
Wasserman Building
Jules Stein Eye Institute
Health Sciences
Center for Health Sciences Plaza
Marion Davies Childrens Center
Dentistry
Parking
P1


95% Ellipse
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(Jenks)
Sedentary
Light
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No Accel. Data
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1,500 Meters
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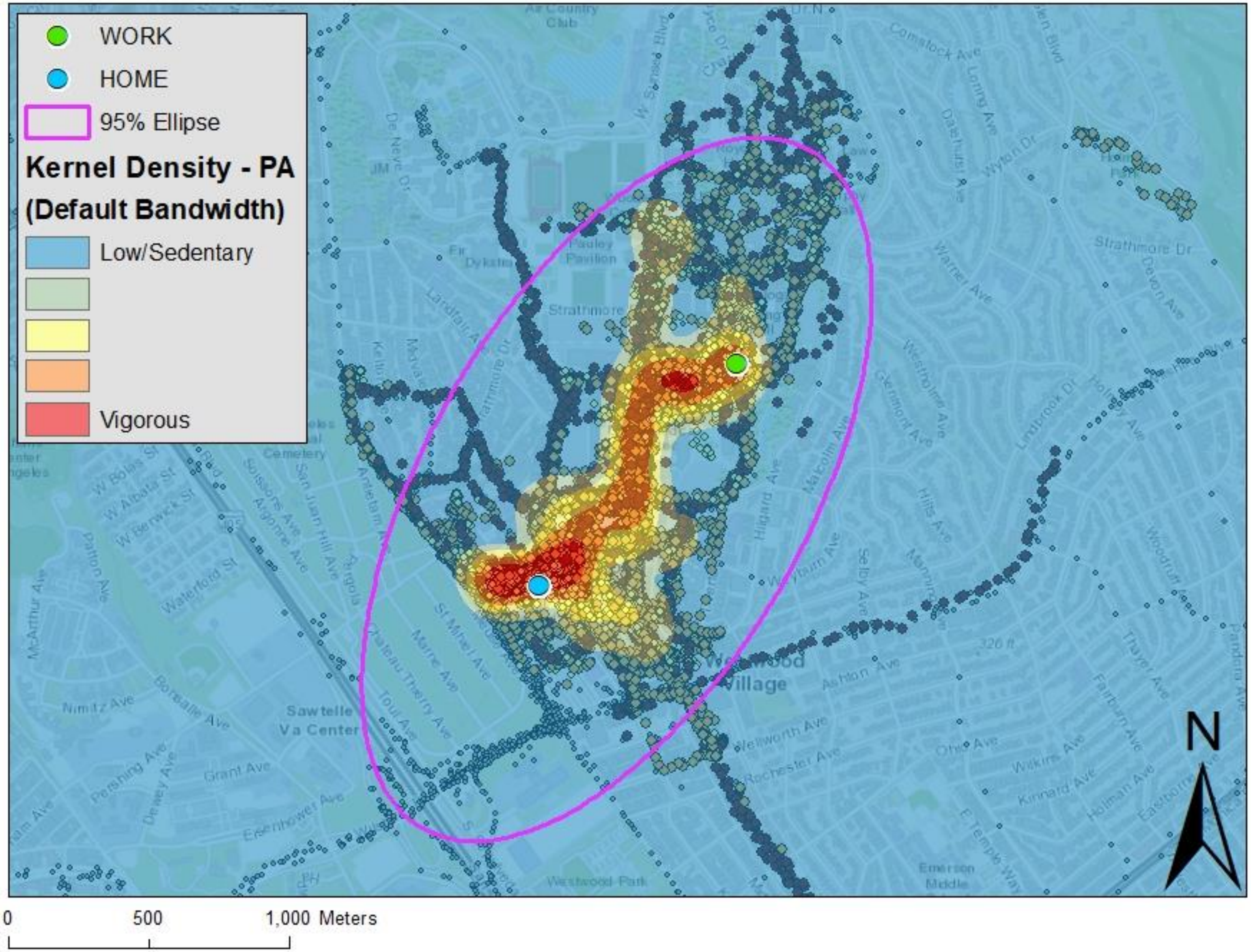

WORK
HOME
95% Ellipse
Kernel Density - PA
(Default Bandwidth)
Low/Sedentary
Vigorous
N
0
500
1,000 Meters

Nested Validation Study

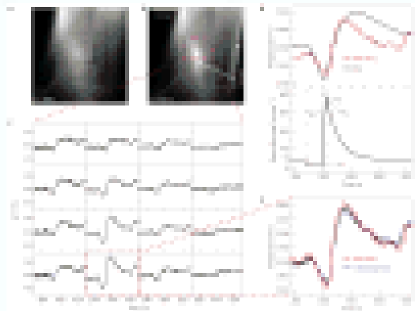
(subsample of 150 participants used *to validate MOVES app data using research-grade monitoring devices)*

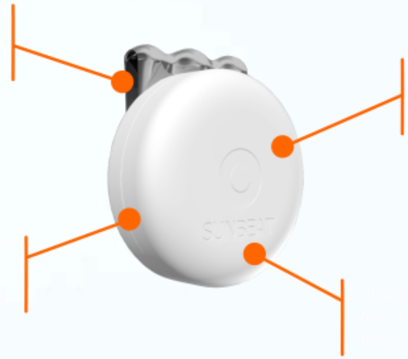
ActiGraph wGT3X-BT for *accelerometry*

GlobalSat BT-500 for GPS/location

External Sensors, Technology Moving Fast

Radiation





Environmental Science & Technology

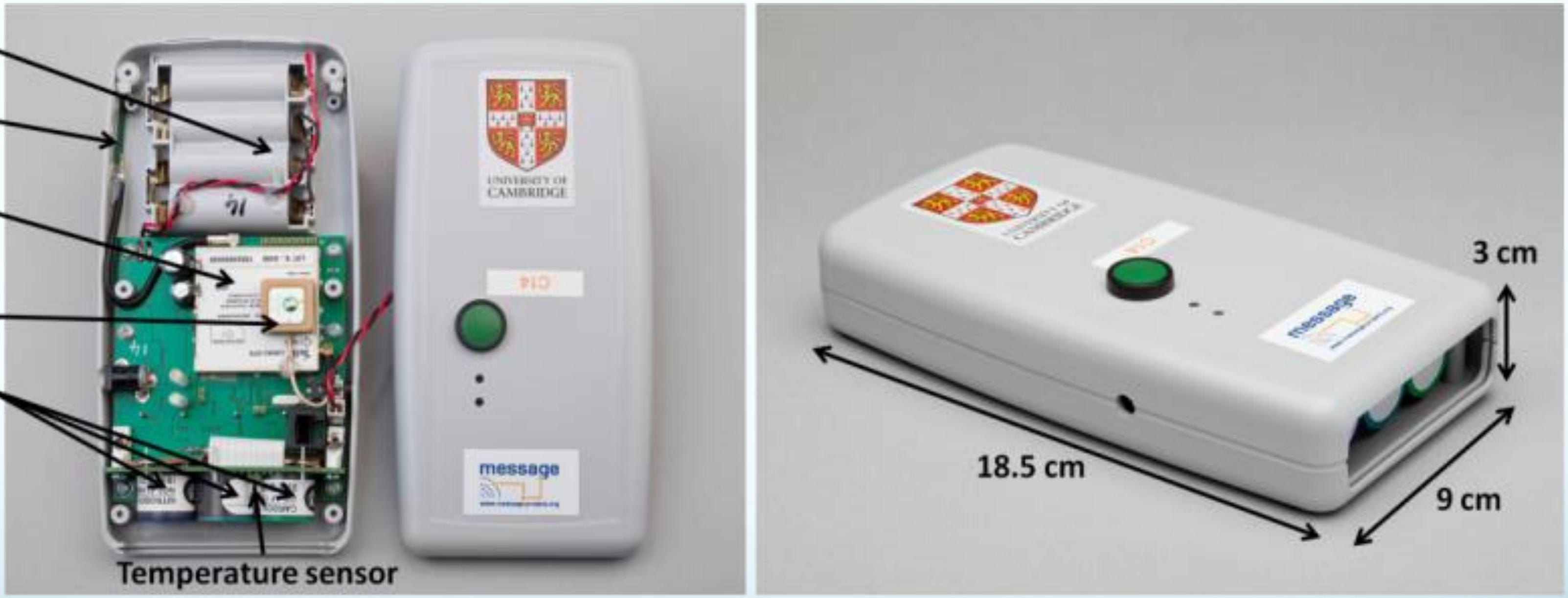
Feature

pubs.acs.org/est

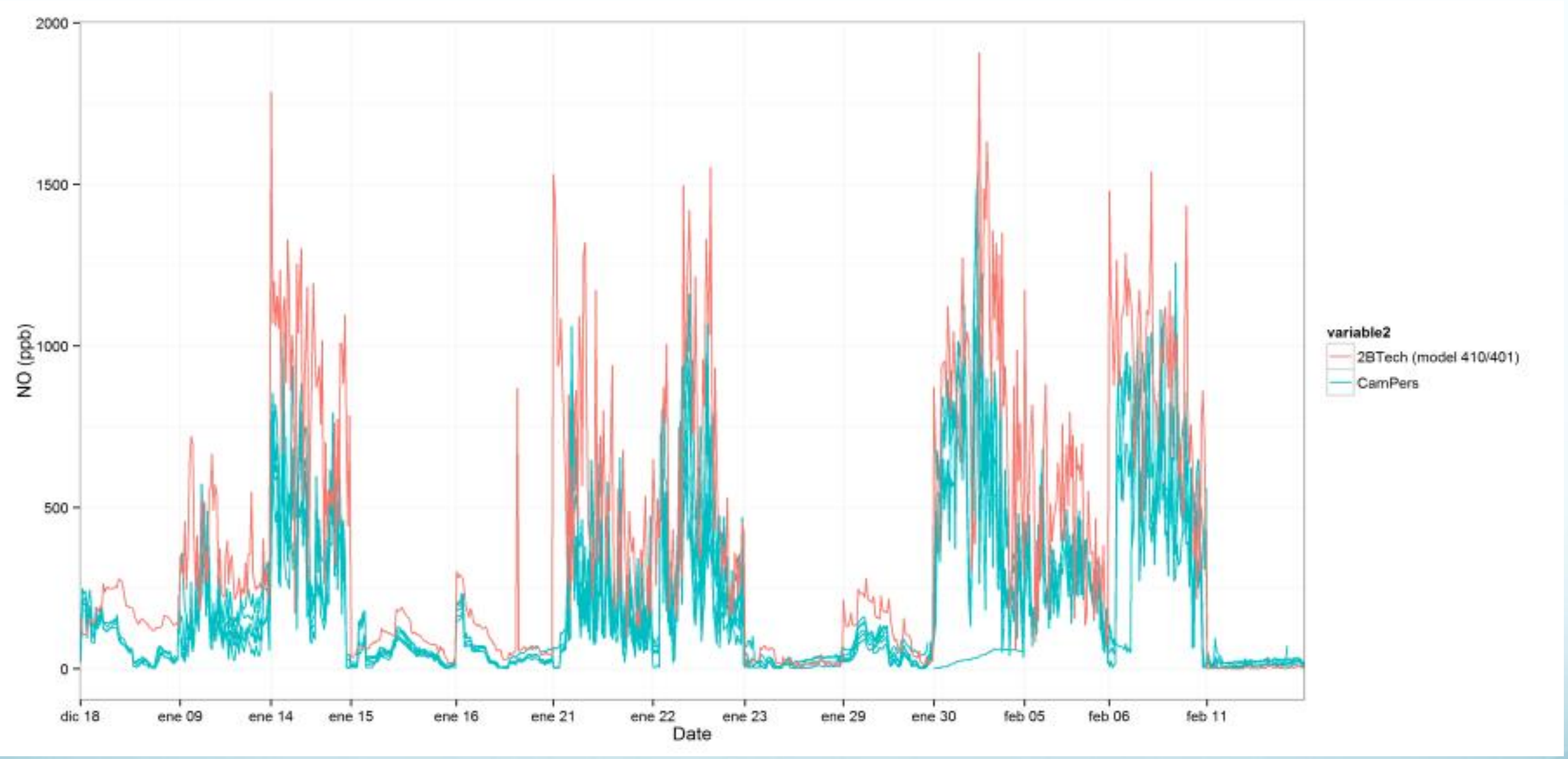
The Changing Paradigm of Air Pollution Monitoring

Emily G. Snyder,*[,†] Timothy H. Watkins,[†] Paul A. Solomon,[‡] Eben D. Thoma,[†] Ronald W. Williams,[†] Gayle S. W. Hagler,[†] David Shelow,[§] David A. Hindin,[∥] Vasu J. Kilaru,[†] and Peter W. Preuss[⊥]

Cambridge Pollution Monitor (R. Jones)



Correlation of NO with Reference Monitor



Differentiating Micro-Environments

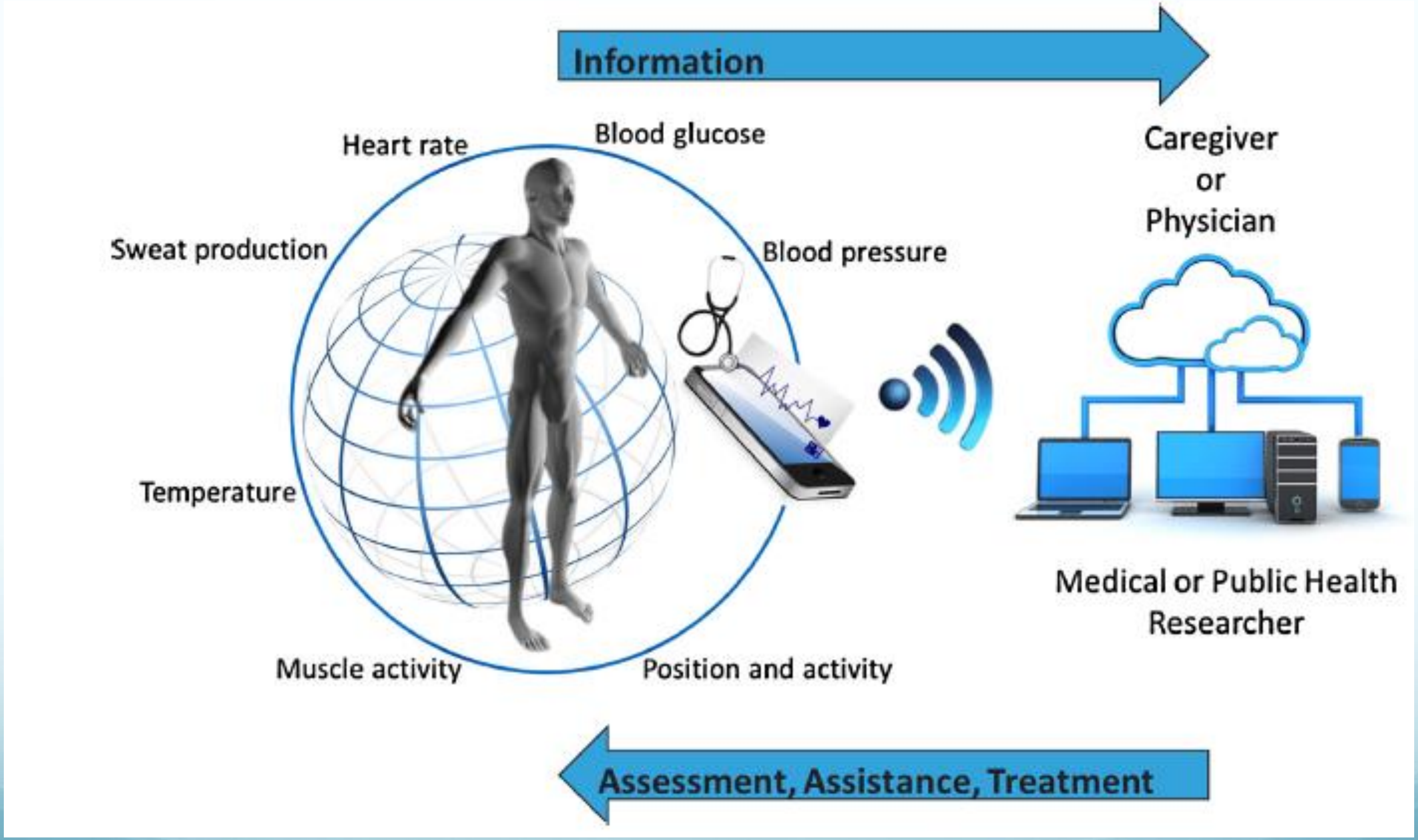
	NO (ppb)	CO (ppm)
	Coefficient (95% CI)	Coefficient (95% CI)
Intercept (Urban Background)	55.6 (46.1 , 65.2)	1.46 (1.37 , 1.55)
Blue Space	-32.3 (-35.5 , -29.1)	-0.68 (-0.73 , -0.63)
Green Space	-32.8 (-36.0 , -29.6)	-0.71 (-0.76 , -0.66)
Free Living	3.6 (1.0 , 6.3)	-0.17 (-0.21 , -0.13)
In-vehicle	89.4 (85.1 , 93.6)	1.27 (1.2 , 1.33)
Indoors in Lab Setting	-14 (-17.2 , -10.7)	-0.25 (-0.30 , -0.20)
Low Traffic	-34.6 (-38.2 , -30.9)	-0.46 (-0.52 , -0.40)
High Traffic	284 (280.3 , 287.8)	2.69 (2.64 , 2.75)
Pseudo R-square	0.47	0.28

Source: Jerrett et al. 2017

Lessons

- Decent correlation with reference instruments, but there is bias, unreliability and extensive post processing needed
- Human resource cost of post-processing counterbalances low cost of equipment
- Currently infeasible for large studies, but potentially useful for smaller studies with lots of $$

Rapid Development of Real-time Biomonitoring

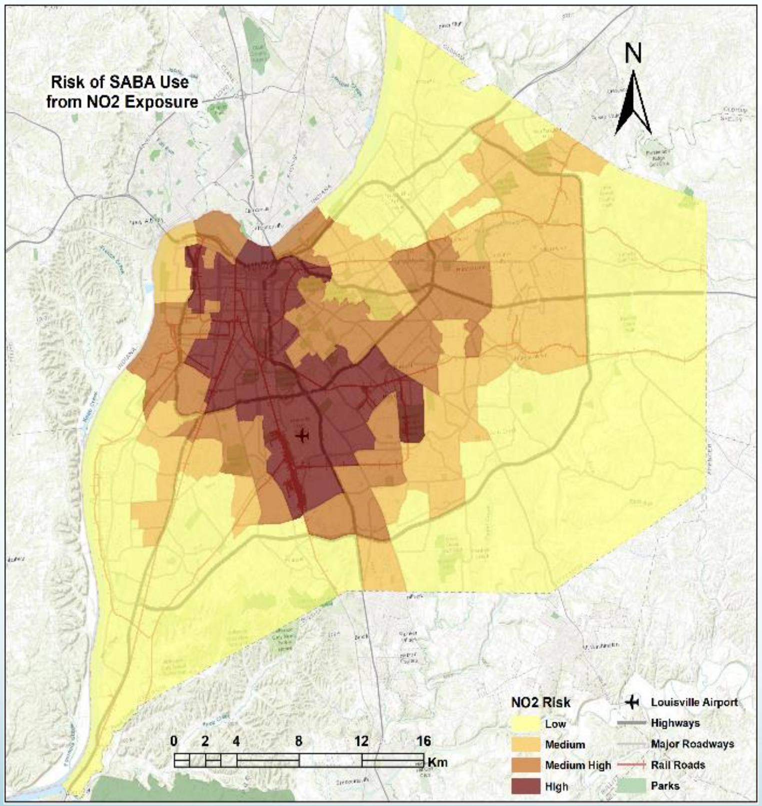


Source: Smoulders and De Boever 2014

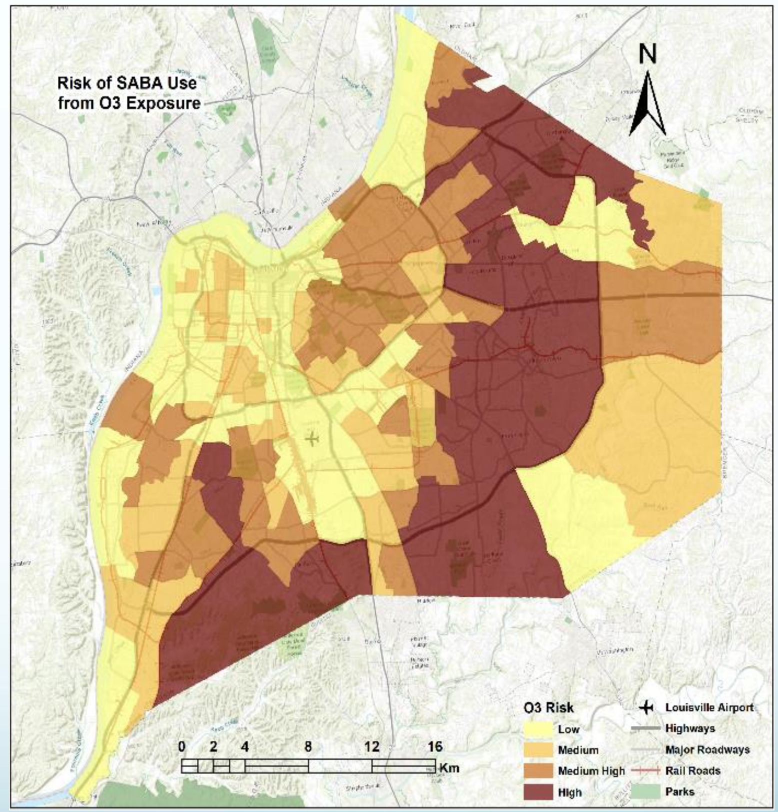
Propeller Health Asthma Sensor

Use of short-acting bronchodilators in relation to nitrogen dioxide and ozone

NO_2



O_3



Source: Su et al. in review

Real-time Biomonitoring

- Offers potential to understand instantaneous biophyiscal response to environmental exposure lifeline

- Leads to much greater capacity to assess causality of observed associations

Citizen Science and Ubiquitous (Embedded) Sensors

- Citizens often very interested and attuned to environment exposures, which gives them motivation to help
- They represent a huge resource for data collection in partnership with government and academics

Imperial Valley CA Location

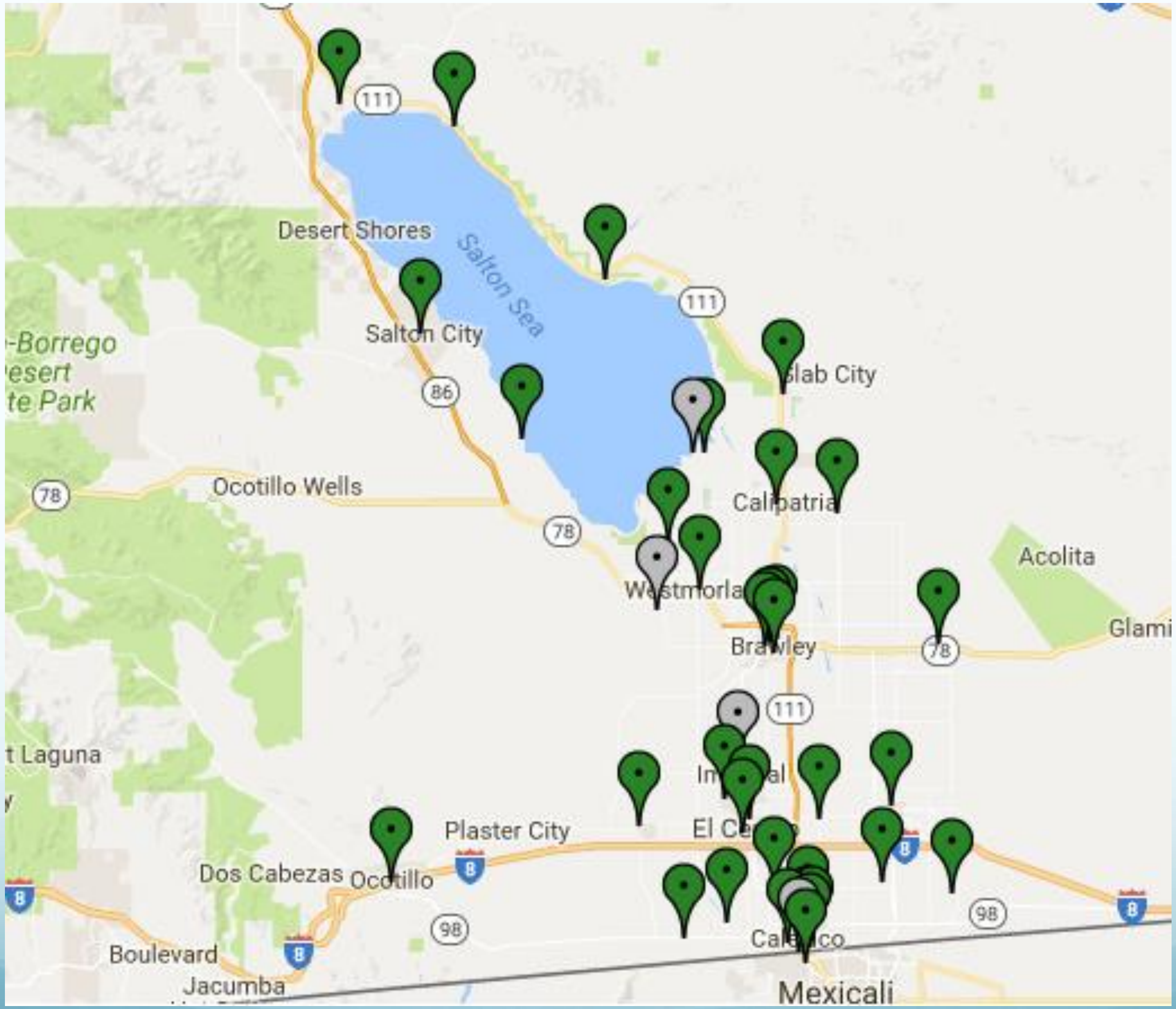
Source: https://www.worldatlas.com/na/us/ca/c-imperial-county-california.html

Community-based mapping and monitoring of air pollution

English P (PI), Bejarano E, Carvlin G, Jerrett M, King G, Lugo H, Meltzer D, Northcross A, **Olmedo L**, Seto E, Wilkie A, Wong M

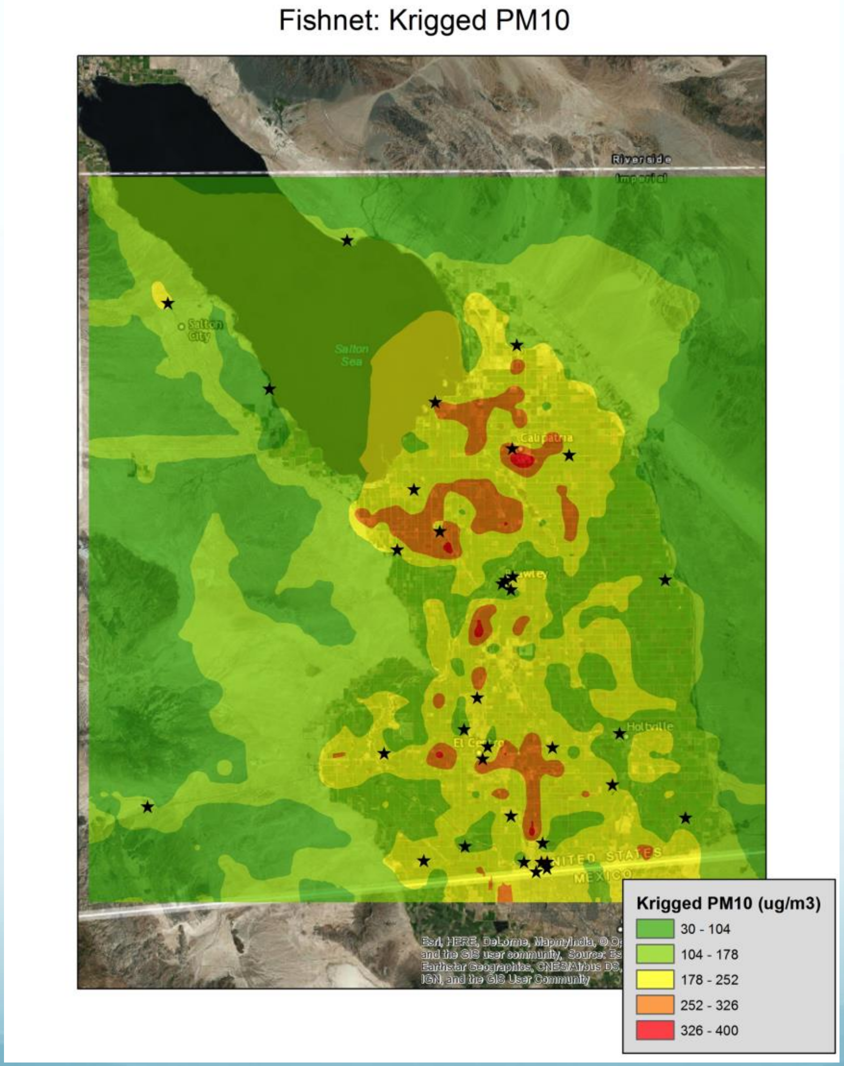
Major Problems with Agricultural Crop Burns: Episodic Beijing Levels of Pollution

Current Sensor Distribution
Largest Community Air Network in U.S.



Citizen Scientists with Dylos Particle Monitor and Enclosure

Land Use Regression Model with Smoothed Prediction Surface



Slide Courtesy of C. Carvlin and E. Seto

Detecting Pollution Episodes

- Community monitors detected 1426 episodes of $PM_{2.5}$ above 35 ug/m^3 for 1 hour or more over 11 months
- Government monitoring networks detected only 703 episodes (49% of total)
- Huge increase in the opportunity to warn public about health risks

Lessons

- Higher spatial and temporal coverage could lead to much better predictions of exposure for epidemiological studies and public health protection
- When combined with locational and physical activity data can provide near real-time exposure estimates
- Data analyses extremely laborious

Routine Video Monitoring

- Routine collection at millions of sites worldwide
- Can be use for tracking behavior change before and after natural experiments occur
- Particularly useful for tracking pedestrian and bike flows

Source: Hipp 2017 Pers. Comm.

AMOS

1,114,978,199 images and counting

Welcome to AMOS, the Archive of Many Outdoor Scenes!

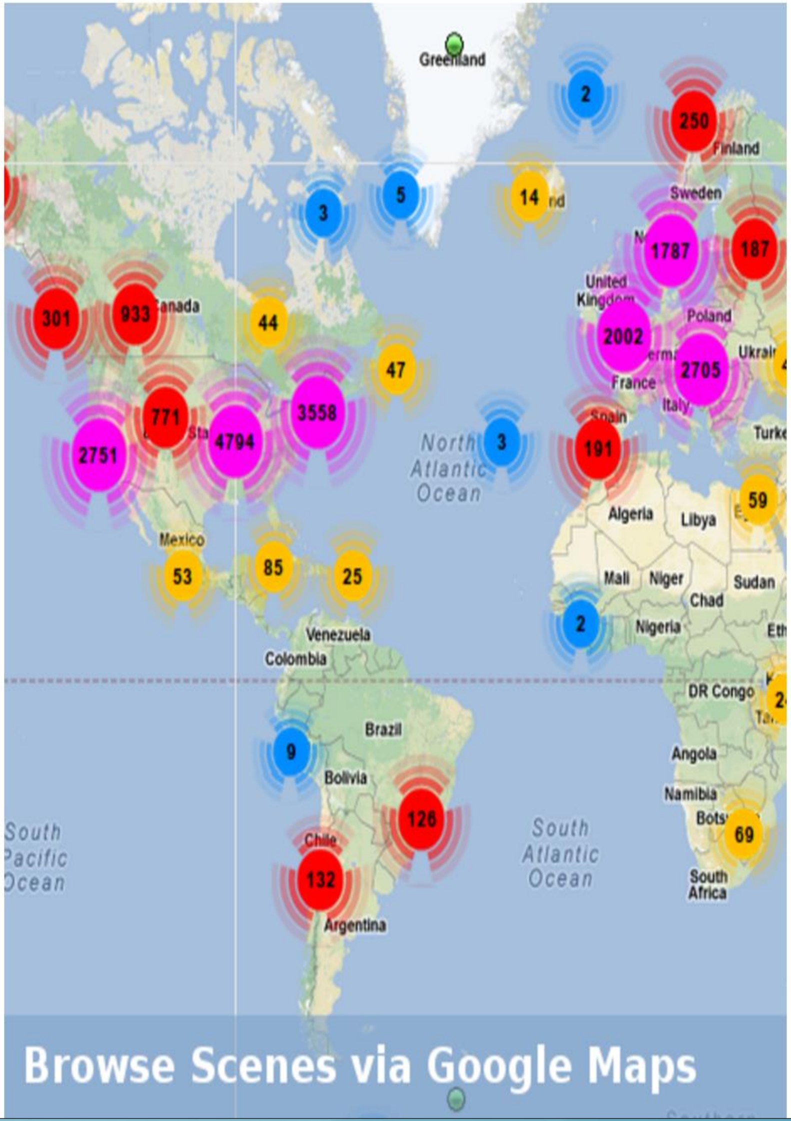
AMOS is a collection of long-term timelapse imagery from publicly accessible outdoor webcams around the world. We explore how to use these images to learn about the world around us, with a focus on understanding changes in natural environments and understanding how people use public spaces.

To support these applications, we work on fundamental research in camera geolocation, camera calibration, camera registration to GIS data, and the automatic annotation of events and objects in a scene.

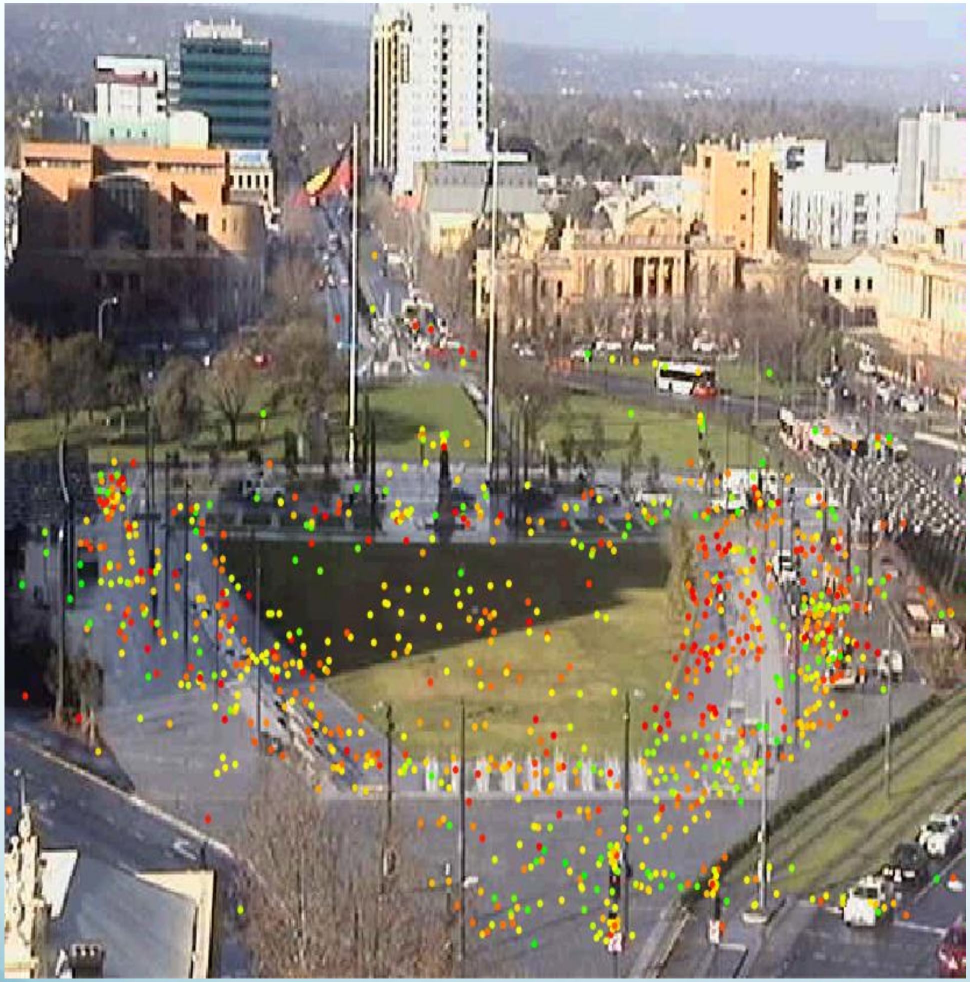
The AMOS project began in March 2006 and is currently maintained at Washington University in St. Louis by Robert Pless and at the University of Kentucky by Nathan Jacobs.

We encourage you to learn more about the AMOS dataset, project participants, and publications. Options for browsing the dataset and contributing webcams to the archive are available through the links on the right.

Acknowledgements [+]



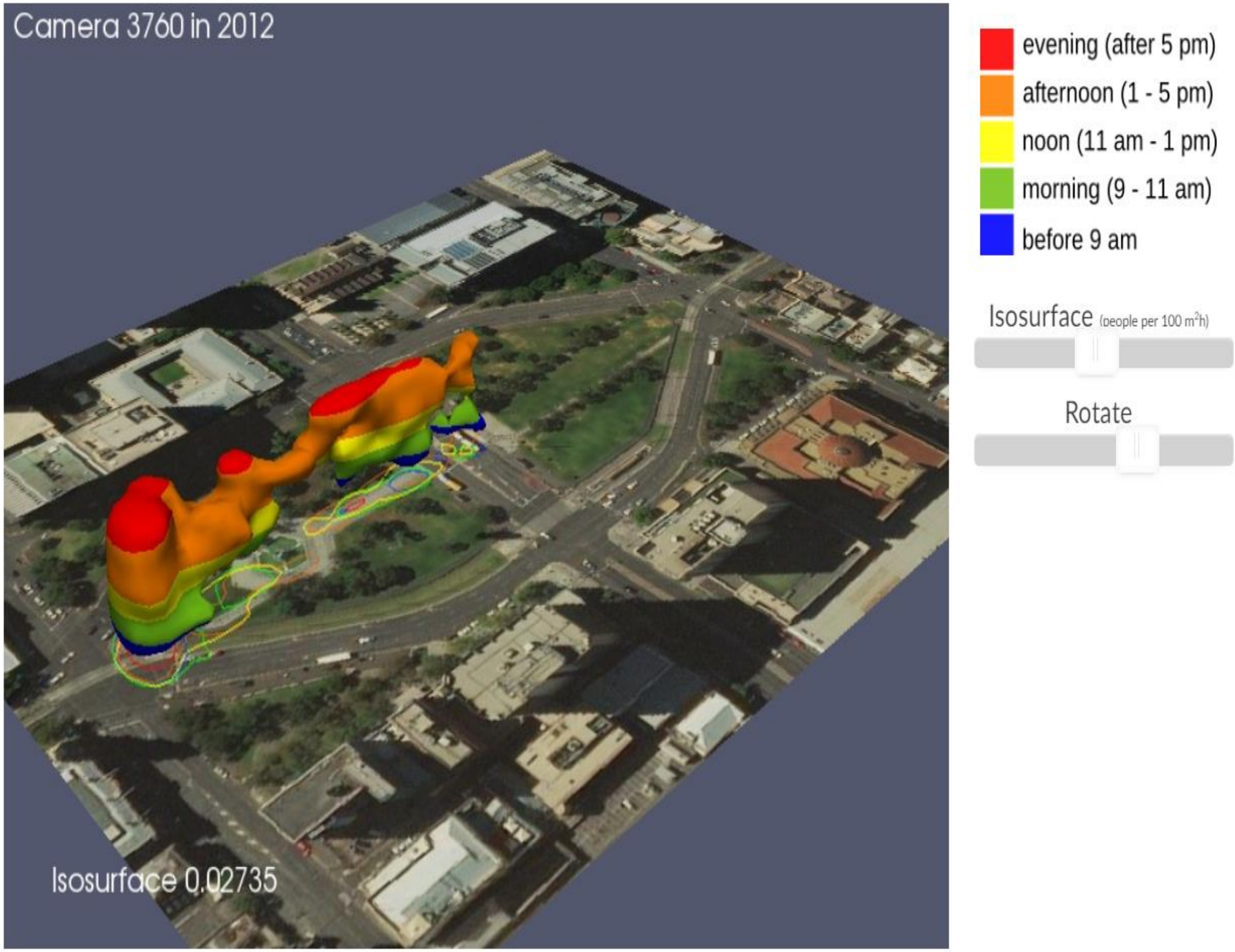




Victoria Square
Wakefield St
Grote St
Reconciliation Plaza
Flinders St
Moonta St
Trades Hall Ln

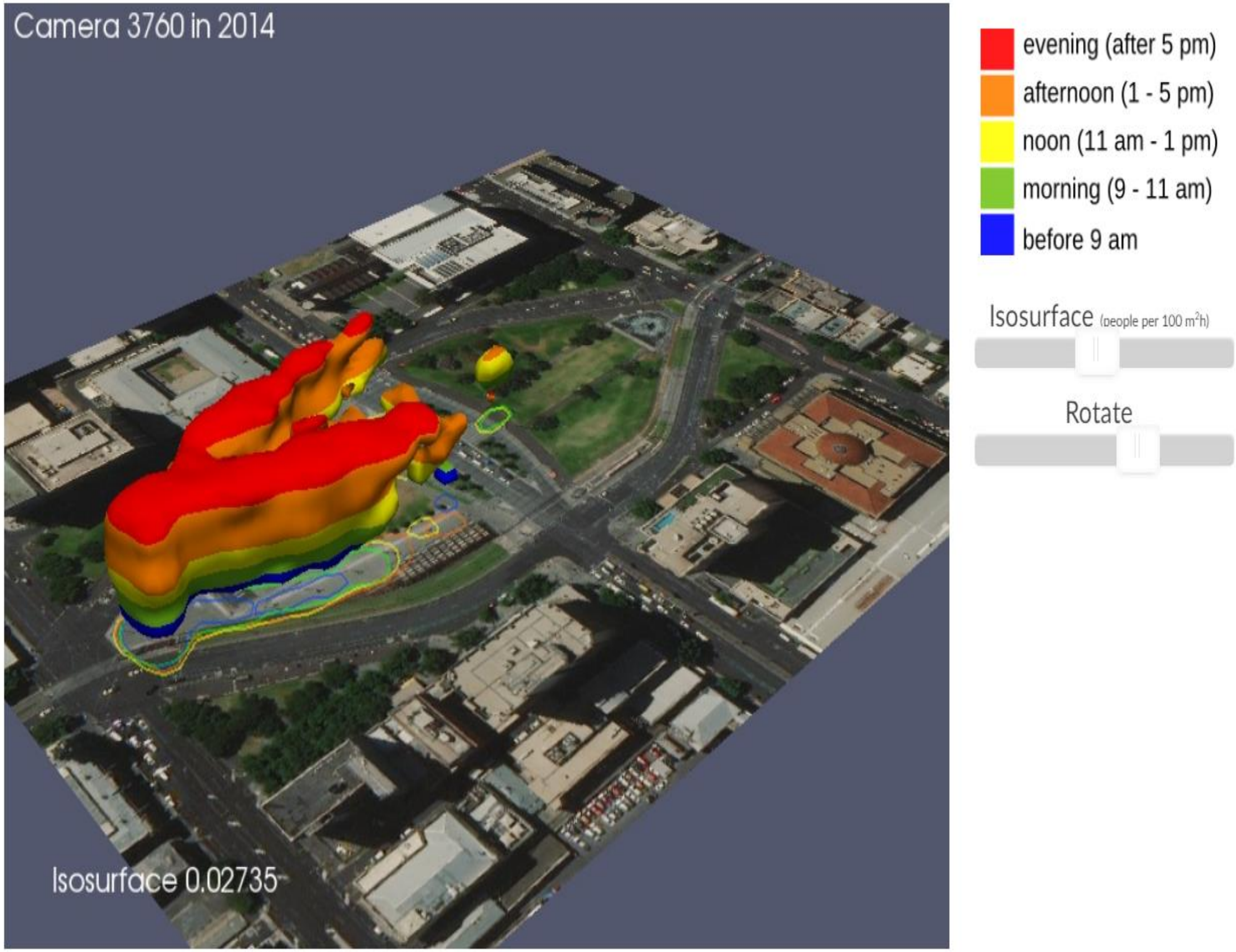
Effects of plaza reconstruction

webcam 3760 in 2012 (Jul - Sep), Victoria Square, Adelaide, Australia

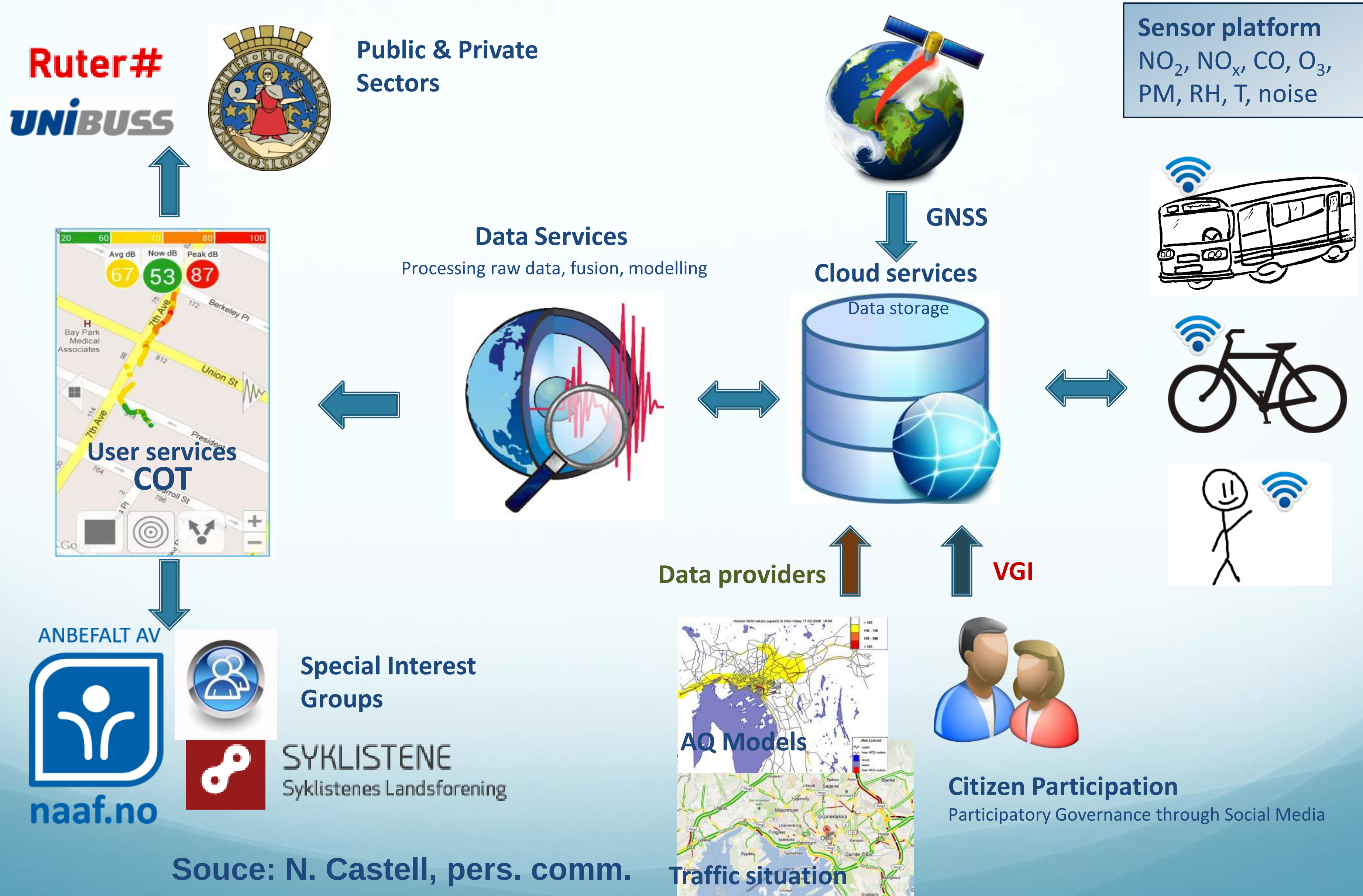


Effects of plaza reconstruction

webcam 3760 in 2014 (Jul - Sep), Victoria Square, Adelaide, Australia



CITI-SENSE-MOB Architecture & Products



Souce: N. Castell, pers. comm.

Challenges with Sensors

Ethical/Institutional

- Privacy issues
- Data ownership and protection
- How to foster participatory sensing on large populations

Analytical

- Data are messy (missingness, GPS errors)
- Massive amounts of data are computationally intensive (biased samples)
- Need more attention to integrating models and measurement
- Need to think about how to analyze too much data rather than too little!

Conclusions

- Location and physical activity essential for linkage to estimating the a time geography of exposure – high quality info possible from smart phones
- Other sensors show promise, but need more evaluation/validation
- New analytical techniques are essential for processing and understanding the BIG DATA that streams from sensors
- More attention to ethical and privacy issues needed

Acknowledgements

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- UCLA Sustainable LA Grand Challenge
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- A. de Nazelle, A. Hipp, N. Castell, G. Carvlin, J. Lipsett, E. Seto, P. English, E. Nameti for sharing slides and figures

THANK YOU!