Harnessing Novel Technologies for Exposure Assessment in Epidemiological Studies

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Assessing Environmental Exposures with Sensing Technologies

- What's possible now with sensing technologies for assessing environmental exposures?
- What's likely to be possible in the near term (3-5 years)?
- What are the benefits and pitfalls of using low cost sensors?

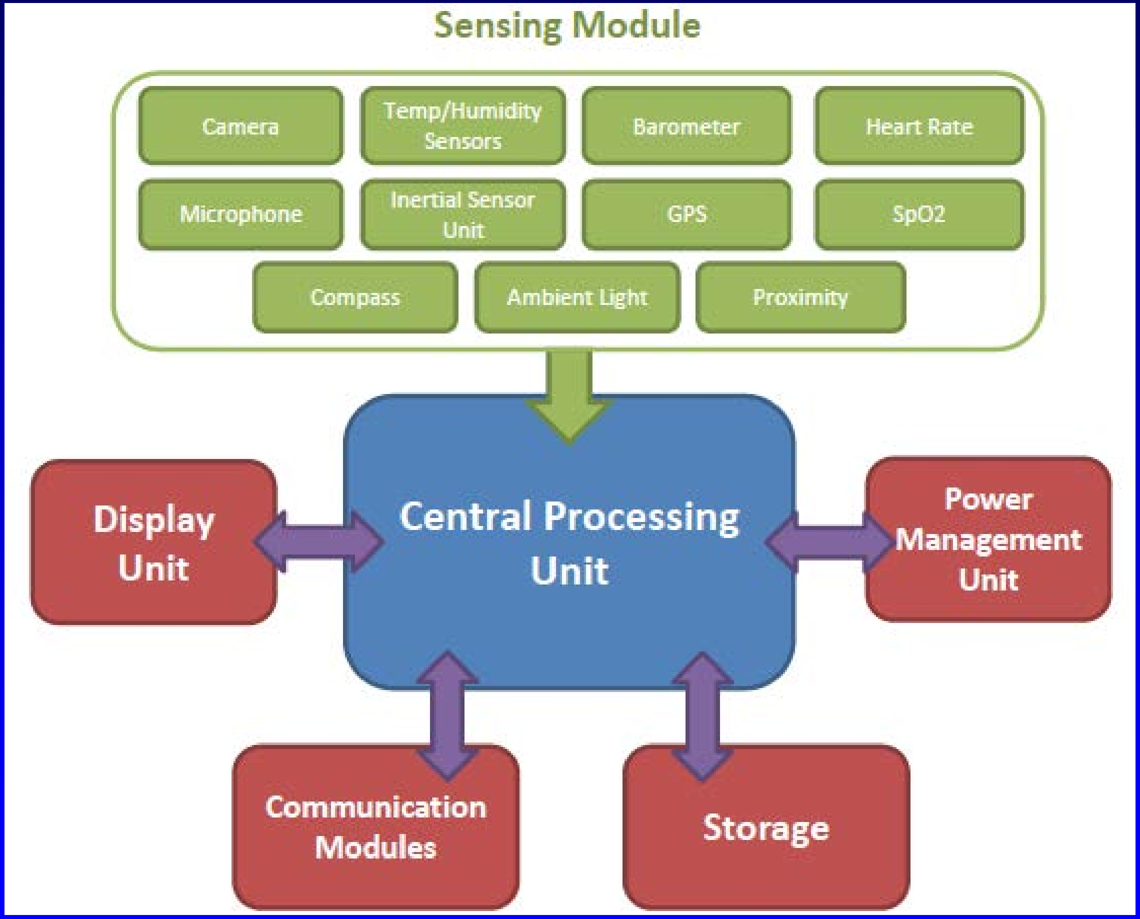
Sensing in a Ubicomp World

- The complete embedding of computational technology into our everyday lives (Weiser 1991)

- Pervasive sensing of personal activity, physiological parameters and ambient conditions increasingly possible

- 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, 2 billion are smart phones)

Components of Cellular Smart Phone



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, Water Pollution, Chemical Exposures, Numerous Biological Functions

Review of 25 Smart Phone Models

Key Points:

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 in review)

	Accelerometer	Barometer	Color spectrum	Fingerprint	Gesture	Gyroscope	Heart rate	Humidity	Iris scanner	Magnetometer	Proximity	Sensor core	SpO2	Temperature	UV
Smartphone Model	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: Activity patterns & 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]

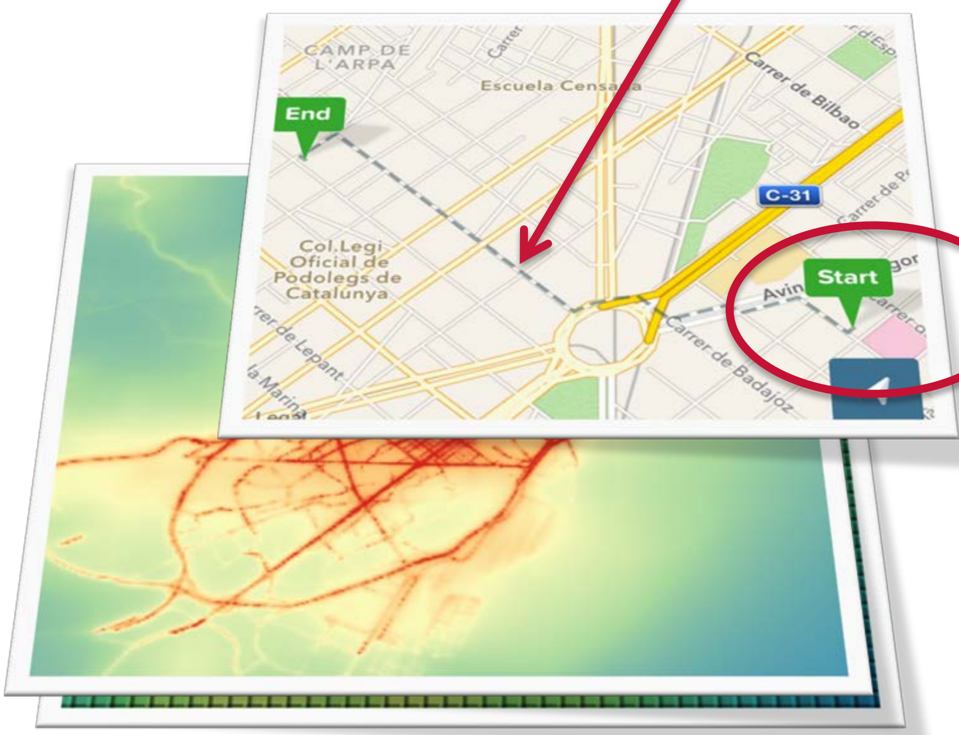
A. Methods

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

Slides Courtesy of A. de Nazelle

Air pollution inhalation

GPS tracking and physical activity for 1 workday for each volunteer + air pollution map (NO_2)

Travel microenvironments, air pollution, and health

Travel microenvironments

(Barcelona sample, de Nazelle et al. 2013):

6% Time

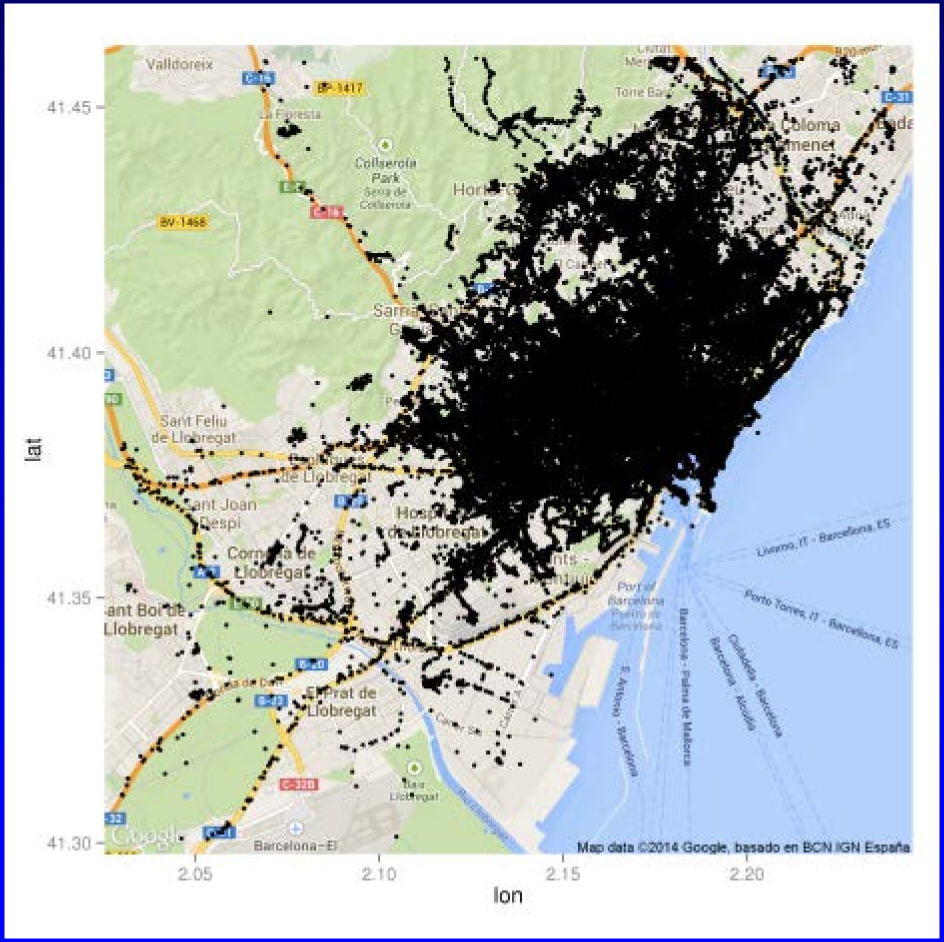
11% NO_2 exposure

24% NO_2 inhalation

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!

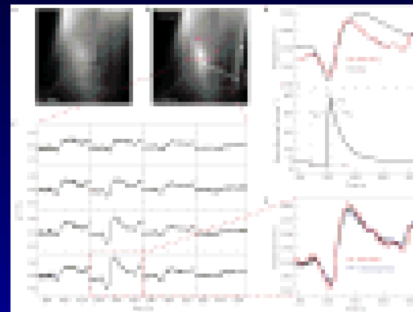


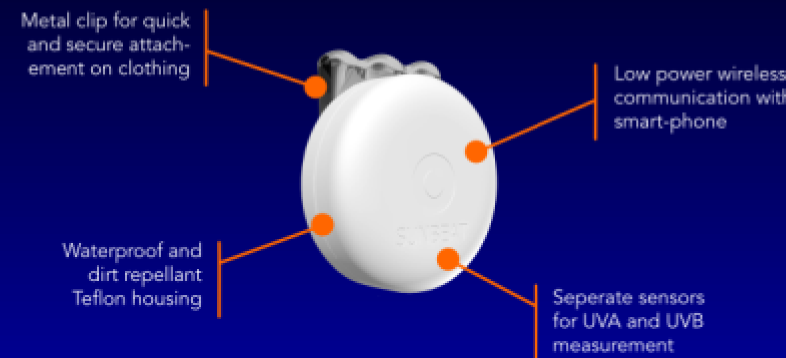
Lessons

- Location and physical activity can be accurately measured on cell phones
- This information can significantly improve estimates when fused with models
- Data are very big and messy

External Sensors, Technology Moving Fast

Radiation






Environmental Science & Technology

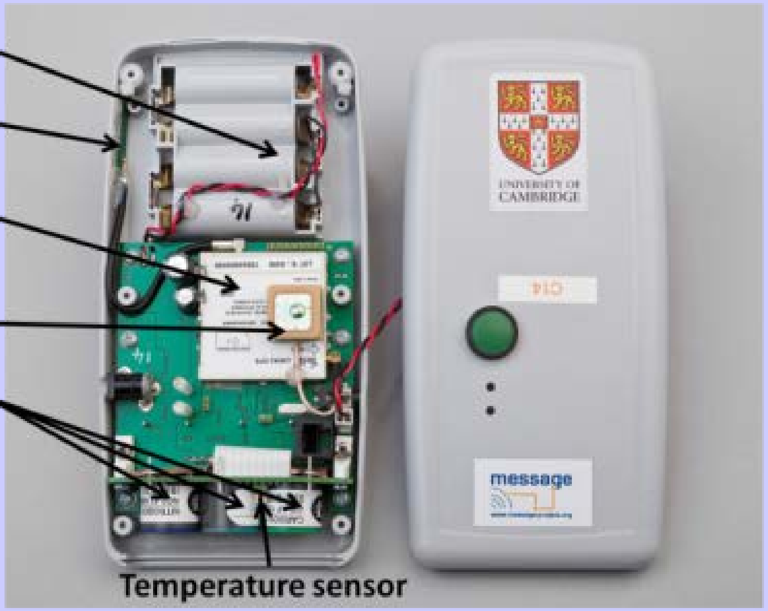
Feature

pubs.acs.org/est

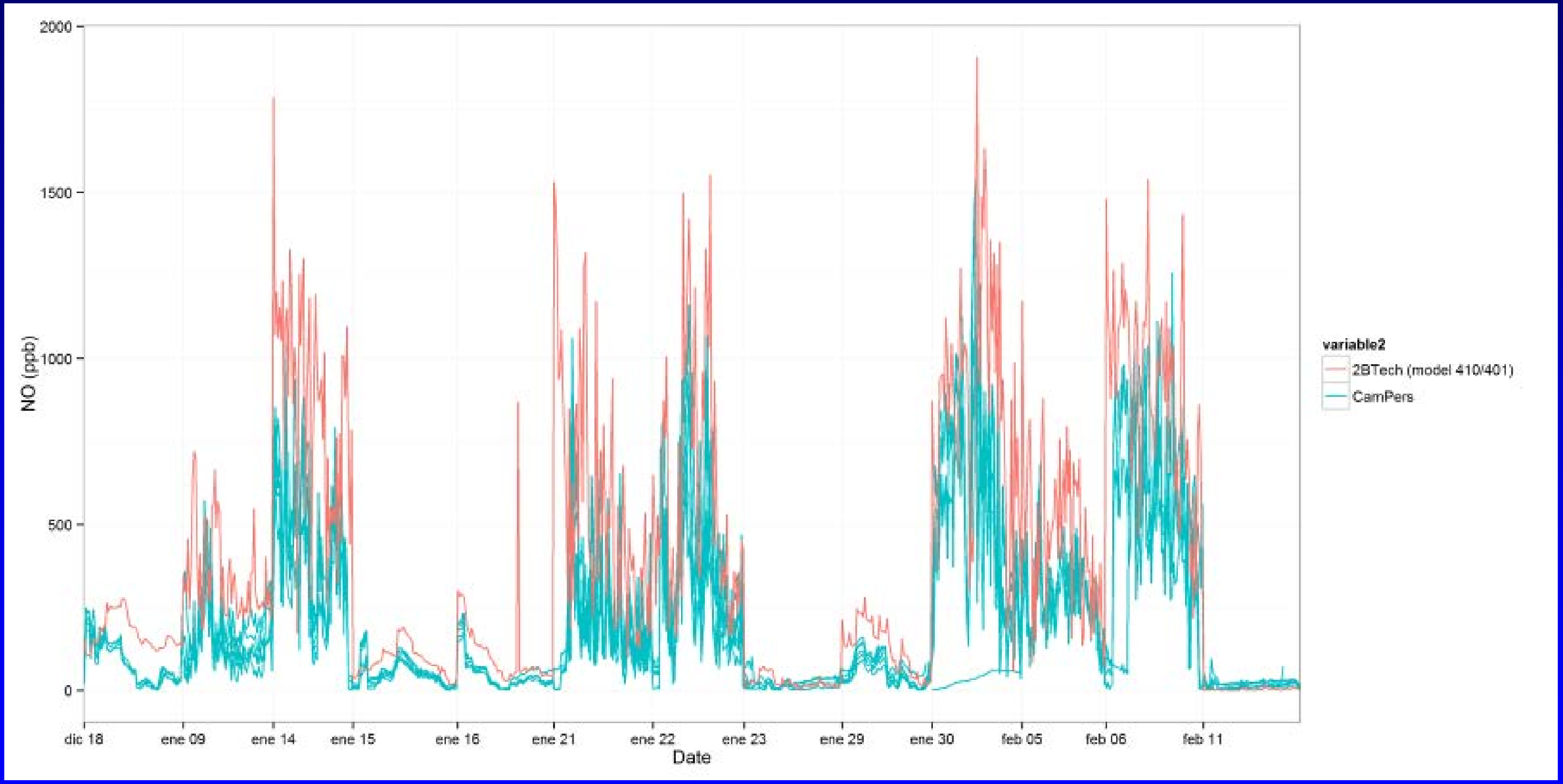
The Changing Paradigm of Air Pollution Monitoring

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

Paper Coming Out this Week!

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com

Validating novel air pollution sensors to improve exposure estimates for epidemiological analyses and citizen science

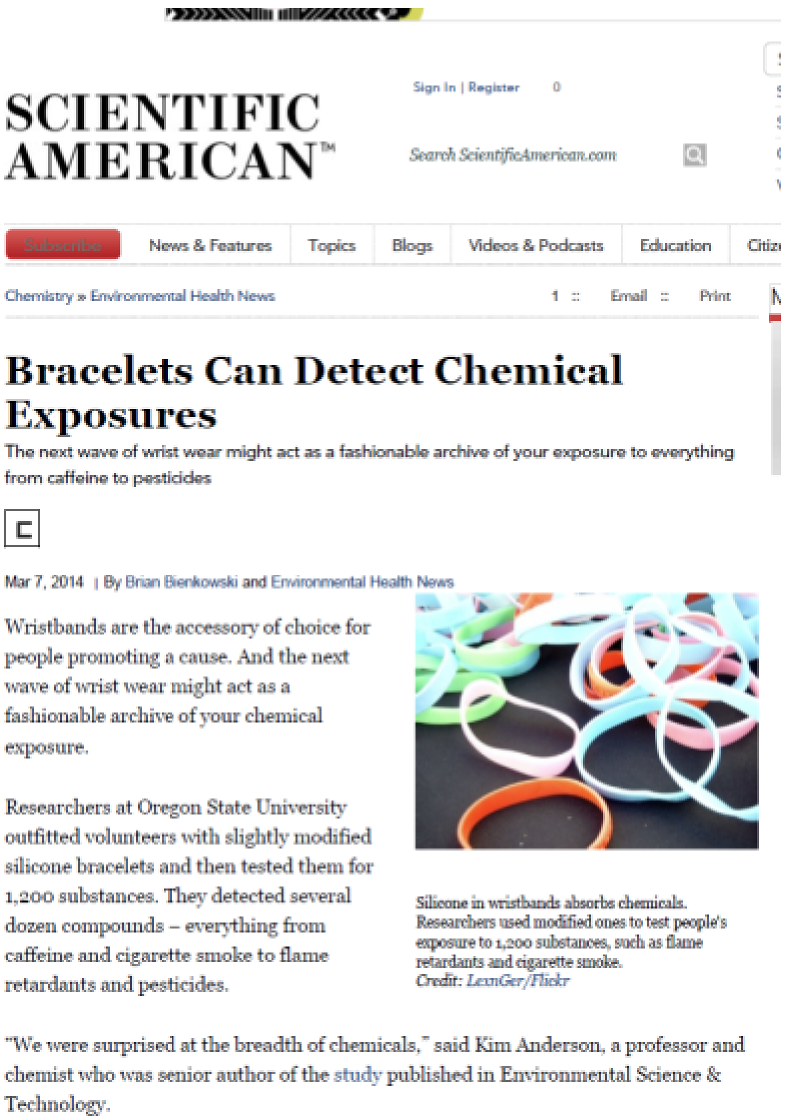
Michael Jerrett[a,*], David Donaire-Gonzalez[b], Olalekan Popoola[c], Roderic Jones[c], Ronald C. Cohen[d], Estela Almanza[e], Audrey de Nazelle[f], Iq Mead[g], Glòria Carrasco-Turigas[b], Tom Cole-Hunter[b], Margarita Triguero-Mas[b], Edmund Seto[h], Mark Nieuwenhuijsen[b]

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 $$

New Sensors & Technology

Example: Passive sampler wristbands (as bracelet, lapel, etc)



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Bracelets Can Detect Chemical Exposures

The next wave of wrist wear might act as a fashionable archive of your exposure to everything from caffeine to pesticides

Mar 7, 2014 | By Brian Bienkowski and Environmental Health News

Wristbands are the accessory of choice for people promoting a cause. And the next wave of wrist wear might act as a fashionable archive of your chemical exposure.

Researchers at Oregon State University outfitted volunteers with slightly modified silicone bracelets and then tested them for 1,200 substances. They detected several dozen compounds – everything from caffeine and cigarette smoke to flame retardants and pesticides.

Silicone in wristbands absorbs chemicals. Researchers used modified ones to test people's exposure to 1,200 substances, such as flame retardants and cigarette smoke.
Credit: LexnGer/Flickr

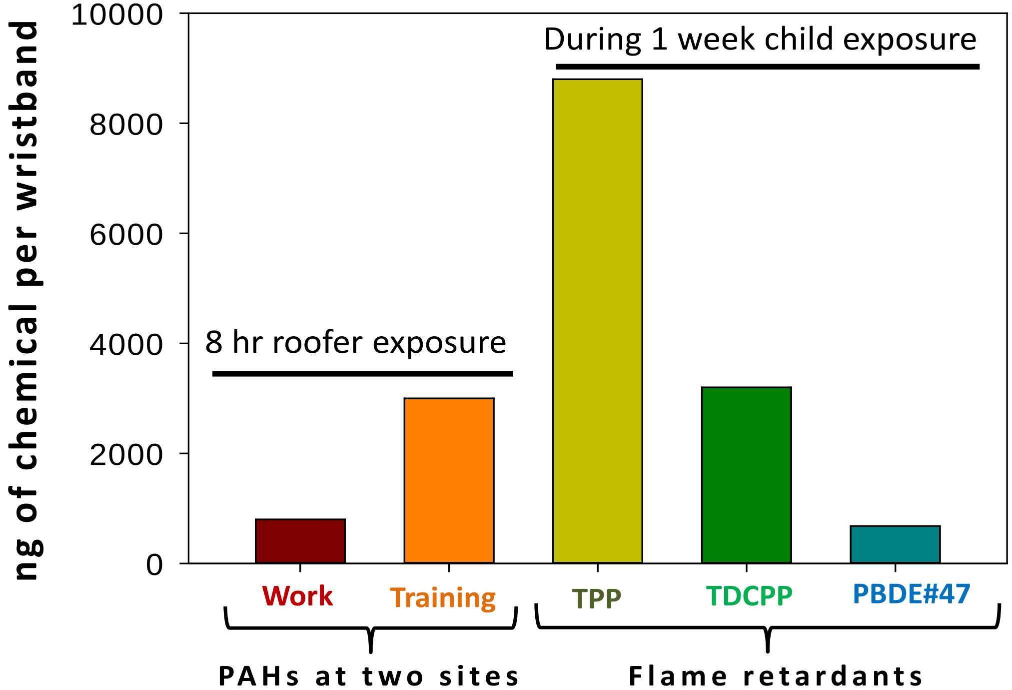
"We were surprised at the breadth of chemicals," said Kim Anderson, a professor and chemist who was senior author of the study published in Environmental Science & Technology.

Wristbands

Children, occupational, natural gas extraction, agricultural,....

Children: Flame Retardant Exposure

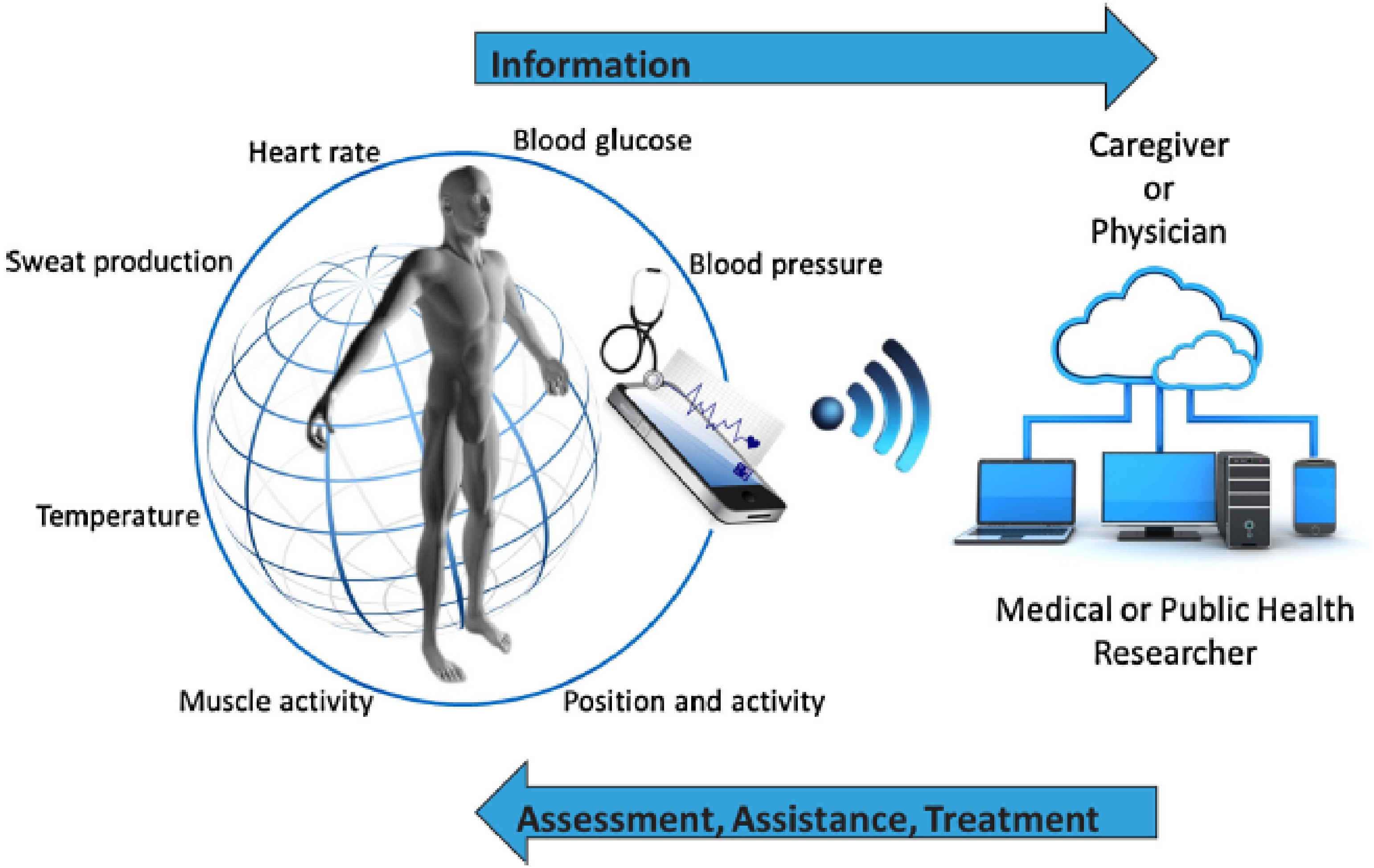
Roofers 8 hrs wristband: PAHs



Abbreviations used : ng = nanograms, hr = hours, PAHs = sum of 33 polycyclic aromatic hydrocarbons; TPP = triphenyl phosphate, TDCPP = tris(1,3-dichloro-2-propyl) phosphate, PBDE#47 = pentabromodiphenyl ether congener 47.

Source: Anderson Pers. Comm.

Rapid Development of Real-time Biomonitoring



Smoulders and De Boever 2014

Citizen Science and Ubiquitous (Embedded) Sensors

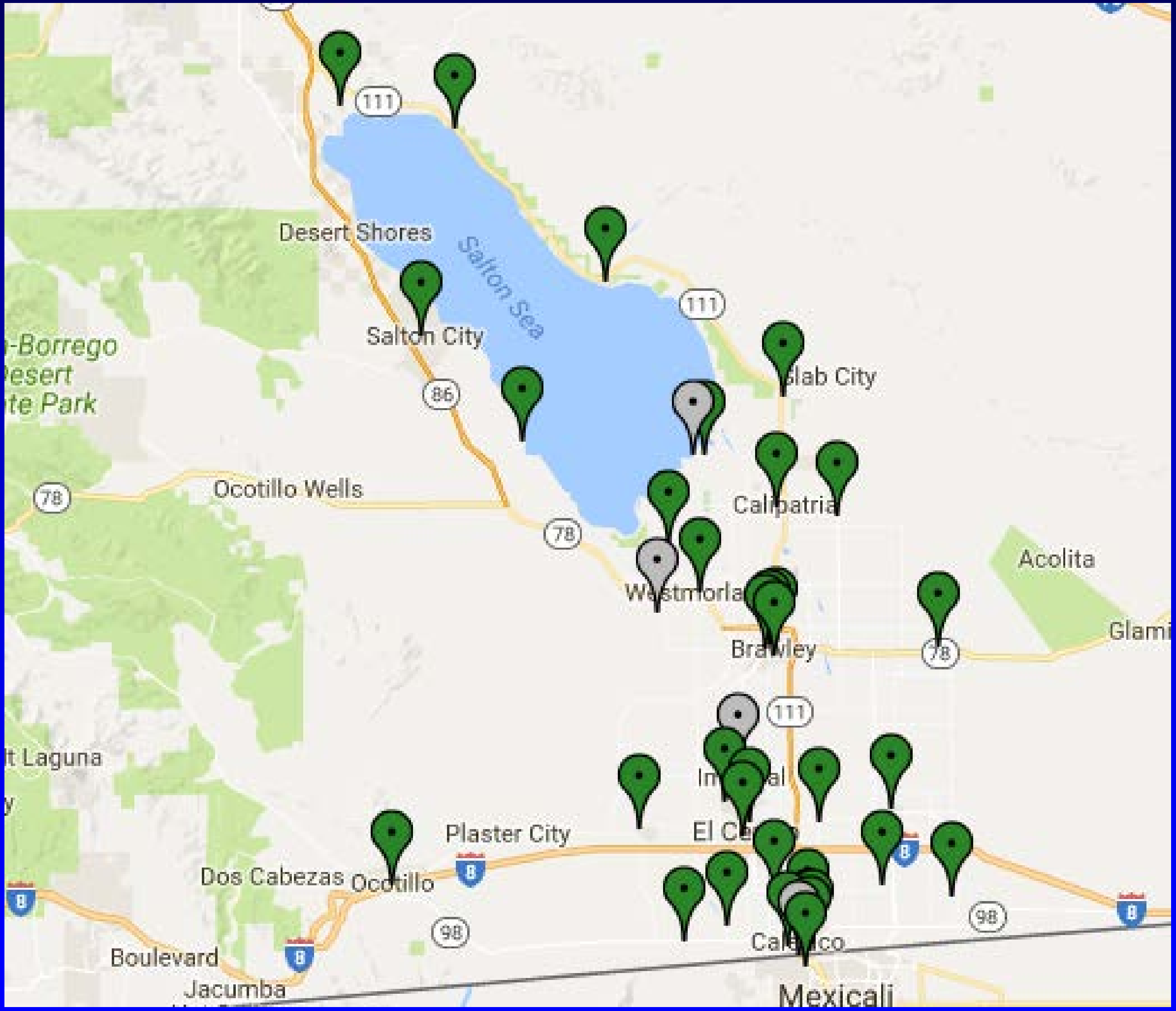
- Citizens often very interested and attuned to environment exposures, which gives them motivation to help

- They represent a huge resource for data collection in partnership with government and academics

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

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



Citizen Scientists with Dylos Particle Monitor and Enclosure

Lessons

- Higher spatial and temporal coverage could lead to much better predictions of exposure for epidemiological studies
- Working with communities time-consuming, but rewarding
- Sustainability of network an issue

Conclusion

- Location and physical activity essential for linkage to modeled and measured environmental exposures – high quality info possible from smart phones
- Other apps for noise, travel behavior, other exposures show promise, but need more evaluation/validation
- Variable type and quality of sensors on phones presents challenges

Conclusions (Cont’d)

- Direct personal sensors not there yet, but likely in near term, both wearable and awarable
- Embedded sensors now possible for air pollution and other important risk factors like traffic volume
- Citizen science and volunteered geographic information show tremendous promise

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THANK YOU!