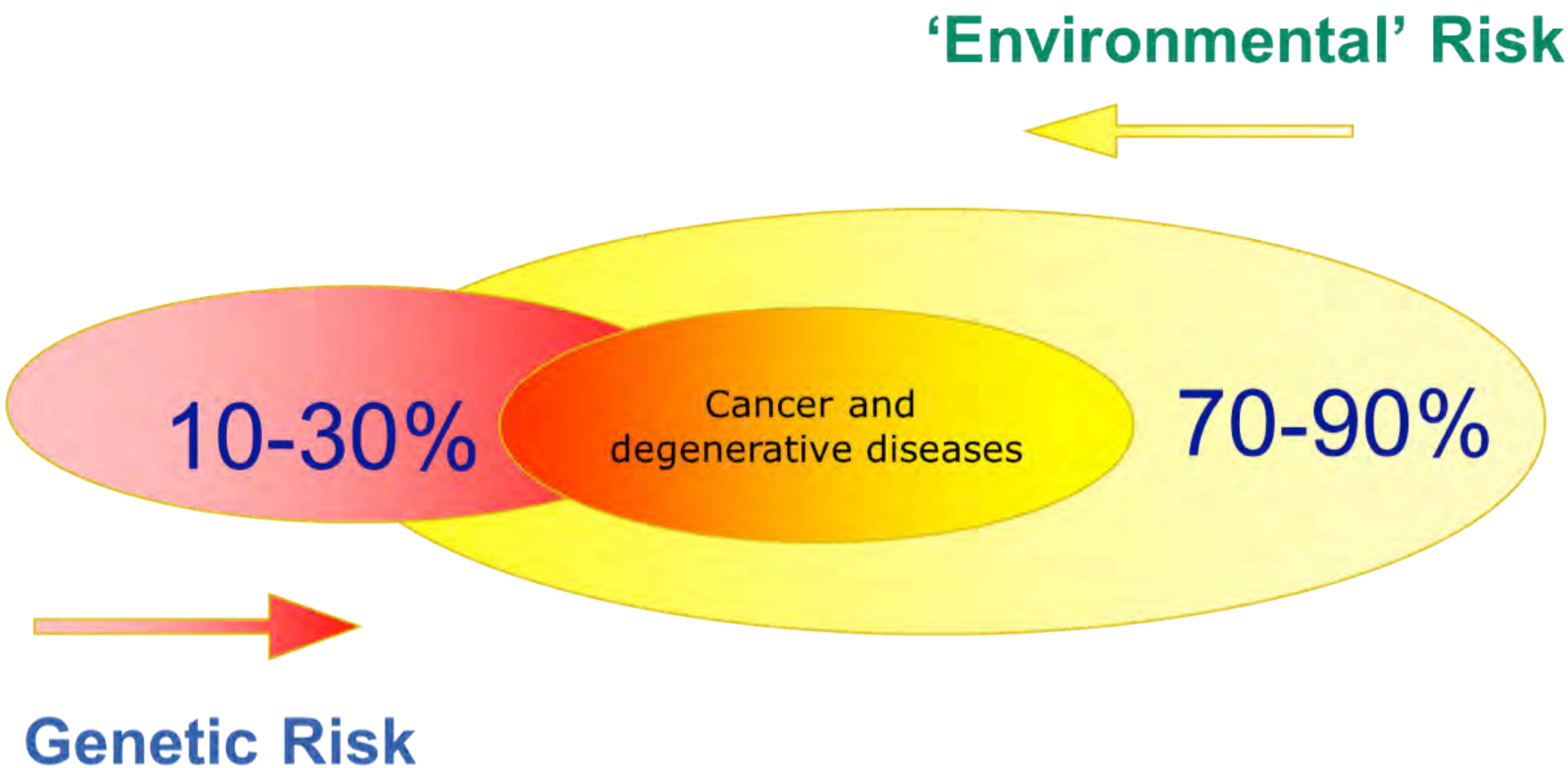
Leveraging New Technologies to Measure and Model the External Environment

Perry Hystad. Oregon State University

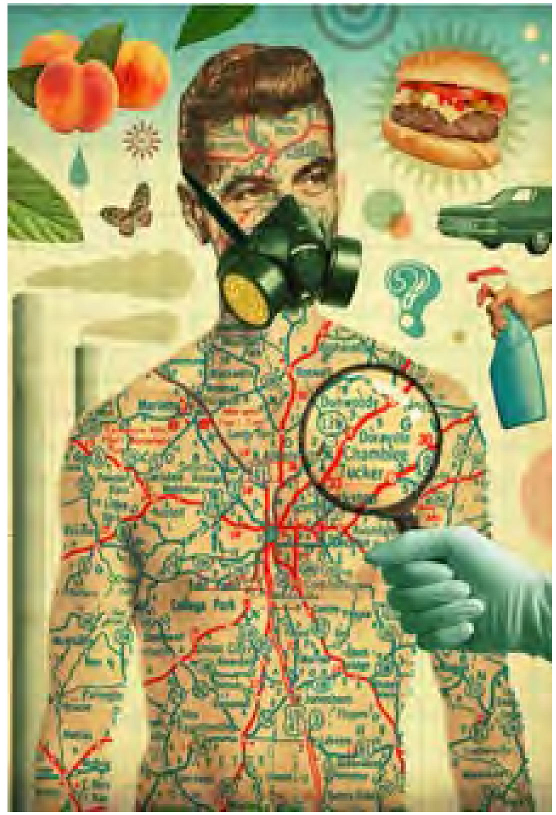
Why Do We Need New Measurement Tools?

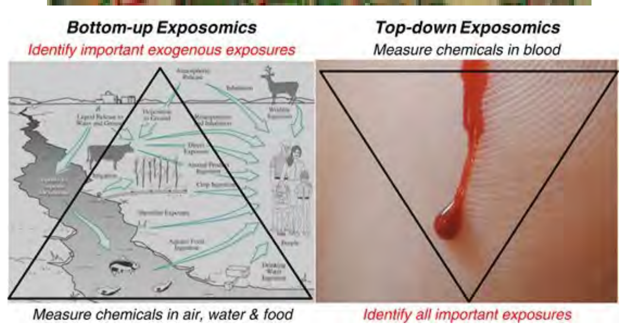


The "Exposome"

External Exposome

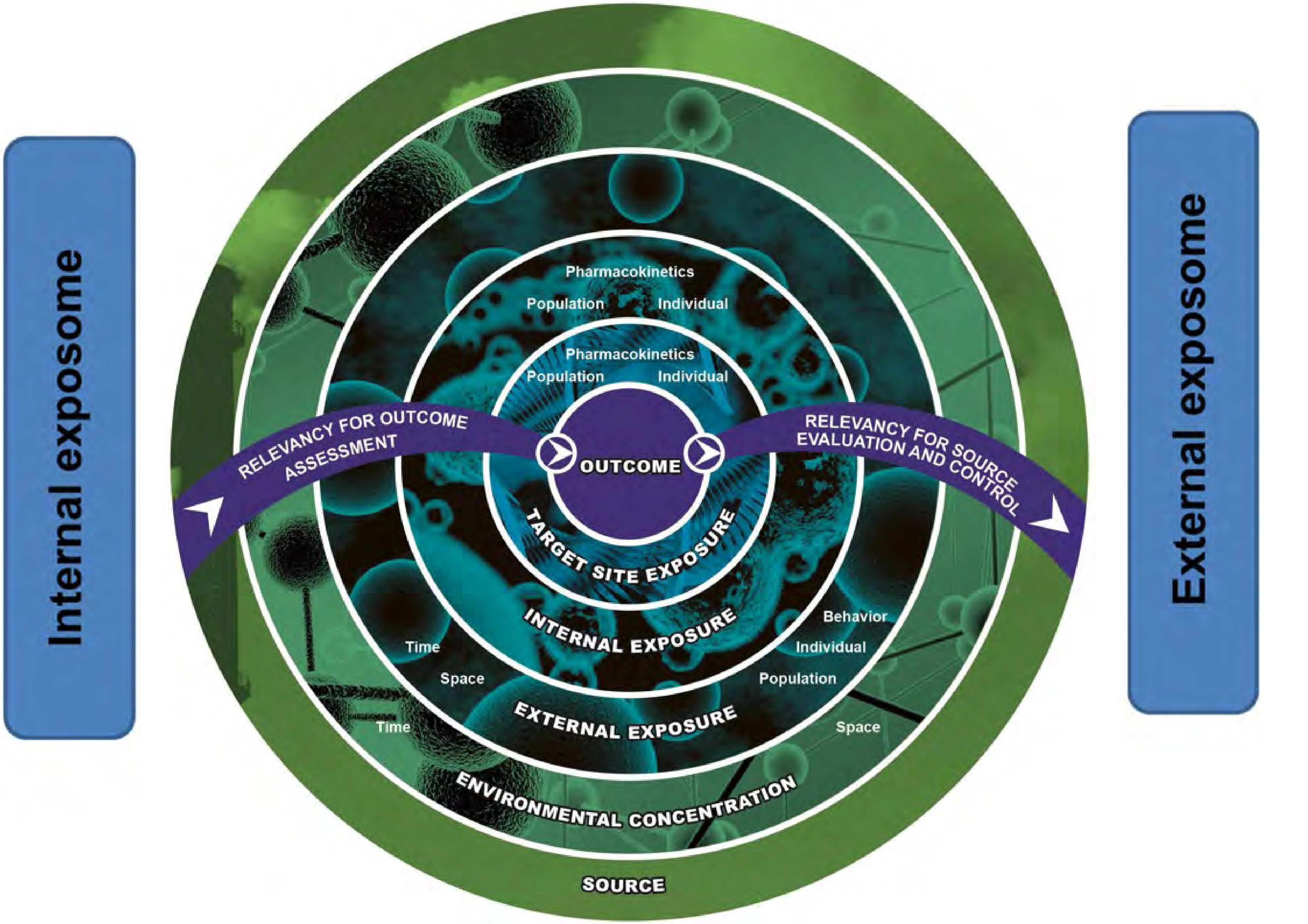
- Contextual factors
- SES
- Climate
- Physical activity
- Diet
- Air pollution
- Occupational exposures
- Noise
- Radiation
- Chemical exposures
- Green space
- Etc.



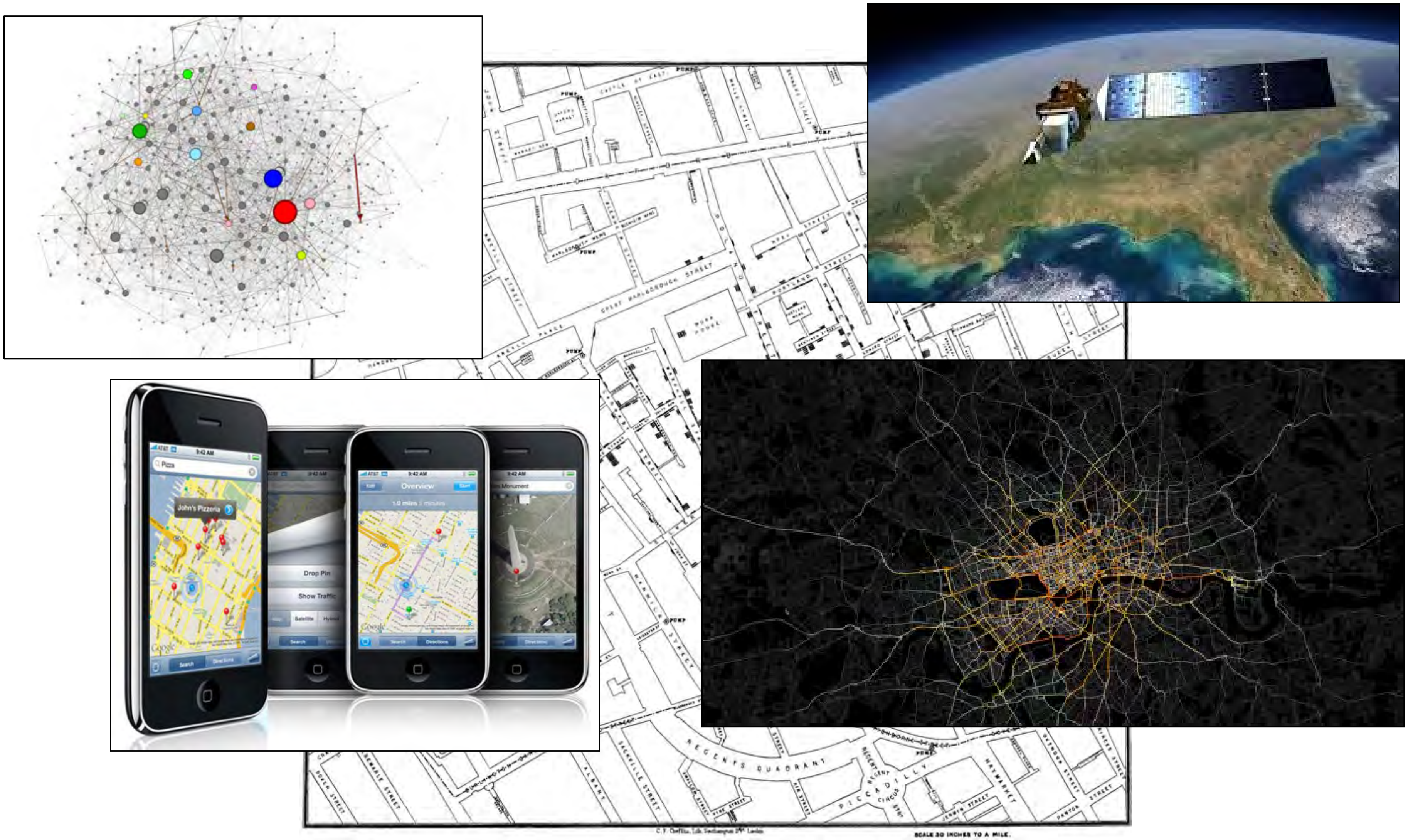


Internal Exposome

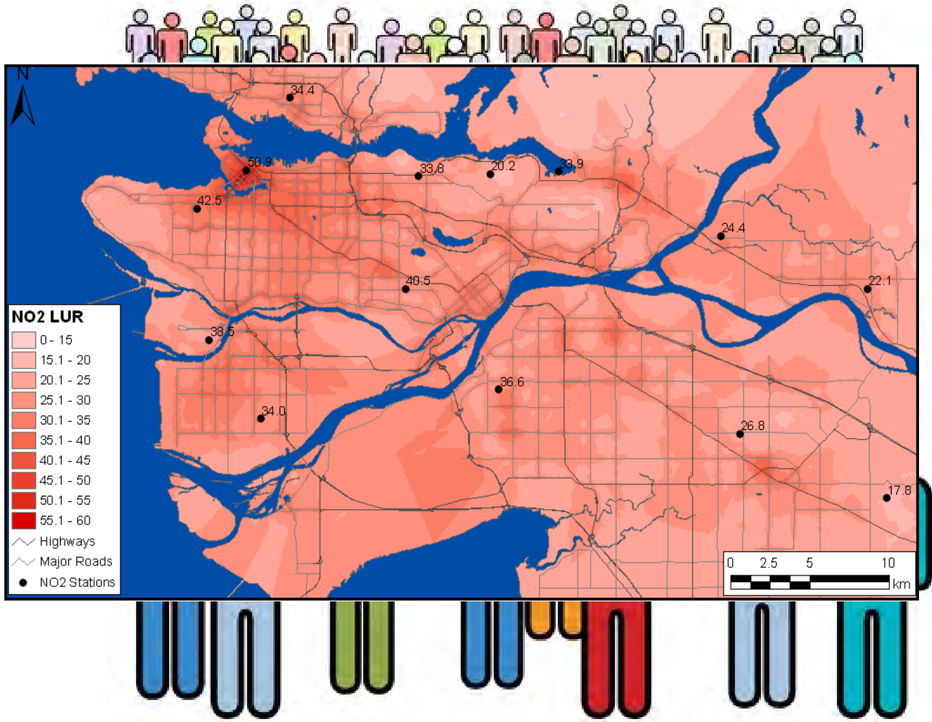
- Inflammation
- Oxidative stress
- Metabolomics
- Transcriptomic
- Proteomics
- Epigenetics
- Microbiome
- Lip peroxidation
- Immunomics
- Adductomics
- Etc.


Internal exposome
External exposome
Pharmacokinetics
Population
Individual
Pharmacokinetics
Population
Individual
RELEVANCY FOR OUTCOME ASSESSMENT
RELEVANCY FOR SOURCE EVALUATION AND CONTROL
OUTCOME
TARGET SITE EXPOSURE
INTERNAL EXPOSURE
Behavior
Individual
Population
Time
Space
EXTERNAL EXPOSURE
Time
Space
ENVIRONMENTAL CONCENTRATION
SOURCE

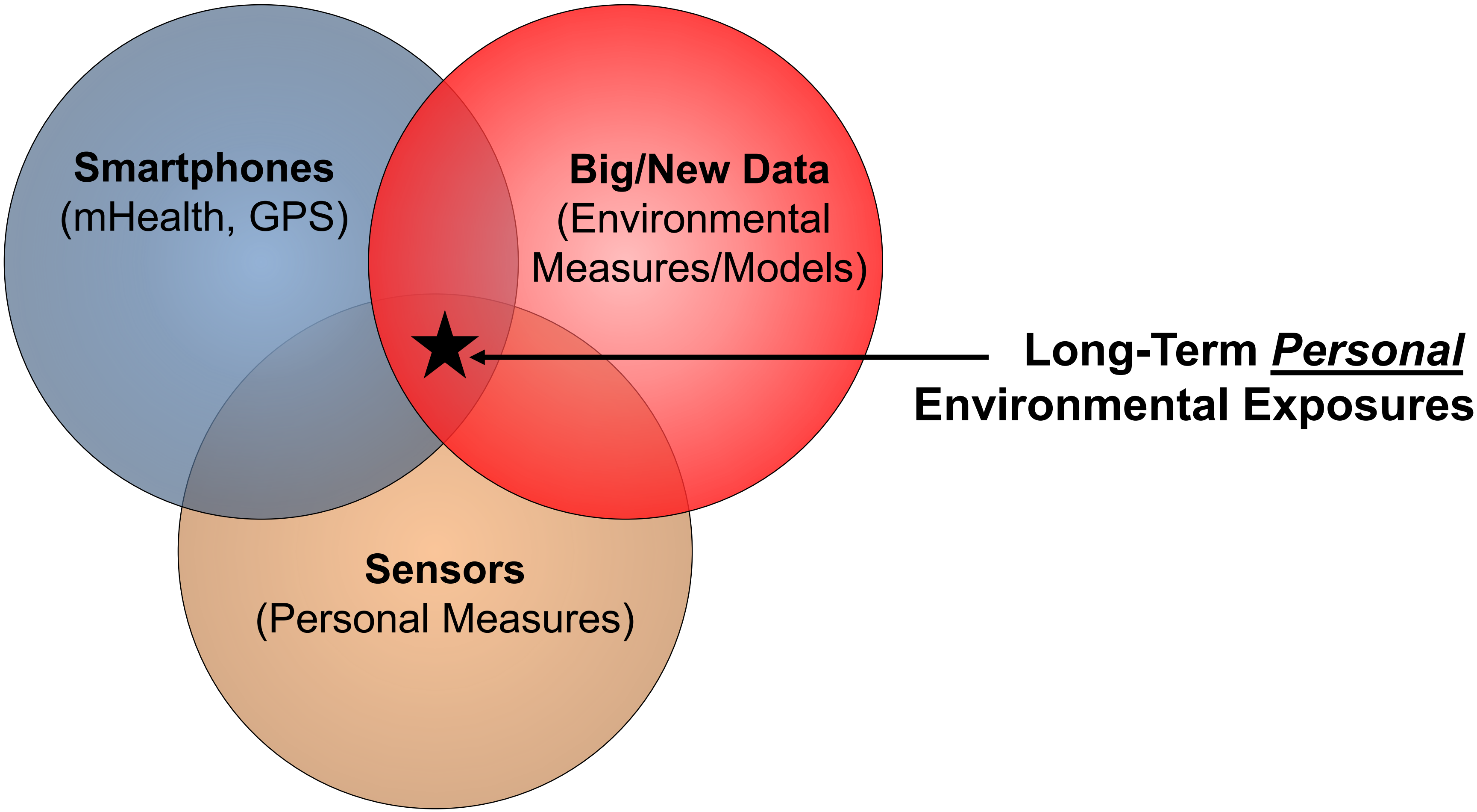
“Modern” Environmental Epidemiology



Population Models



Individual Measurements



Curr Envir Health Rpt (2017) 4:463–471
DOI 10.1007/s40572-017-0163-y

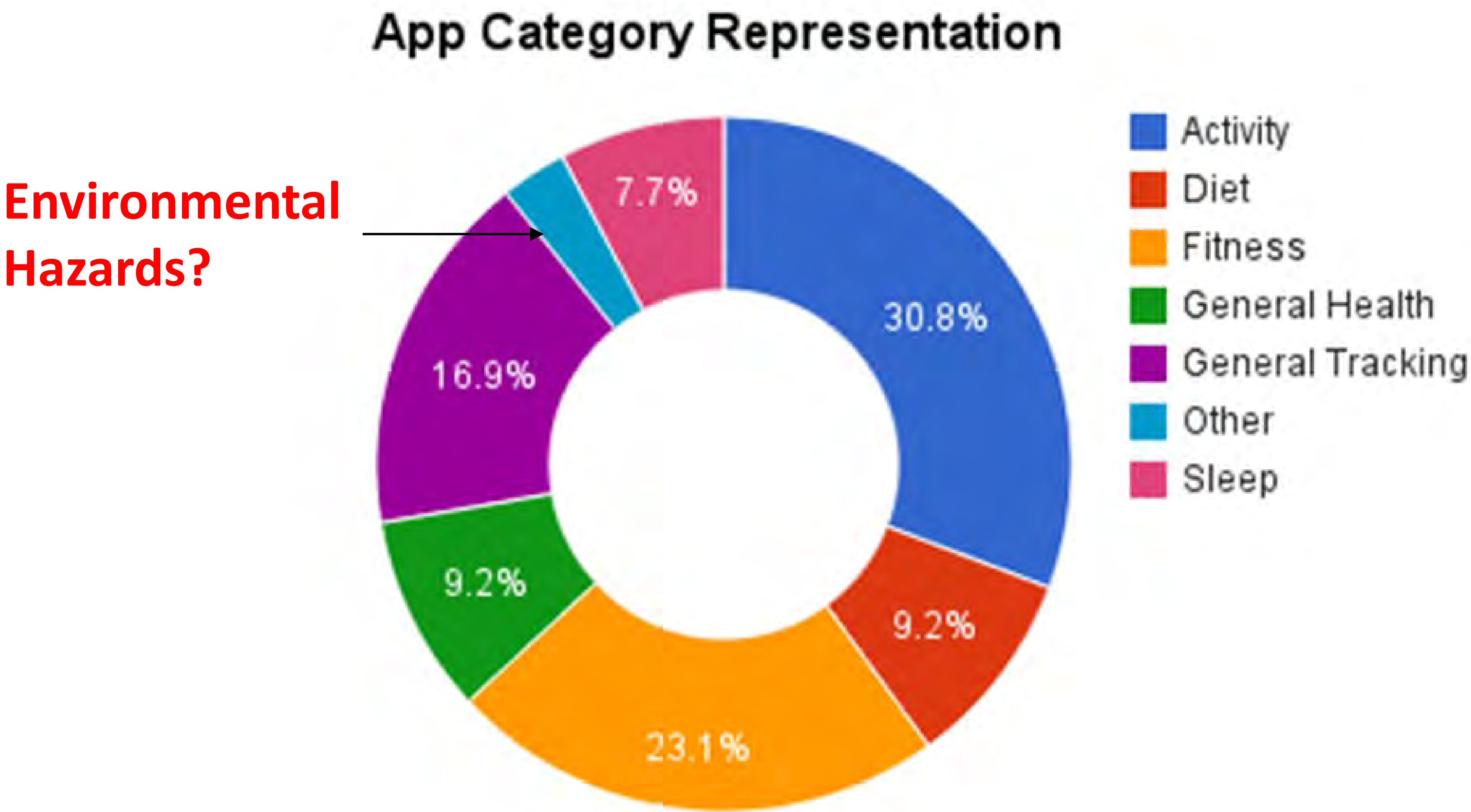
AIR POLLUTION AND HEALTH (S ADAR AND B HOFFMANN, SECTION EDITORS)

Towards Personal Exposures: How Technology Is Changing Air Pollution and Health Research

A. Larkin[1] · P. Hystad[2]

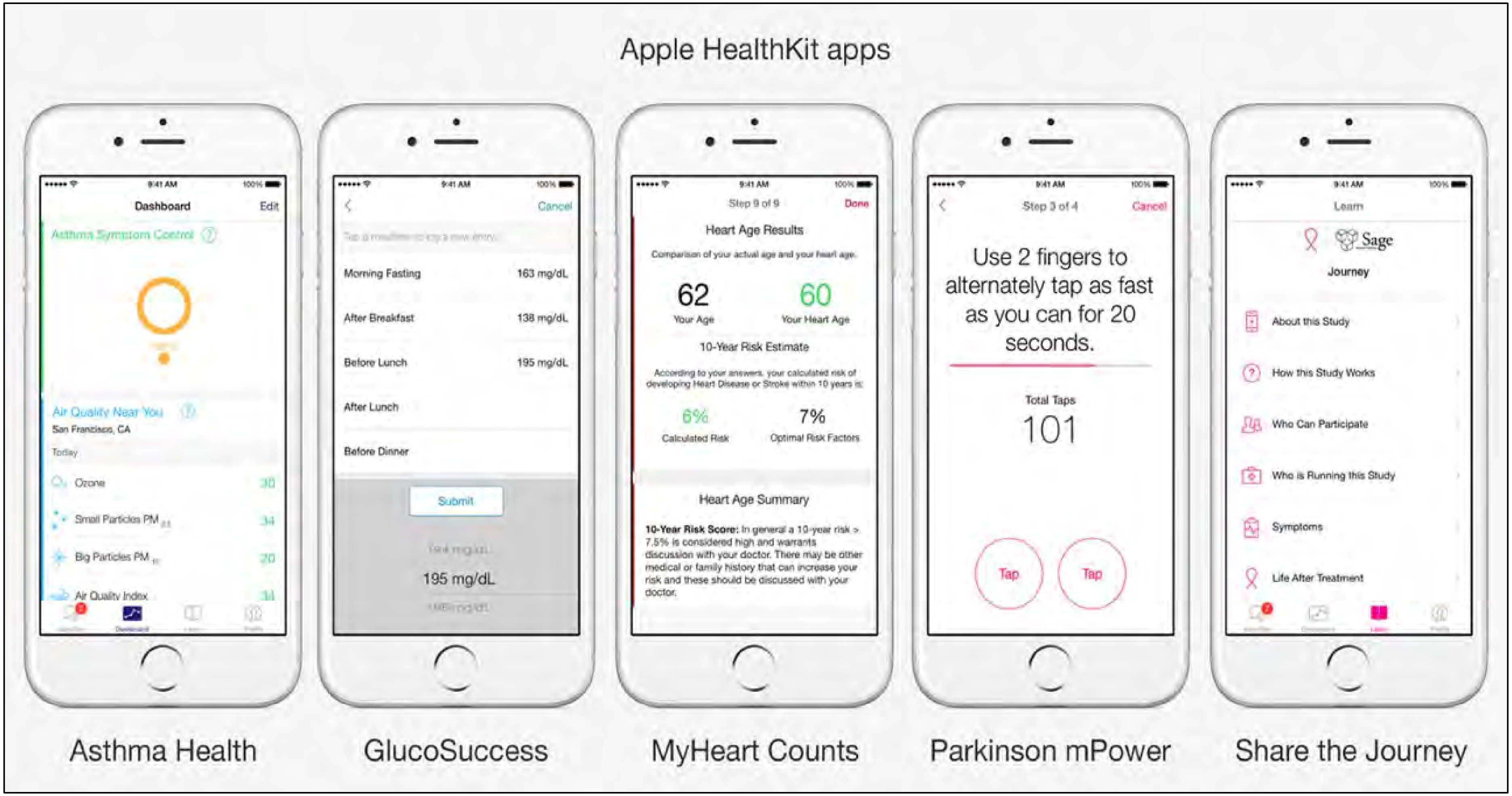
Smart Phones:

1. Data collection tool for existing health studies.
2. Platform for new environmental health studies.
3. Collect GPS time-activity data.
4. Enable personal sensor measurements.

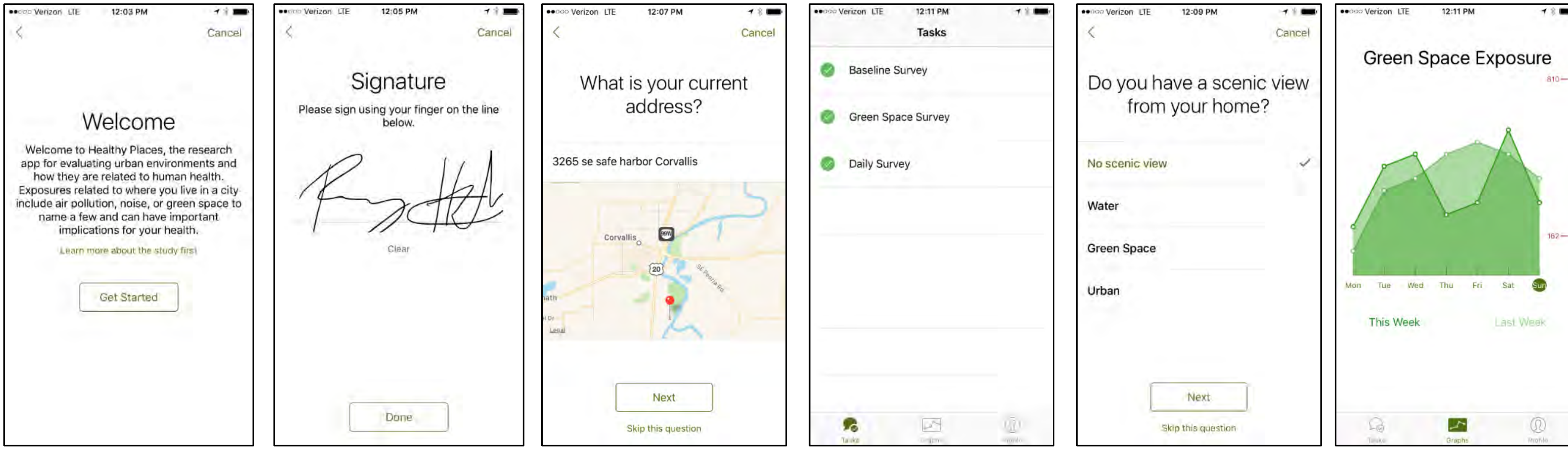


- 90% of the worlds population expected to have a smart phone in 10 years
- 50% of smart phone users have a health app

Low Barrier to Creating New Environmental Health Focused Apps



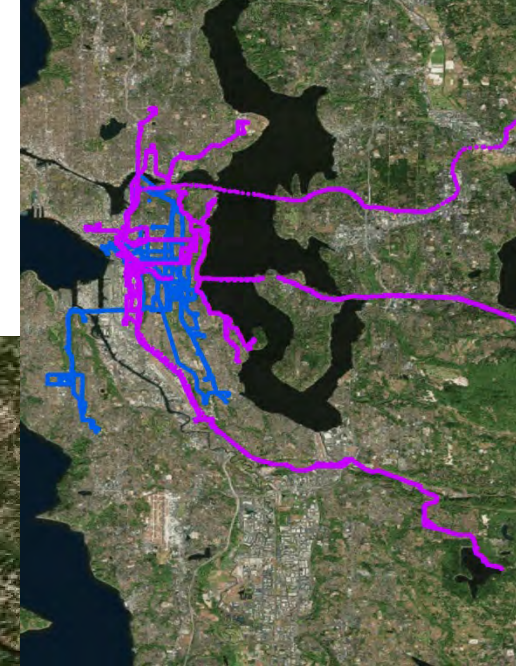
"Healthy Places" Research App

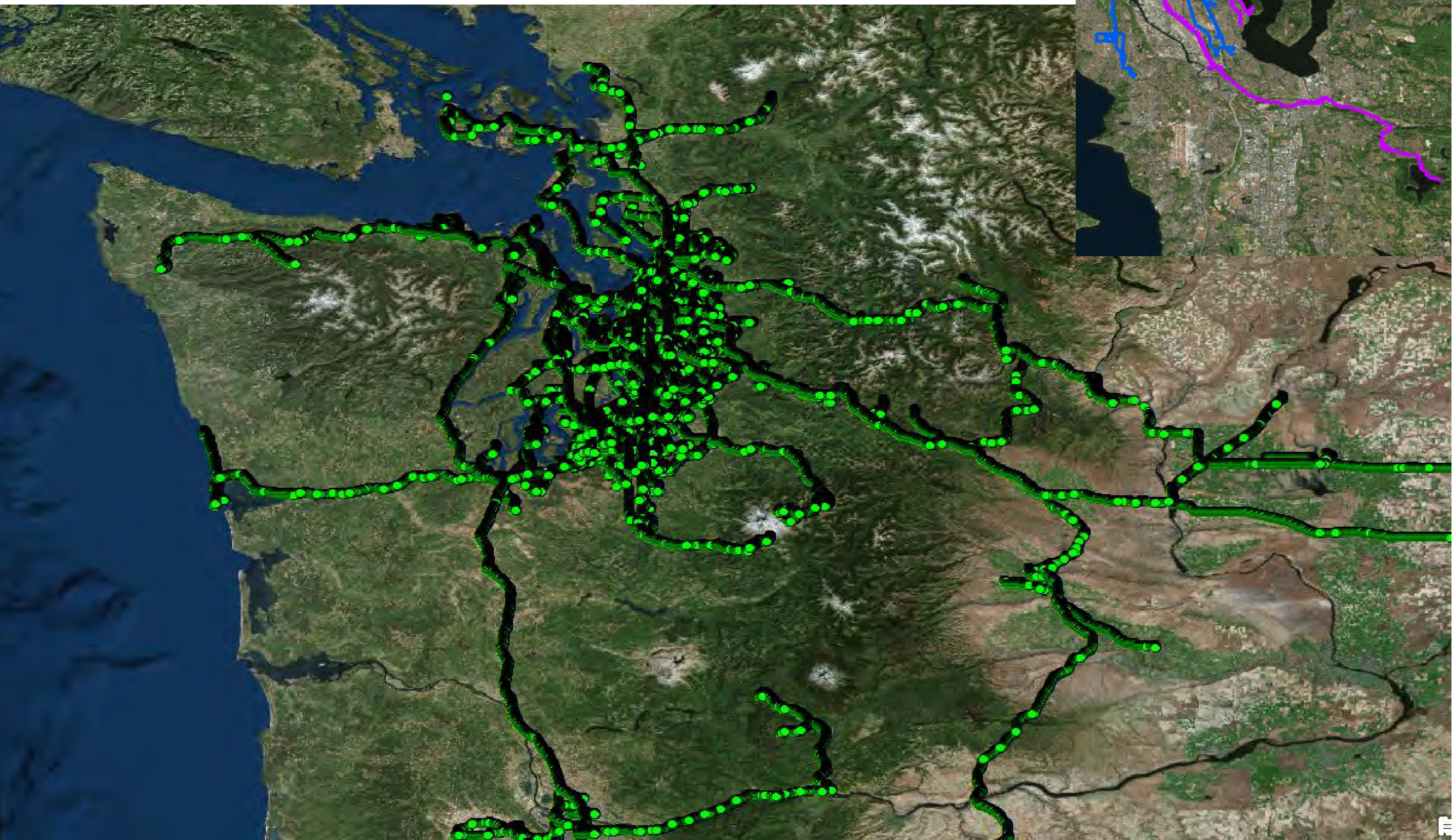


- Track exposures over time
- Compare exposures to others
- Advisories/Warnings
- Route finding
- Etc.

GPS Time-Activity Data

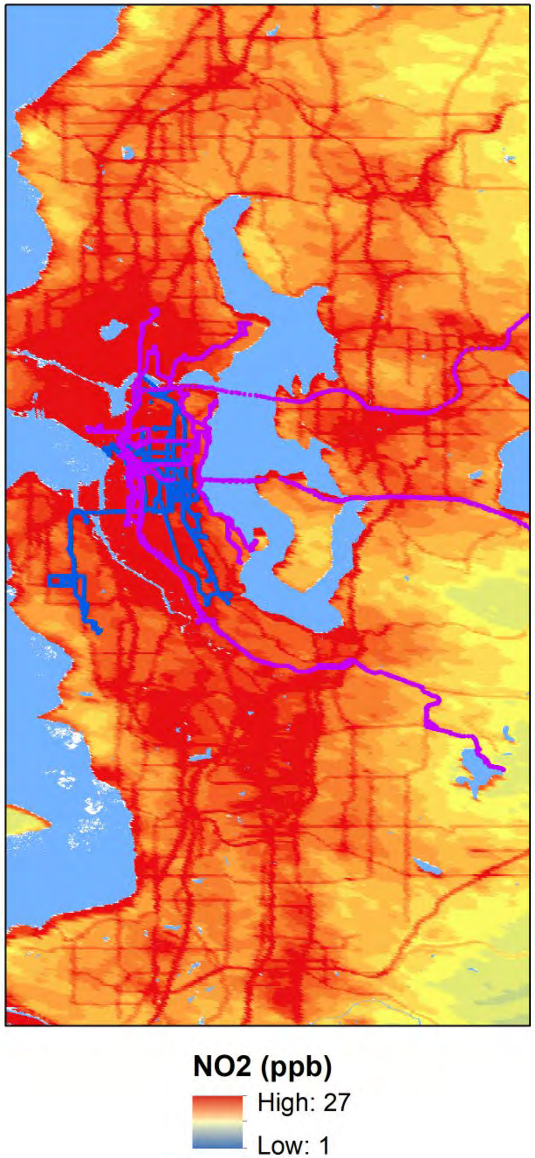
Washington Twin Study: 300 Individuals Monitored for 2 weeks (~30 million points)



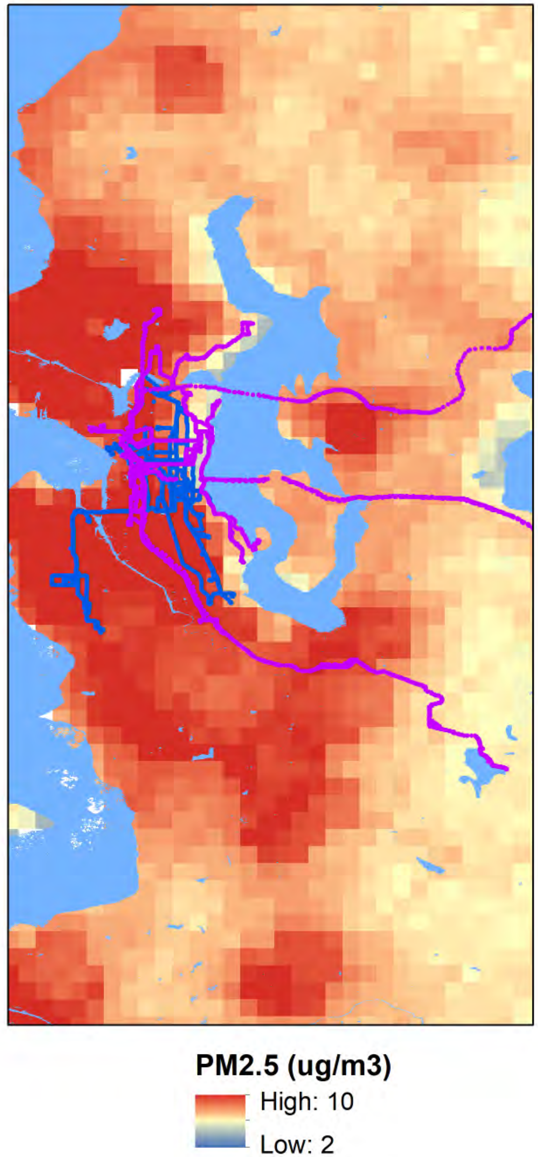


Time-Activity Matters for Fine-Scale Exposures

NO2 Home:GPS Measures
R=0.65



PM2.5 Home:GPS Measures
R=0.80



NDVI Home:GPS Measures
R=0.52

Association between the odds of physical activity and GPS built environment characteristics and physical activity (1 minute resolution)

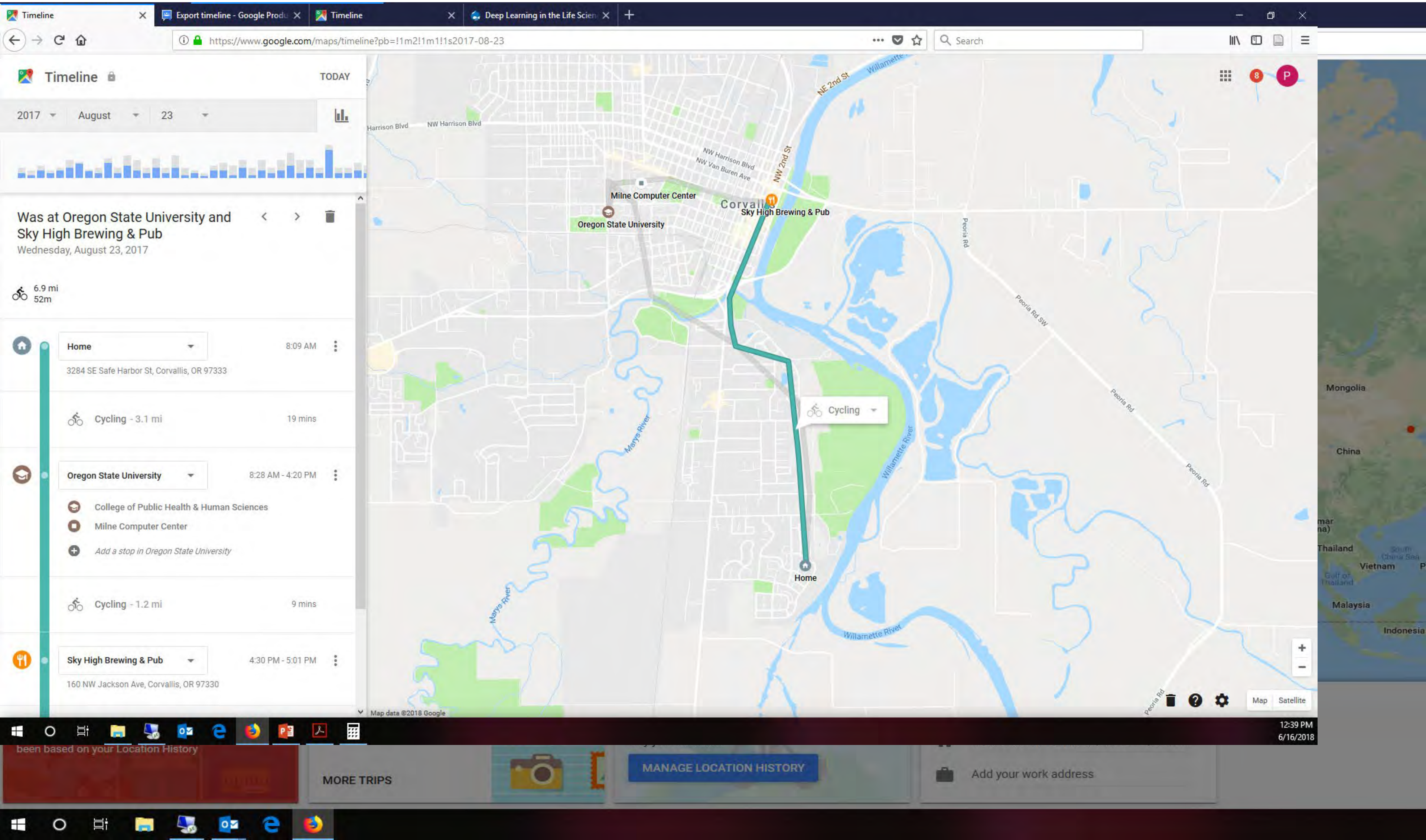
	Model 1	Model 2
	Crude OR (95%CI)	Adjusted OR (95% CI)
NDVI	1.38(1.37-1.39) *	1.42(1.42-1.43) *
Within a Parks	1.14(1.11-1.16) *	1.13(1.10-1.15) *
Near Blue space	1.11(1.09-1.12) *	1.18(1.16-1.19) *
Walkability Index	0.84(0.14-1.54) *	0.89(0.88-0.90) *
Intersection density	0.99(0.99-1.00) *	1.00(0.99-1.00)
Population density	1.04(1.04-1.05) *	1.06(1.06-1.07) *
Traffic air pollution	0.74(0.74-0.75) *	0.72(0.72-0.73) *
Transportation noise	0.31(0.30-0.32) *	0.30(0.29-0.31) *

† Models 1,2 represent estimates for each BE variable in separate models.
Model 1: crude model, includes a random intercept for each participant to account for clustering on each participant.
Model 2: adjusted for age, gender, education, income, marital status and race/ethnicity

Results are Totally Different When Using Exposures Derived From Residential Addresses!

How do we measure long-term time-activity patterns for thousands to millions of individuals?

Smart Phones Enable Long-Term GPS Data Collection (*Passively*) for Large Populations

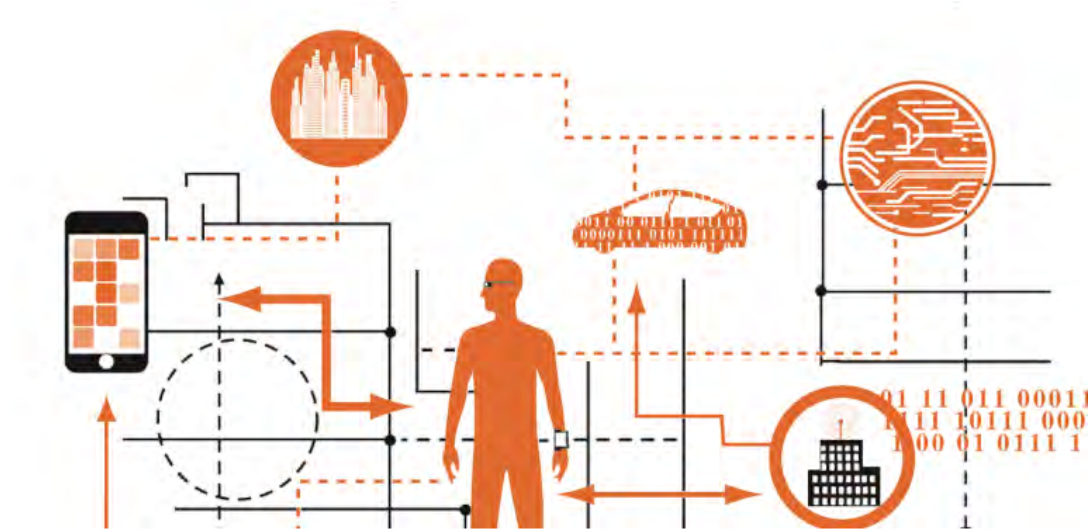


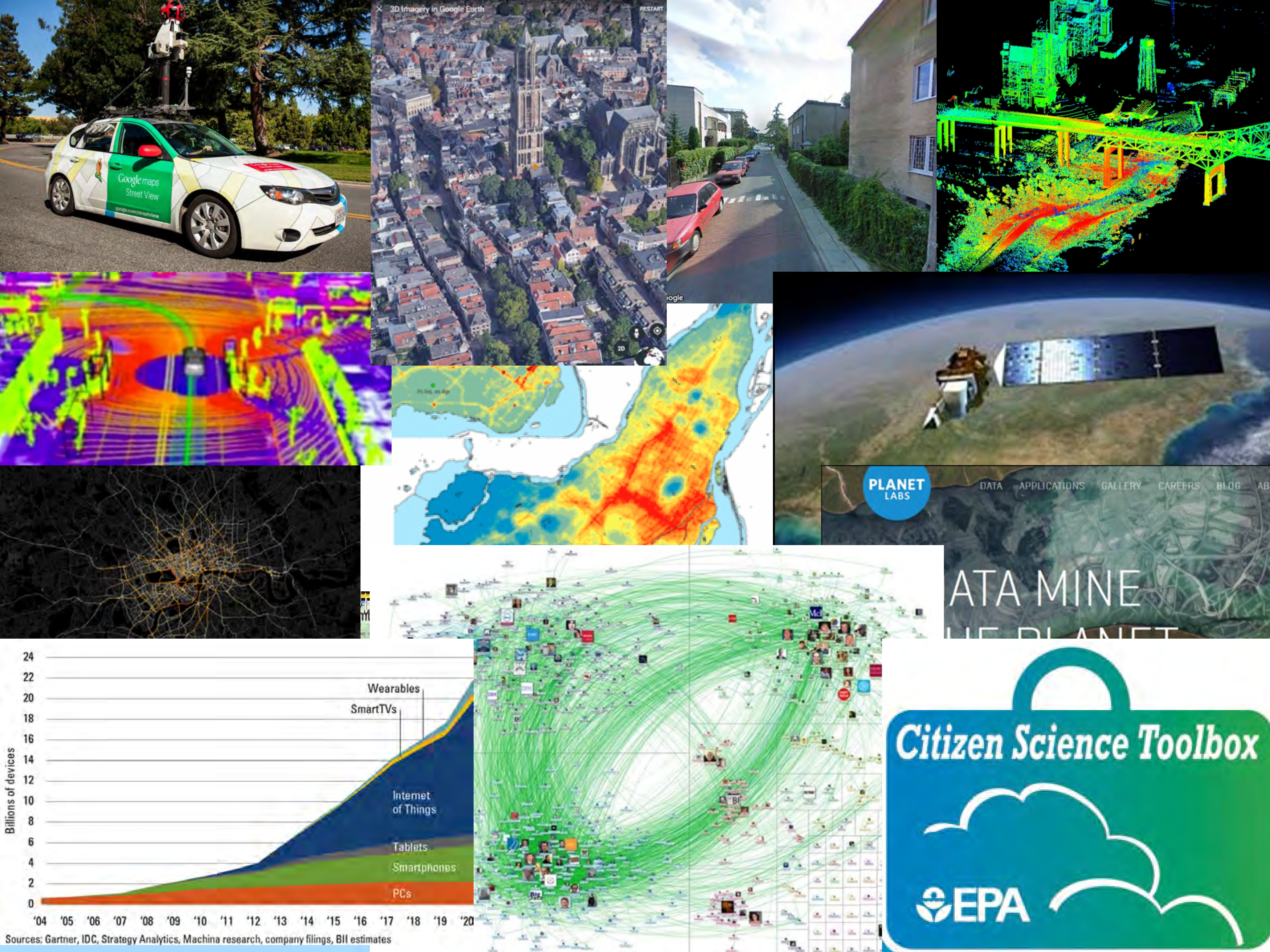
GTL Potential for Environmental Epidemiology

1. Evaluating and applying Google Timeline Data for built environment and physical activity research. *NIEHS*
   - Examine feasibility of collecting GTL data in the WSTR (current response rate ~25%, but early!)
   - Compare accuracy for 288 individuals with GPS monitoring collected.
   - Develop automated pipeline so individuals do not need to provide raw data.
2. Use of Google Timeline Data to assess outdoor physical activity, green space exposure, and their impact on mental health during the COVID-19 stay-at-home orders. *OBSSR*
   - Contact 3,000 participants in the ongoing WSTR COVID study to integrate GTL data.

Big Data: More and New Data

1. Better measures and models of hazards.
2. Examine cumulative impacts of environmental exposures (exposome).
3. Image based exposure assessments.
4. Big Data + robust study designs!





Google maps
Street View
3D Imagery in Google Earth
RESTART
2D
PLANET
LABS
DATA
APPLICATIONS
GALLERY
CAREERS
BLOG
ATA MINE
Wearables
SmartTVs
Internet
of Things
Tablets
Smartphones
PCs
Billions of devices
0
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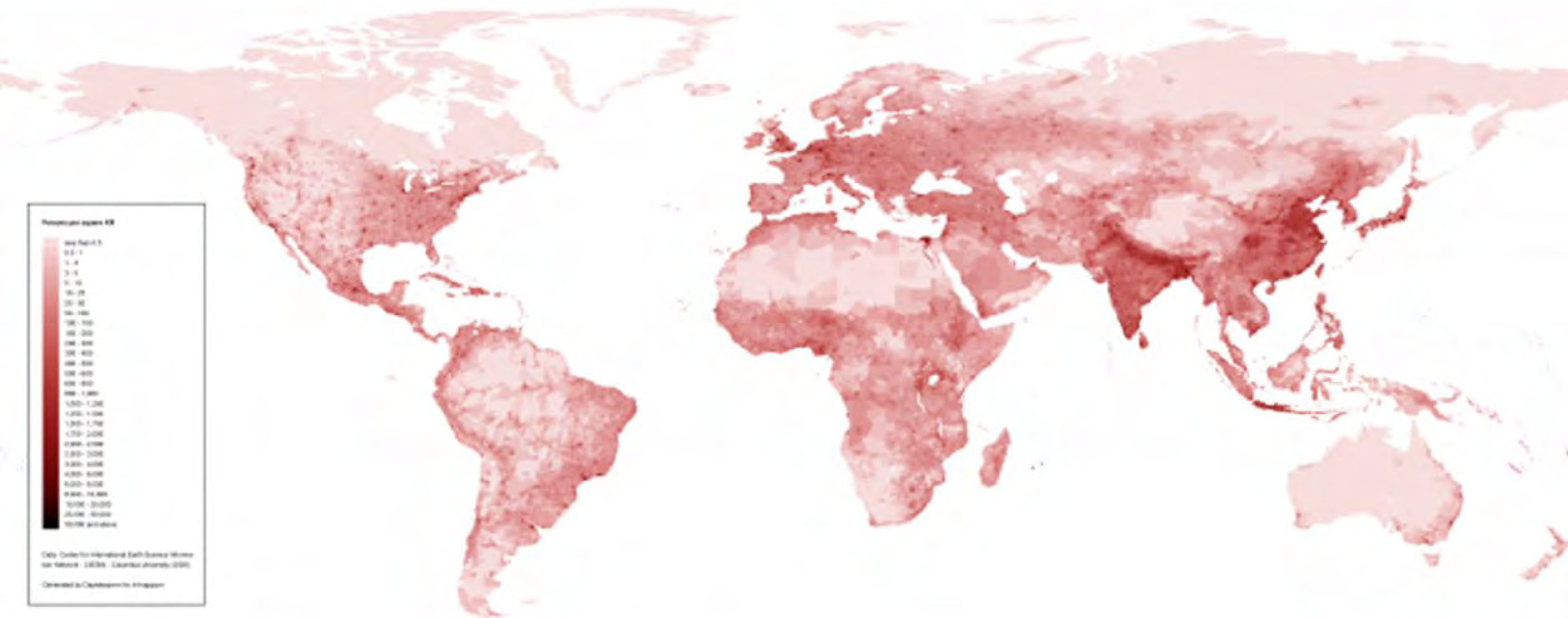
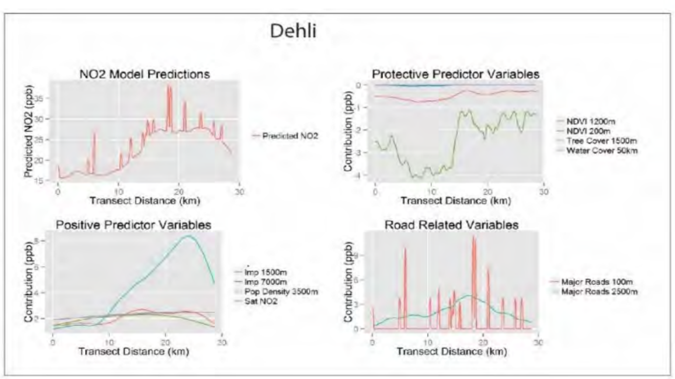
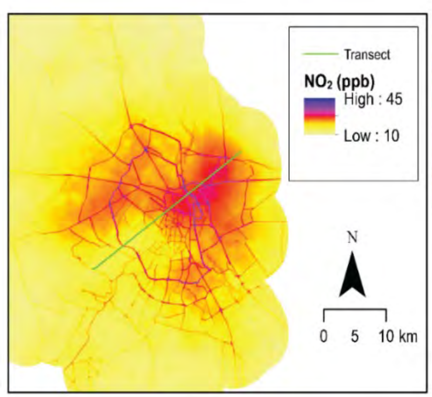
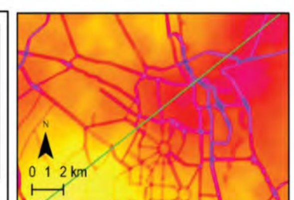
Sources: Gartner, IDC, Strategy Analytics, Machina research, company filings, BII estimates
Citizen Science Toolbox
EPA

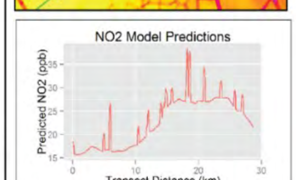
Global LUR NO_2 model (100 meters) created from 5,220 monitors in 58 countries

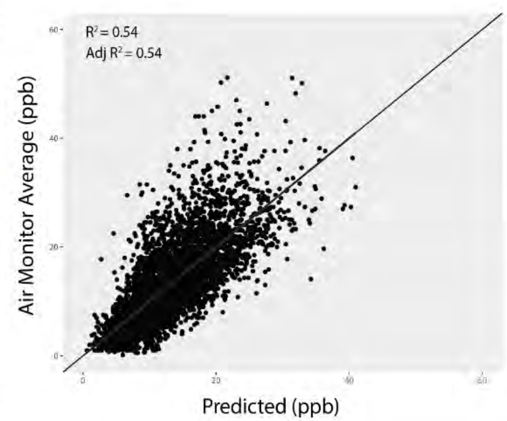


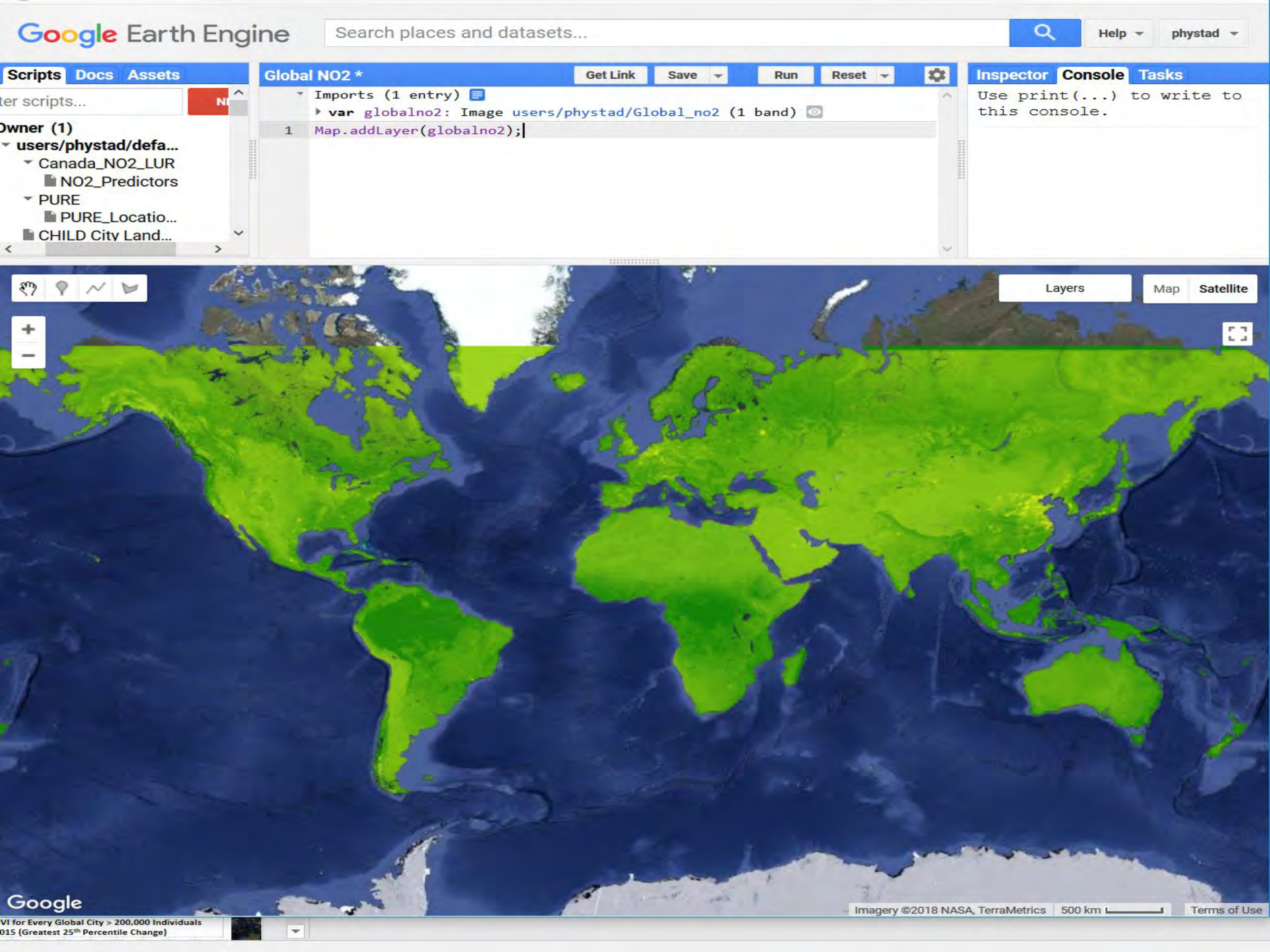












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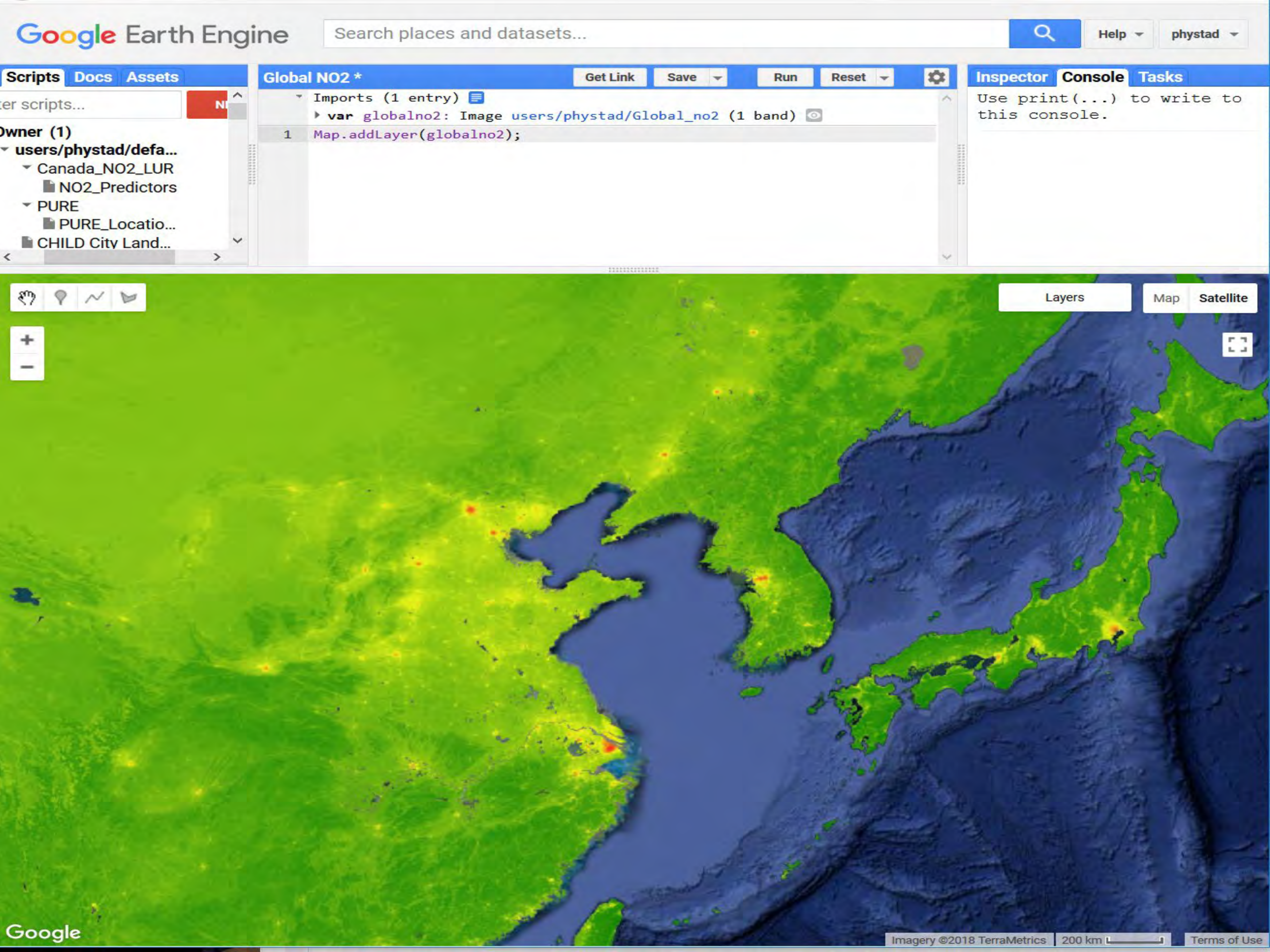
VI for Every Global City > 200,000 Individuals
015 (Greatest 25th Percentile Change)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200 km
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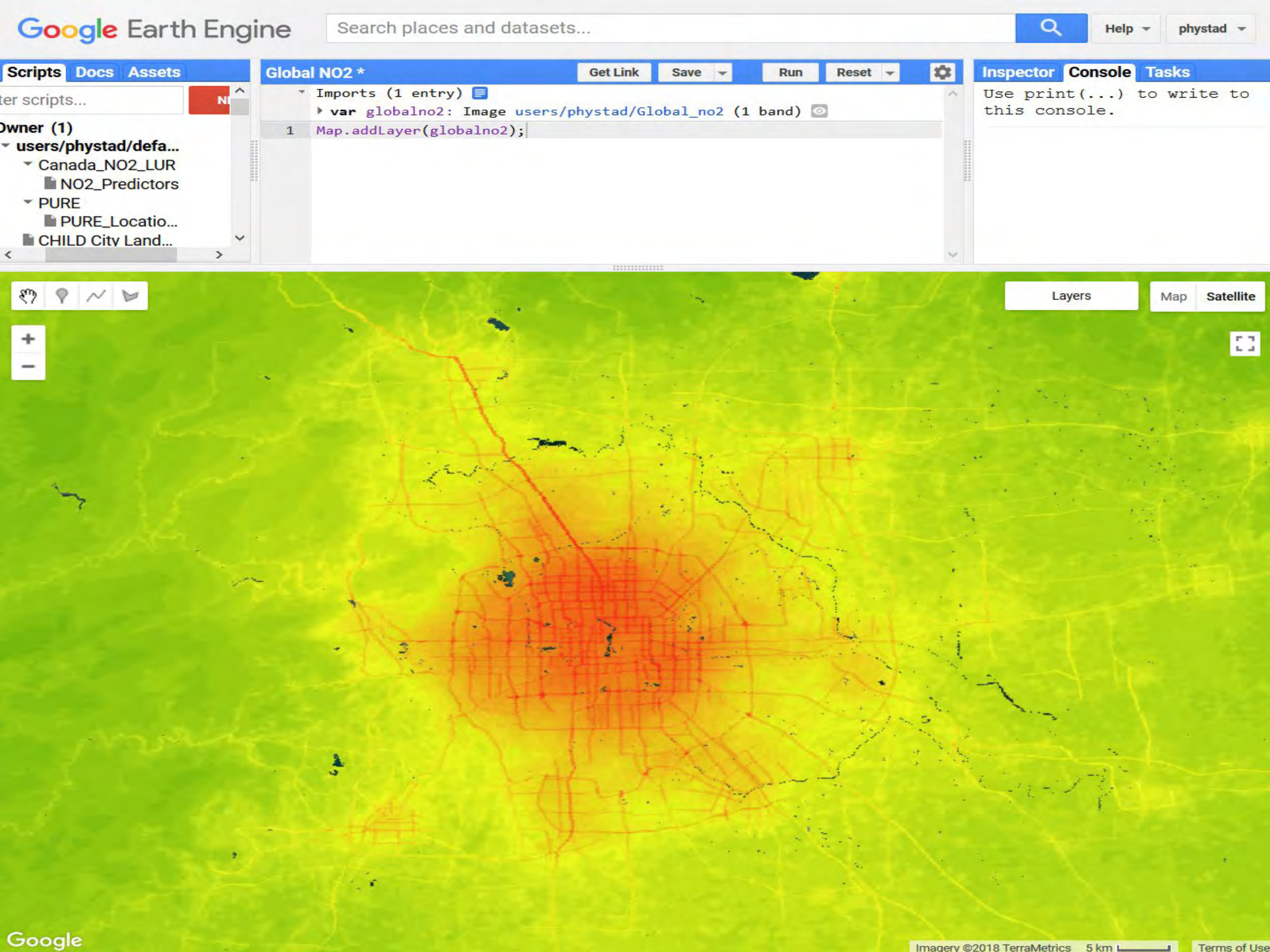
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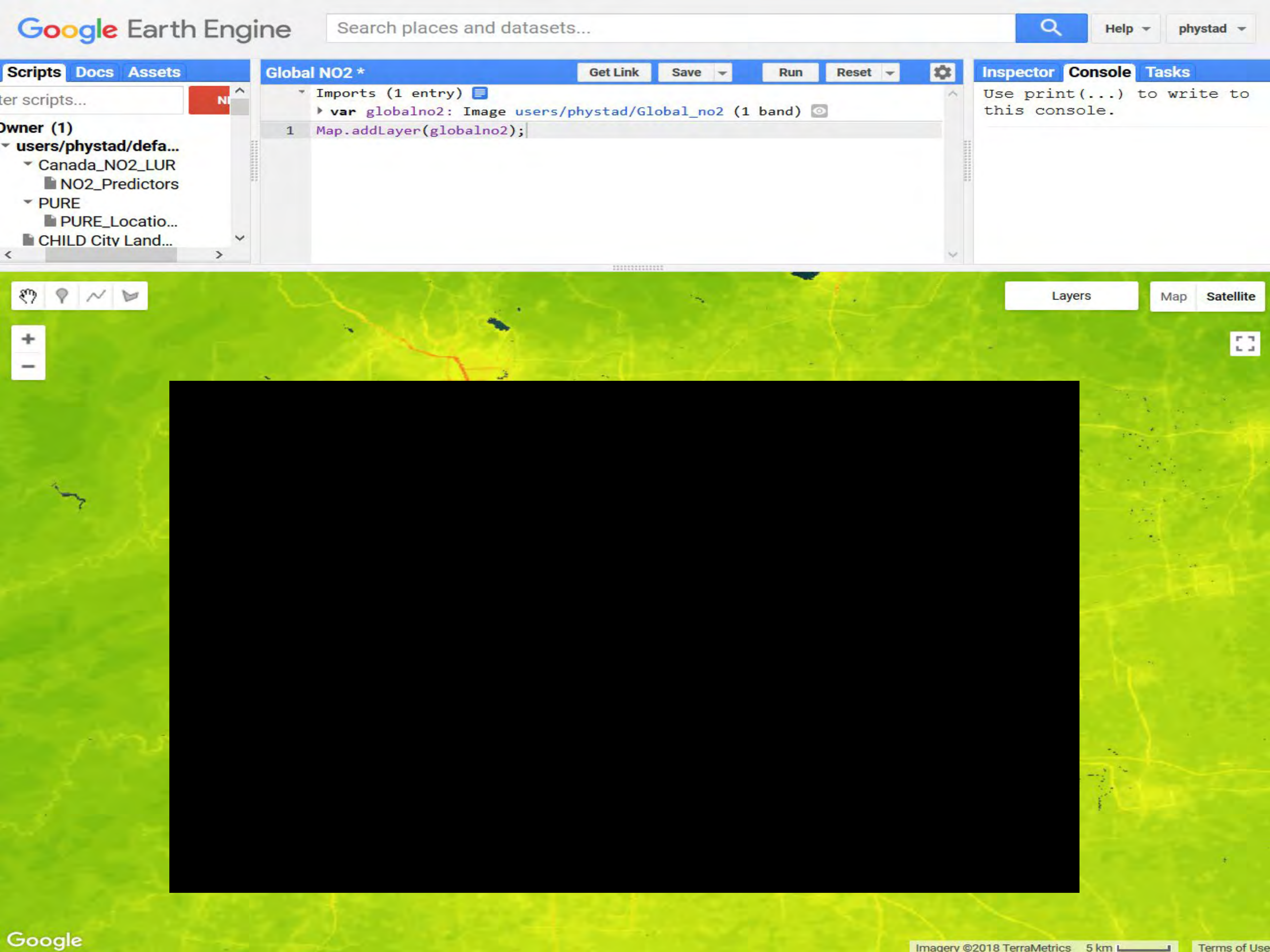
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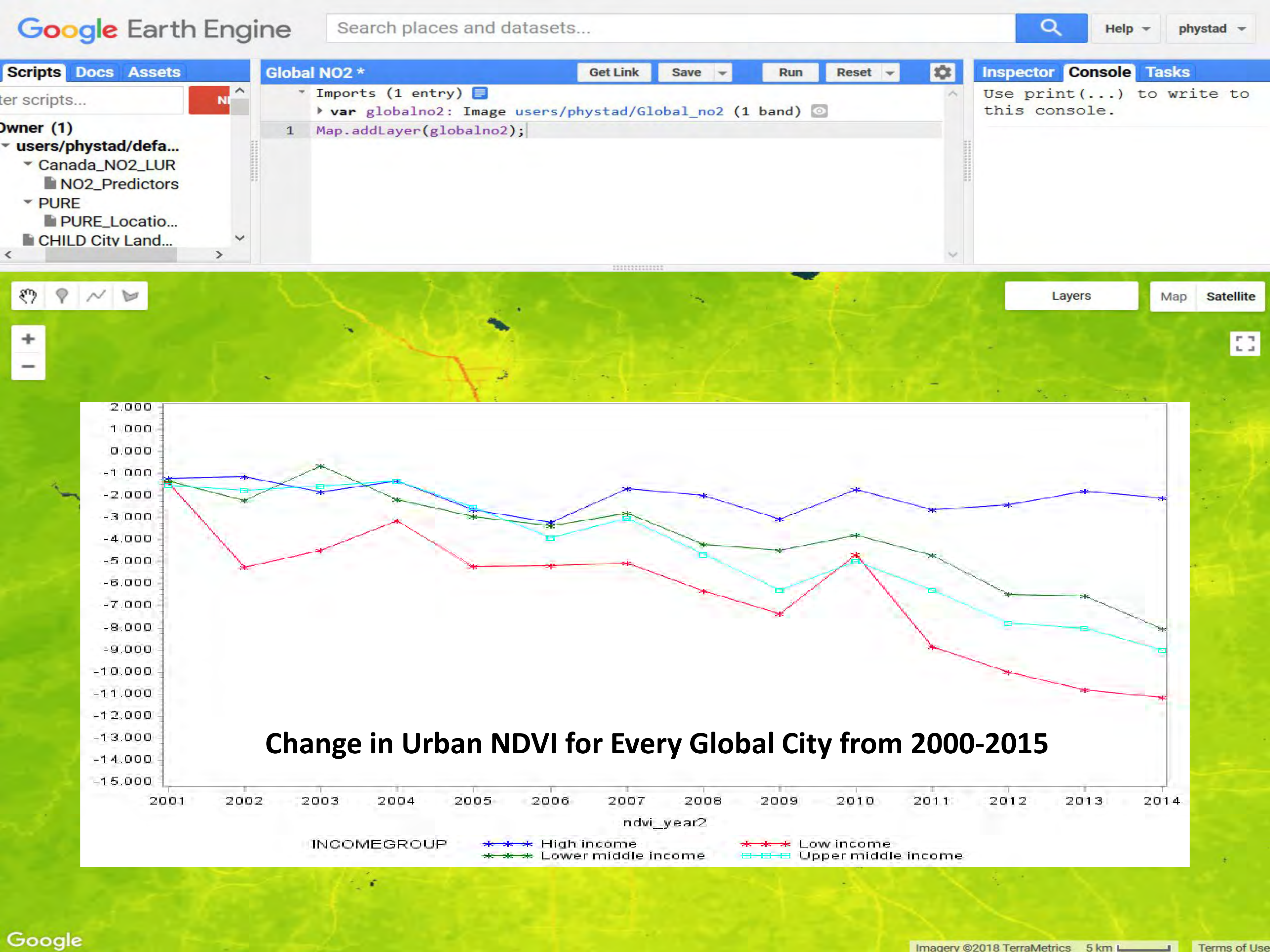
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Change in Urban NDVI for Every Global City from 2000-2015
2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014
ndvi_year2
INCOMEGROUP
High income
Lower middle income
Low income
Upper middle income
Google
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Google Earth Engine Boot Camp: Methods for Using Satellite and Geospatial Data for Environmental Exposure Science

The next live-stream, virtual Google Earth Engine Boot Camp is June 21-22, 2021. Join the email list below to hear about registration opening!

The Google Earth Engine Boot Camp is a two-day intensive training workshop that includes seminars and hands-on case-studies to provide an overview of concepts, techniques, applications and data analysis methods for using the Google Earth Engine to estimate environmental exposures for health research.

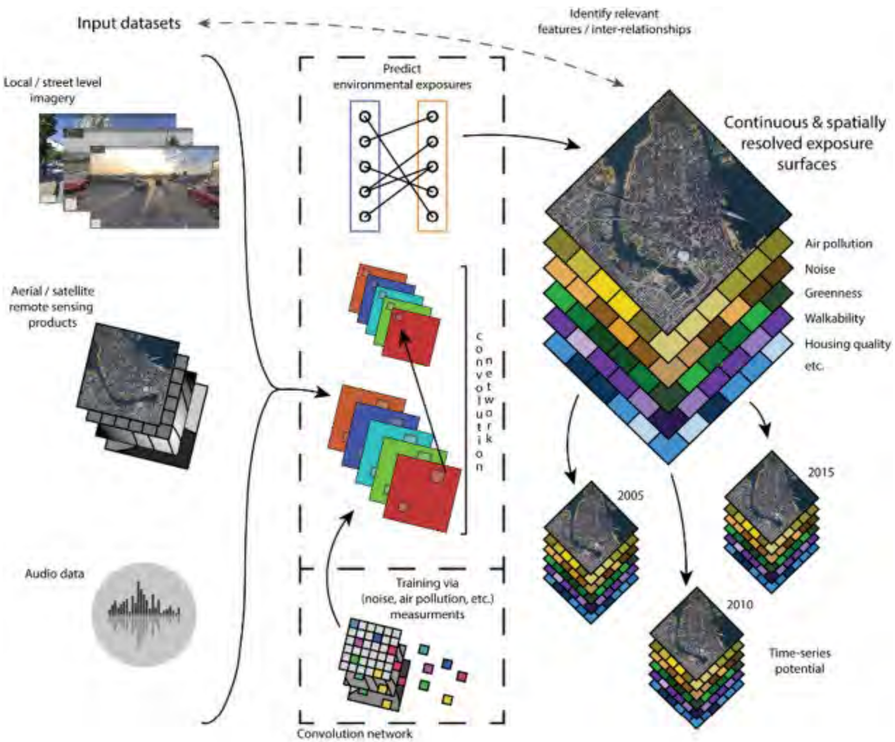
SUBSCRIBE FOR UPDATES

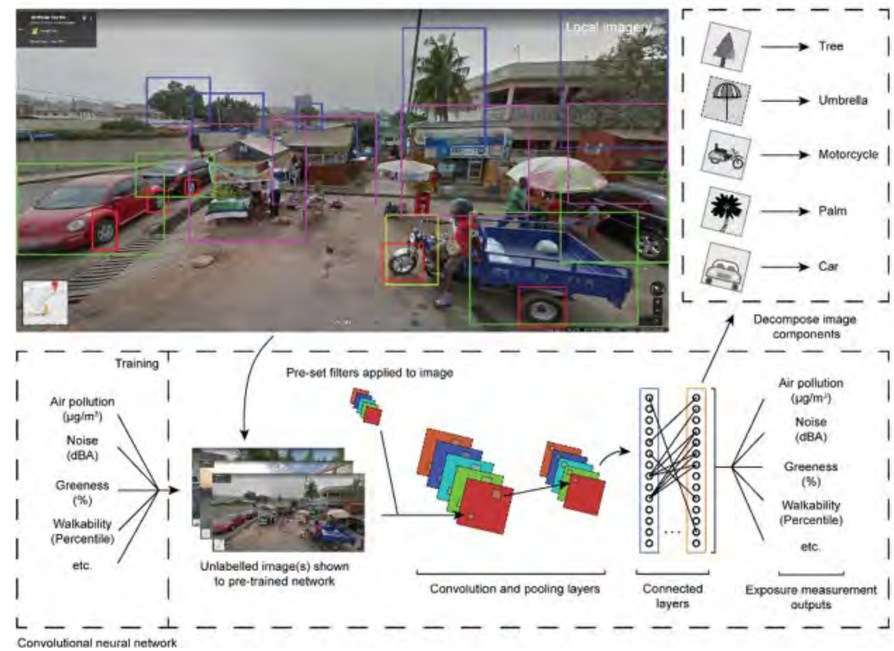
Subscribe for updates on registration and scholarship dates, deadlines, and announcements.

Jump to: Overview | Prerequisites | Instructors | Scholarships | Locations | Registration Fees | Additional Information

Image Based Environmental Exposure Assessment

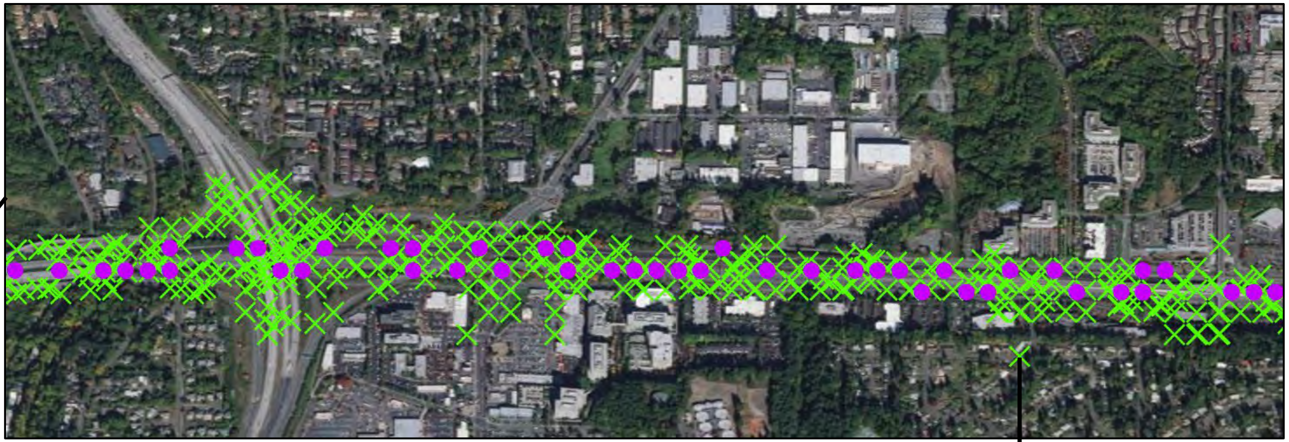
A picture tells a thousand…exposures: Images + Deep Learning Models





A picture tells a thousand…exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology. https://www.sciencedirect.com/science/article/pii/S0160412018322001#f0010

Assessing Green Space Exposure



300 Individuals with GPS Monitored for 2 weeks:
= 3.4 million GSV images (~10 TB, 120 days to process).

Street View Image Segmentation

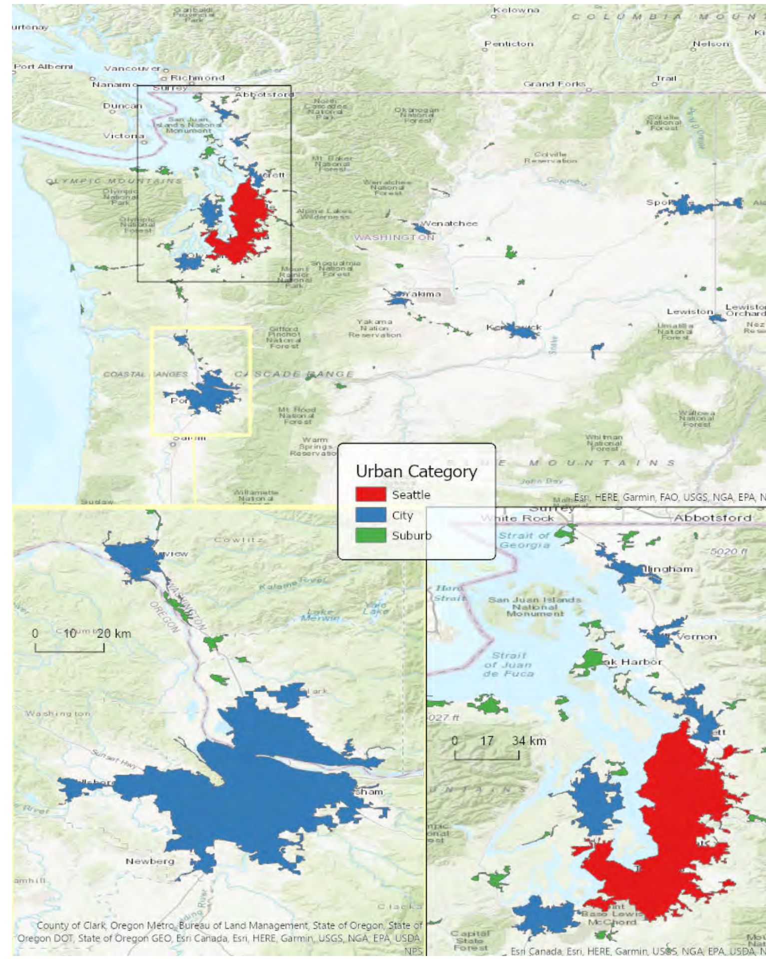
Selected pixel-level features segmented by the PSPNet algorithm for each GSV image	
Exposure Measure	**Segmentation Classes Included**
Physical Features	'wall', ’building', 'road', 'sidewalk', 'house', 'fence', 'signboard', 'skyscraper', 'path', 'stairs', 'door', 'bridge', 'bench', 'awning', 'streetlight', 'pole', ‘fountain', 'swimming pool', 'sculpture', 'traffic light',
Accessibility Features	'sidewalk', 'escalator', 'path', 'stairs', 'stairway', 'streetlight', 'bench', 'step'
Natural Features	'tree', 'grass', 'plant', 'field', 'flower', 'water', 'sea', 'waterfall', 'lake', 'mountain', 'rock', 'sand', 'hill',
Green Space	'tree', 'grass', 'plant', 'field', 'flower'
Trees	'tree'
Blue Space	'water','sea','waterfall','lake'

Predicting Complex Constructs

- Health and behaviour is influenced by perceptions of the local environment.
- Difficult to objectively capture perceptions in large health studies.
- Develop deep learning models to predict:
  - Green space quality
  - Safety
  - Beauty
  - Stressfulness

Deep Learning of Street View Imagery to Assess Urban Green Space Relationships with Mental Health: A Twin Study

- Create training image dataset based on urban categories (150,000 street view images)
- Collect perception data using crowdsourced methods.
- Develop prediction models using transfer learning methods and deep learning models.
- Apply model to street view imagery around residential locations.



Street View Imagery

- For each location download 4 images.
- Adjust for difference between compass and street heading.
- Run Segmentation models to ensure diversity of built environment features.

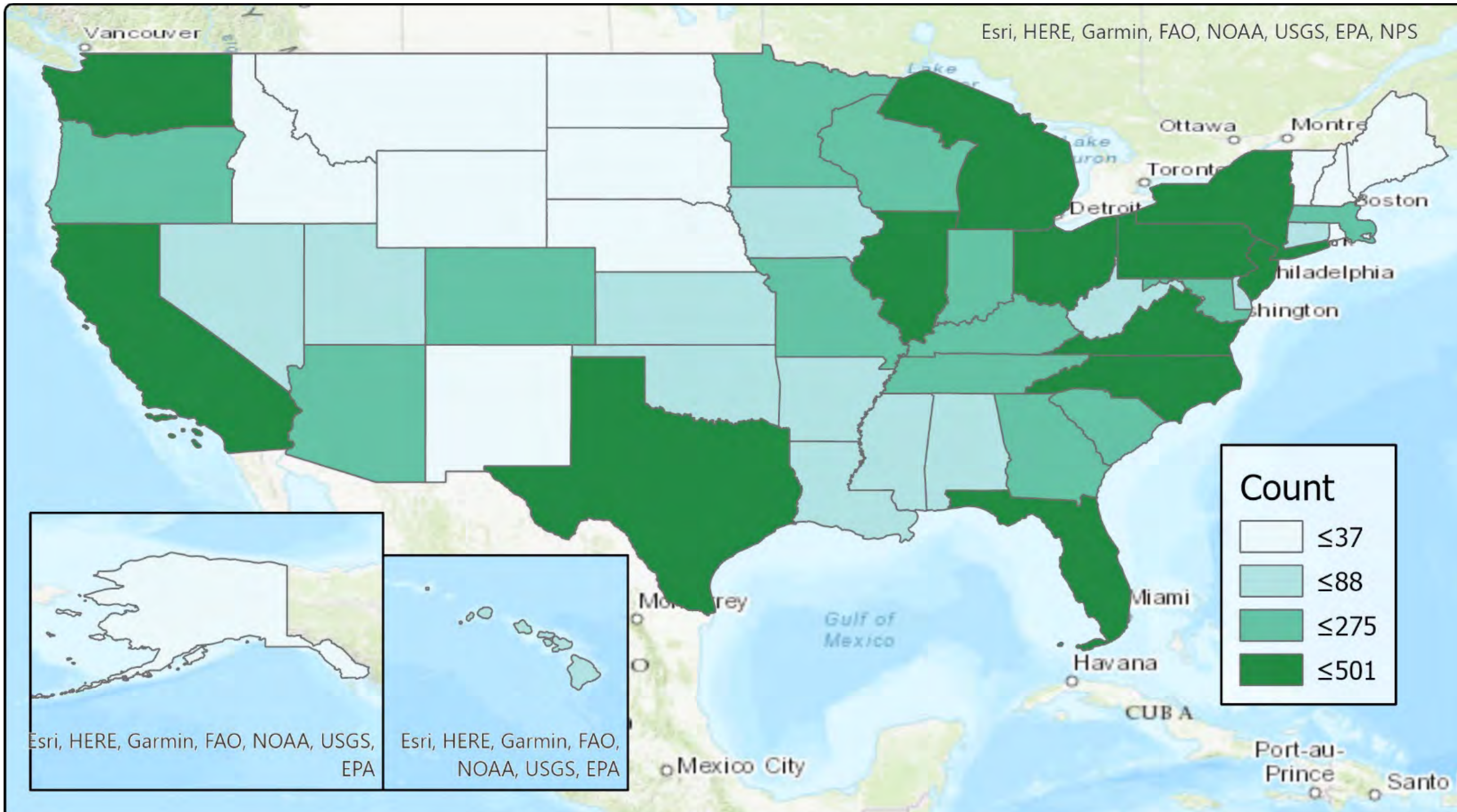
Crowd-Sourcing Perceptions

2. Which street has a higher quality of nature?

Move the slider left or right to make your choice. Move the slider farther if you feel more strongly about your choice. You cannot rank the images as equal.

left street has a higher quality of nature | right street has a higher quality of nature

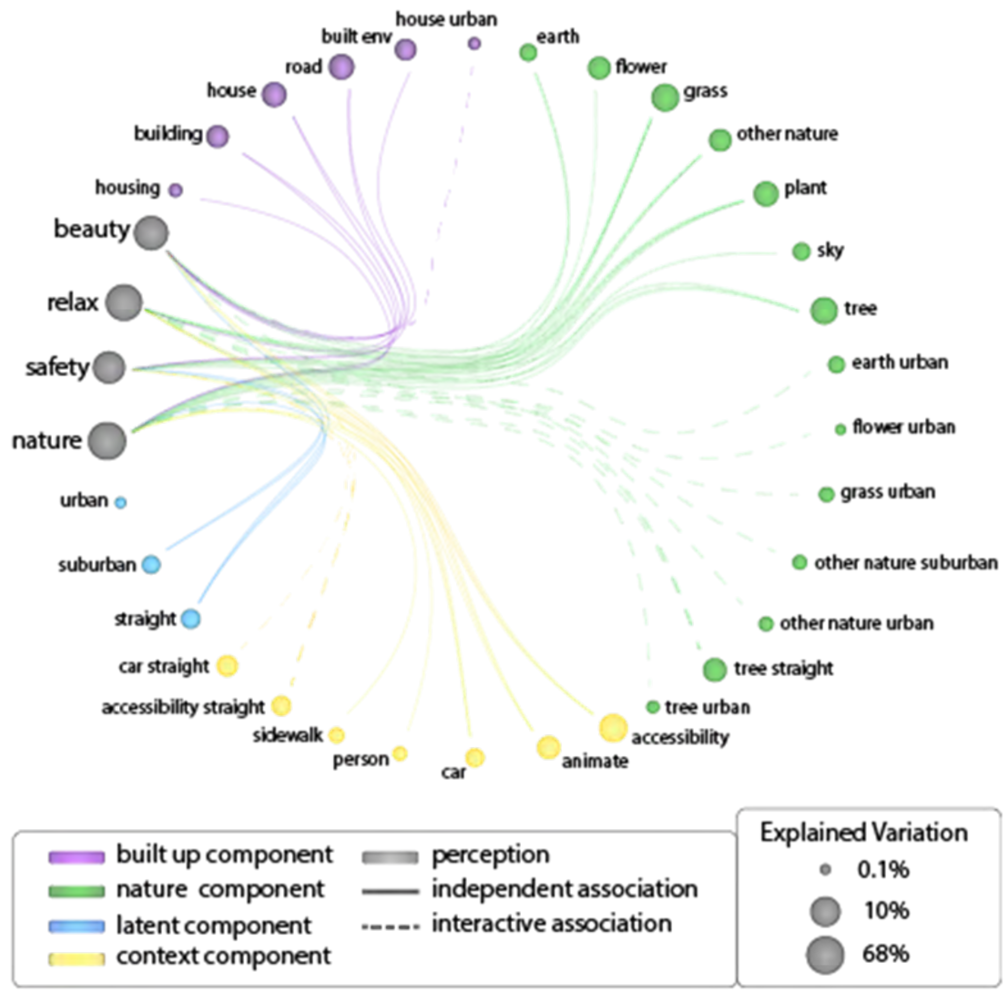
Voter Distribution



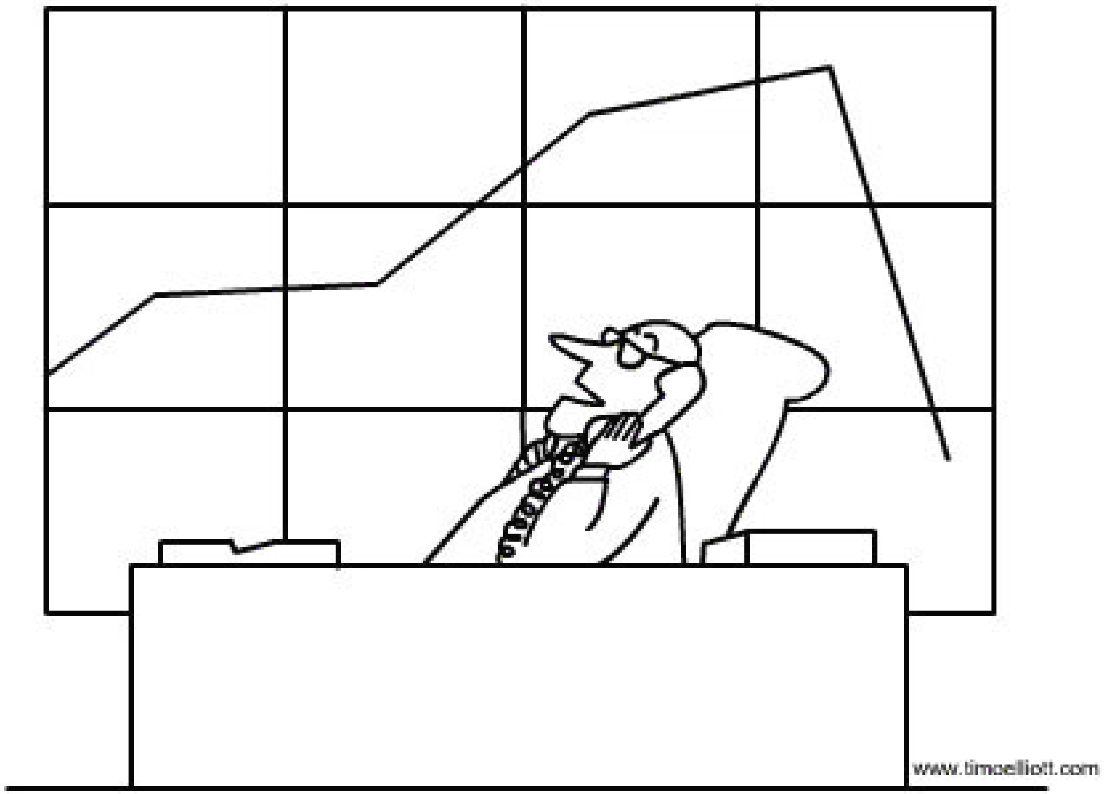
Score Distribution

Deep Learning Model Results – Predicting Winner from Image Pairs

Metric	Initial PlacePulse Data (n=1.2 million	Refined Using Washington Images (n=30,000)
Safety	63.50%	67.42%
Relaxing	66.39%	72.16%
Beauty	63.67%	69.11%
Green Space Quality	na	76.74%



Big Data ≠ Better Information

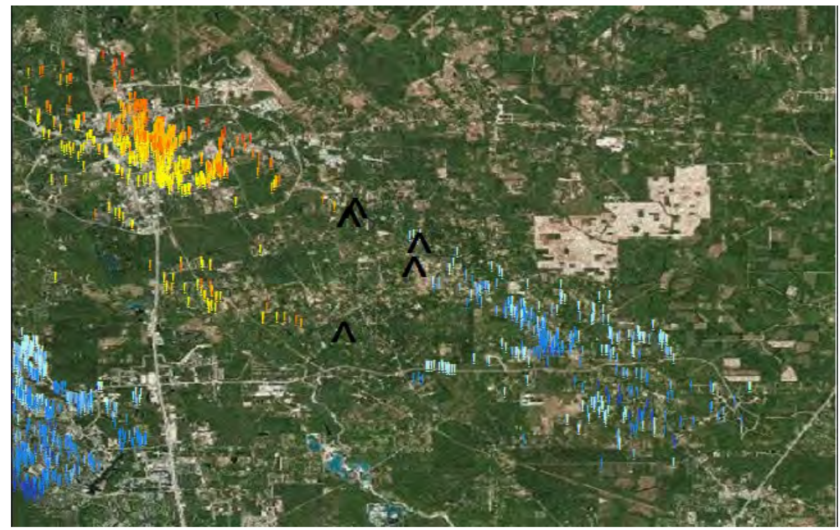


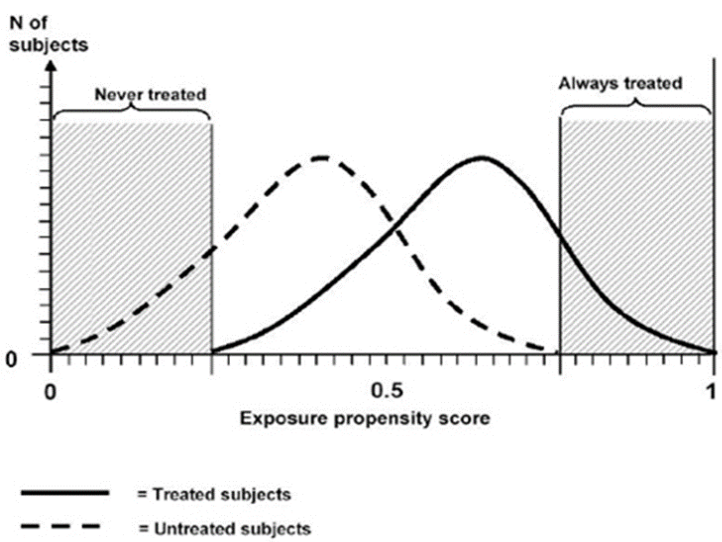
"Yes, I have indeed come to a strategic decision:
I'm going to pretend the bad data doesn't exist... "

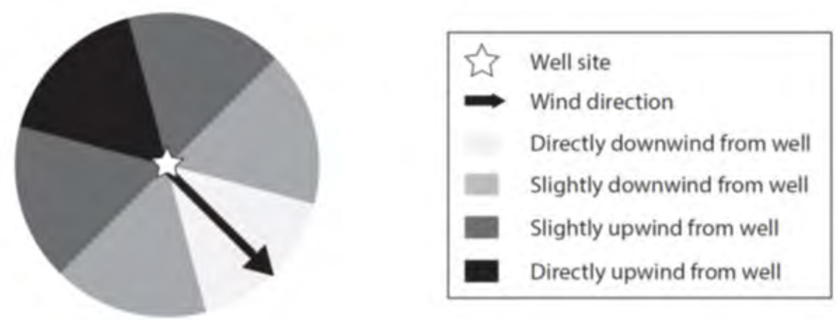
BIG Data + Robust Study Design = Better Environmental Epidemiology

- Big data can reduce exposure measurement error.
- Big data provides more flexibility for exposure assessment methods and study design.
- Can ensure exposure method unrelated to SES and other potential confounding factors.
  - Instrumental variables
- Capitalize on natural experiments and integrate causal inference methods.
  - Difference-in-difference analysis.

E.g., Matching Counterfactual Populations for Oil and Gas Epidemiological Studies







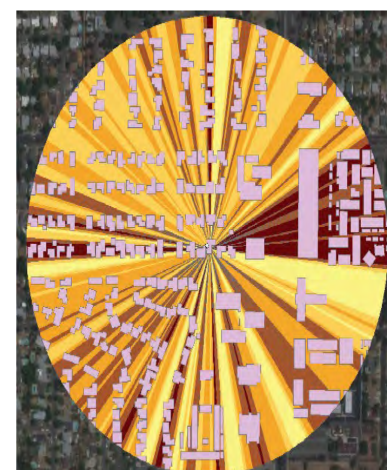
E.g., Incorporating Wind into Air Pollution Exposure Assessments

Upwind/Downwind of Roadways

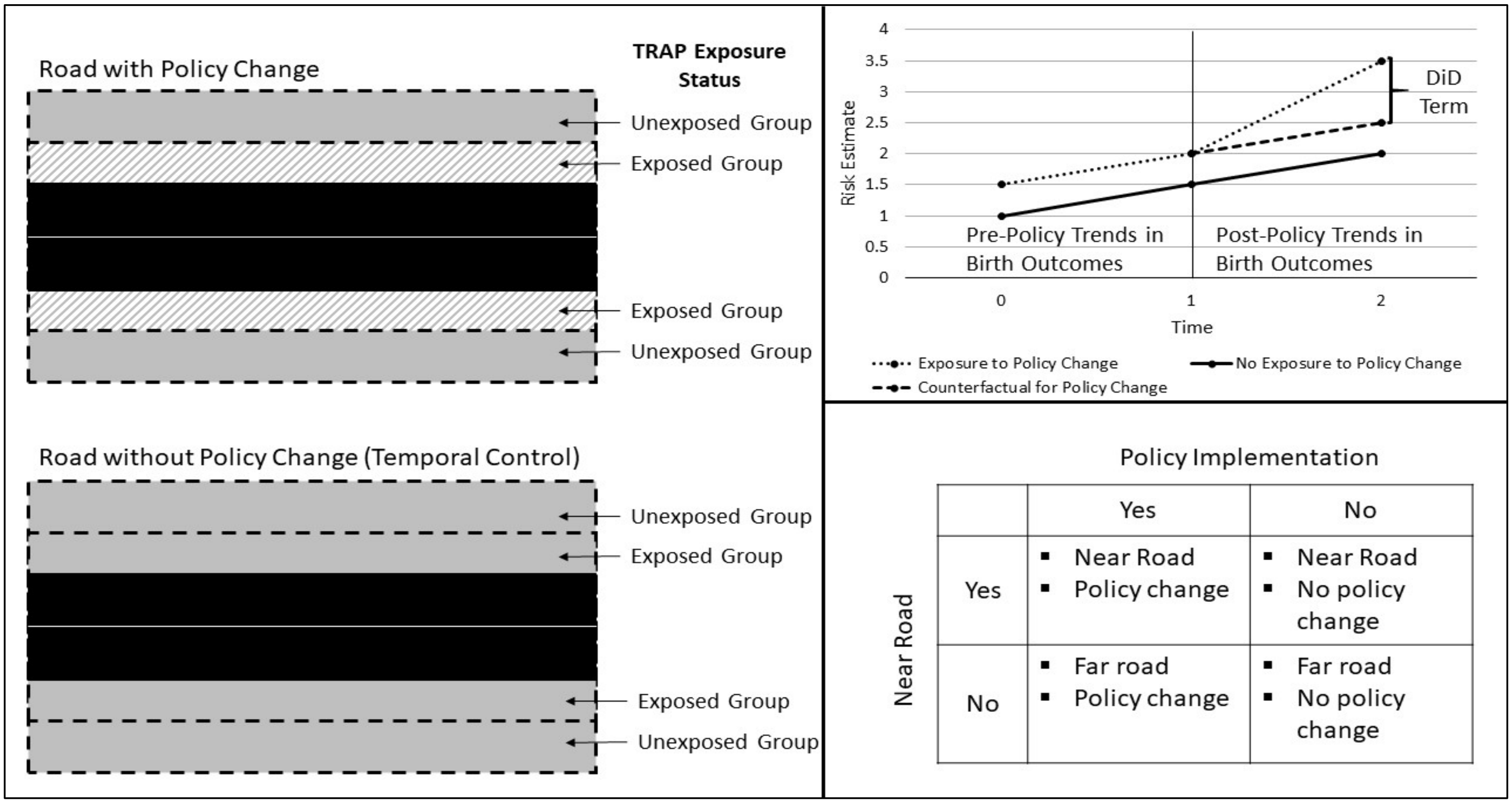
rose wind from NOAA estimates (GoogleEarth Engine)

amount of major and minor roads within 10km upwind

Tree and Building Shielding



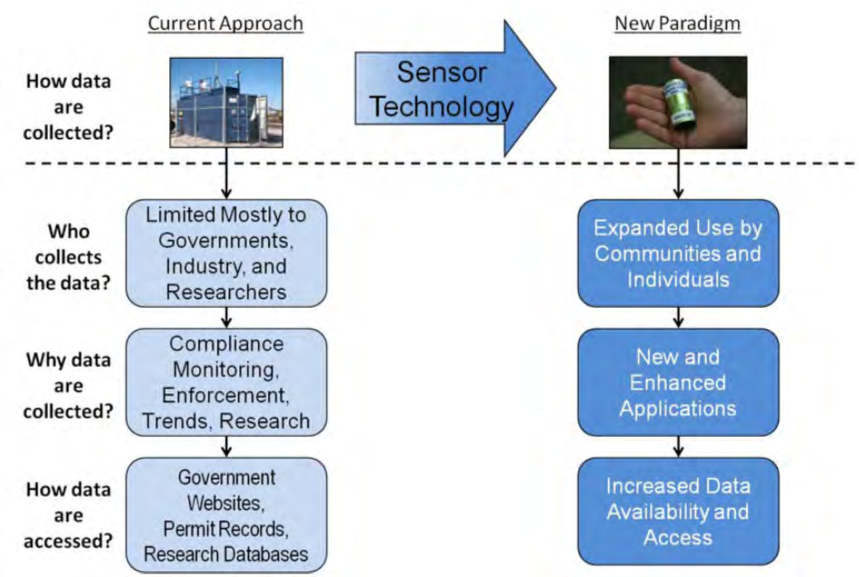
E.g., Local Congestion Programs, Reductions in Air Pollution, and Impact on Adverse Birth Outcomes



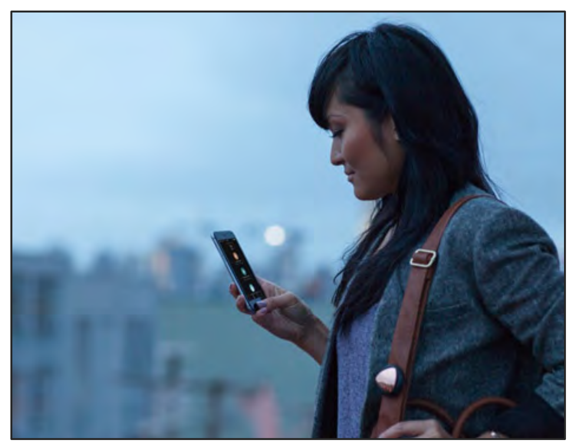
Conceptual Diagram for Proposed Difference-in-Differences Analyses in Aim 2

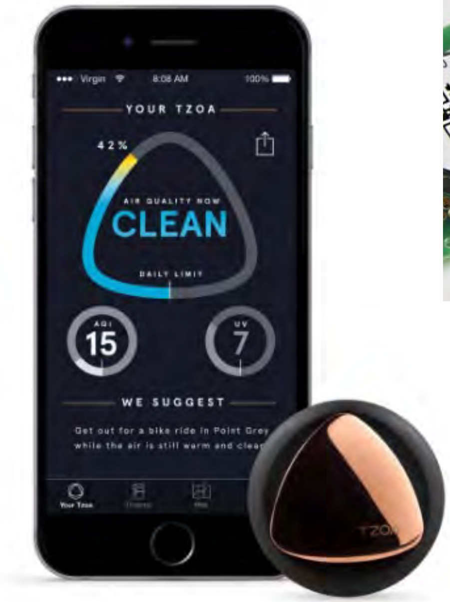
Sensors and Personal Measures:

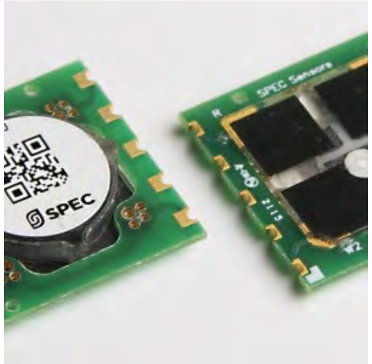
1. The gold standard for external environmental exposures.
2. New paradigm of small inexpensive environmental sensors emerging.
3. Technology changing rapidly!



Snyder et al. 2013

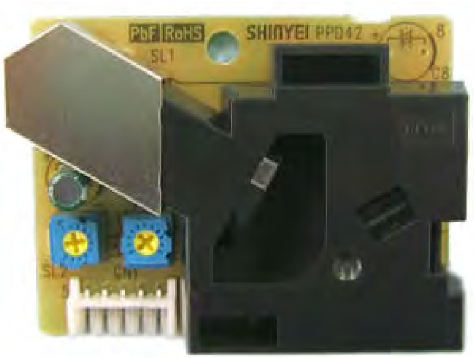



Virgin
8:08 AM
100%
YOUR TZOA
42%
AIR QUALITY NOW
CLEAN
DAILY LIMIT
AQI
15
UV
7
WE SUGGEST
Get out for a bike ride in Point Grey

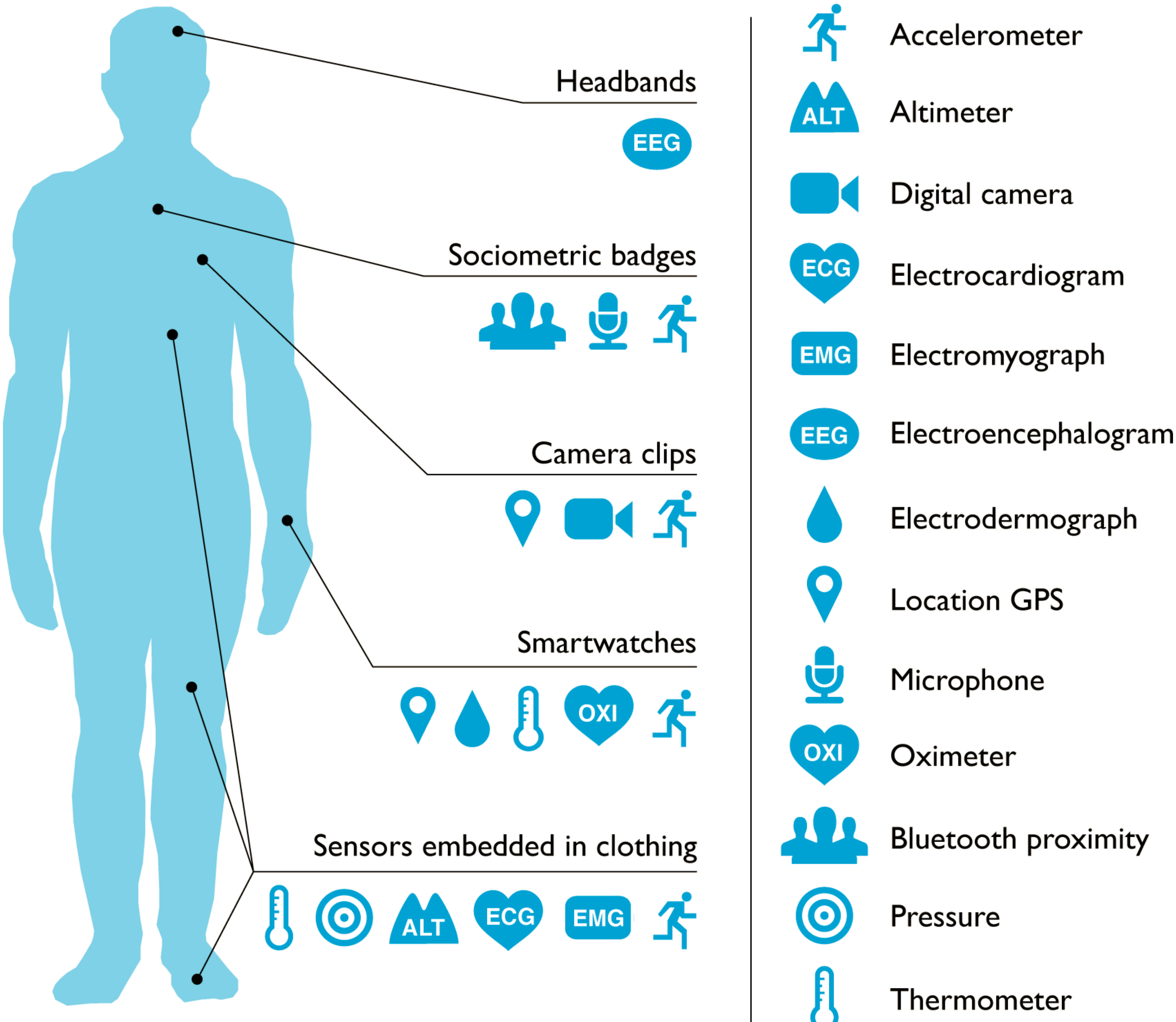

SPEC
SPEC Sensors

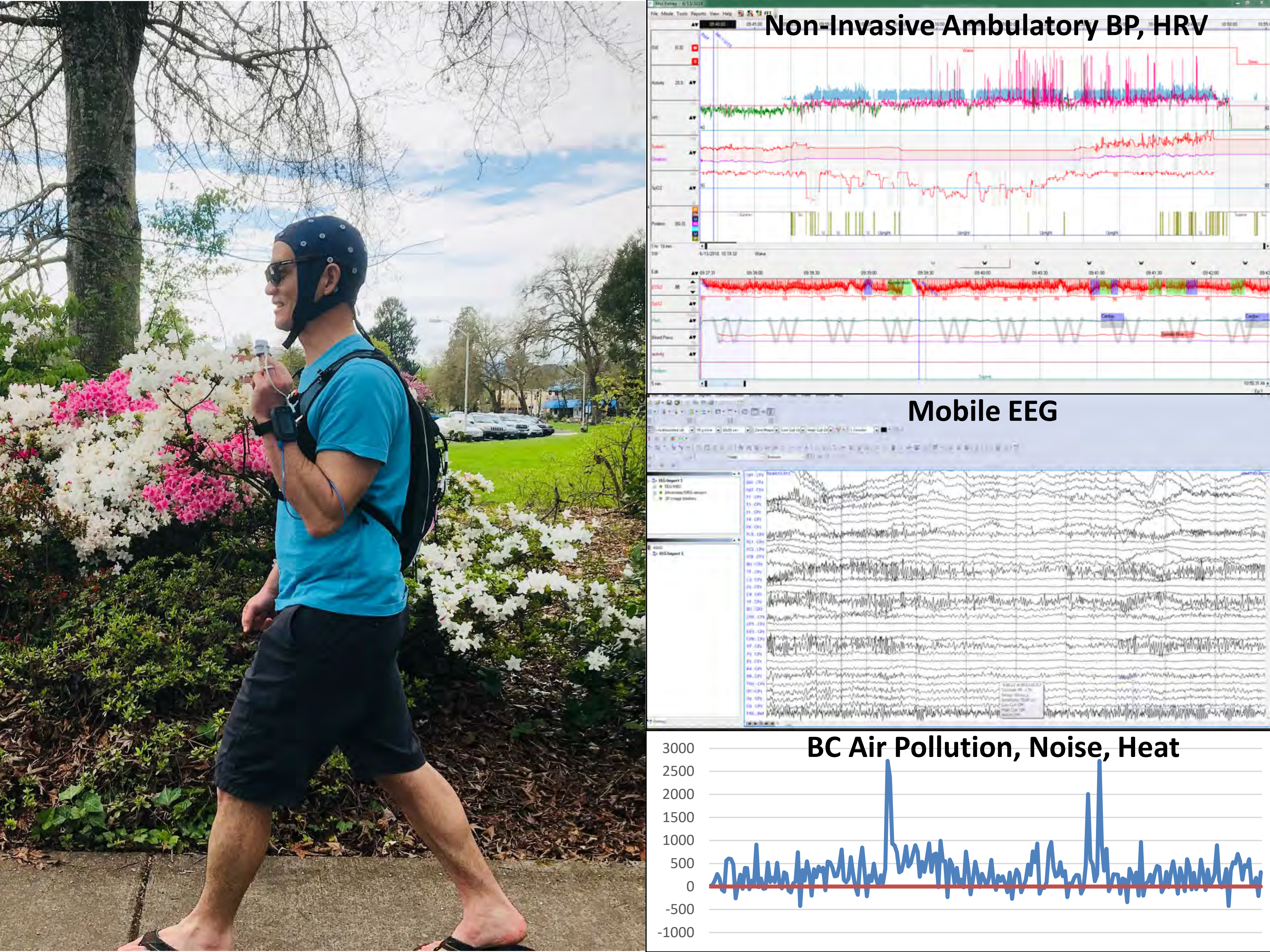

UNIVERSITY


PM2.5センサ


PbF RoHS
SHINYEI PPD42
SL1

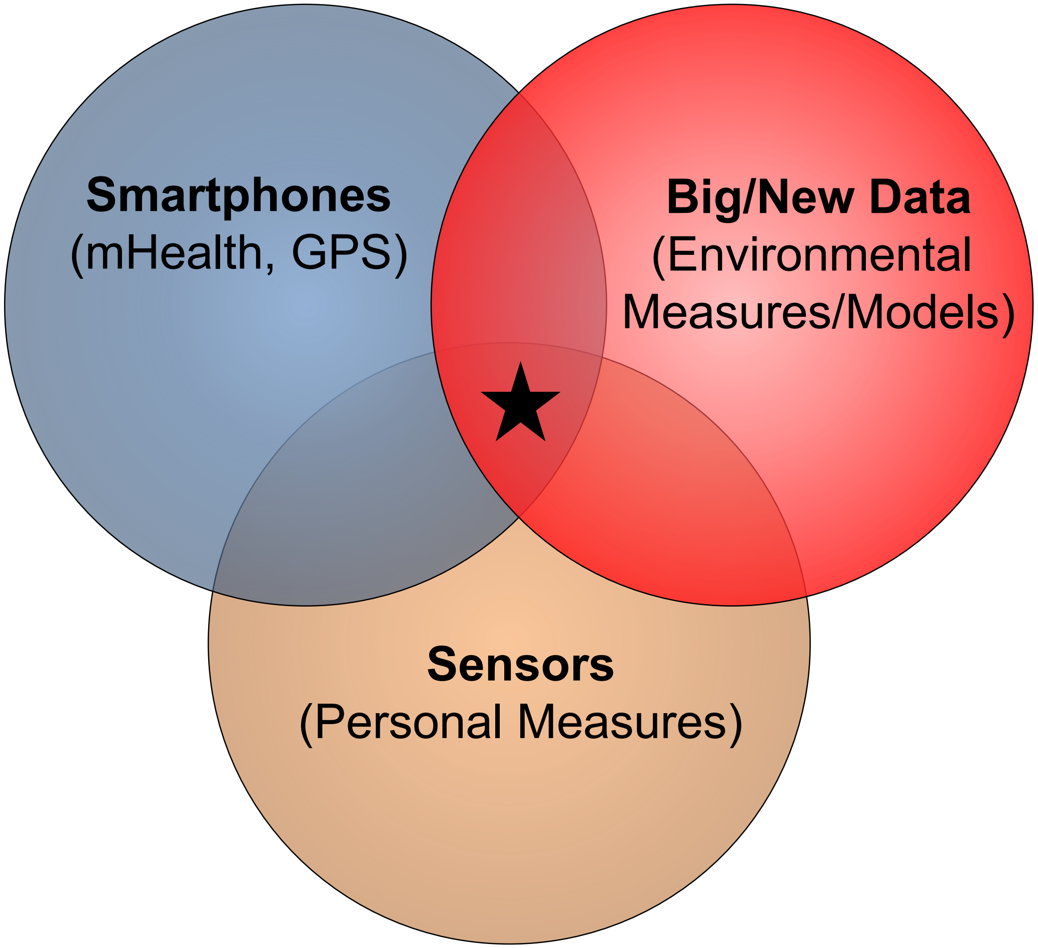

UNITED STATES OF AMERICA
IN GOD WE TRUST
LIBERTY
QUARTER DOLLAR


Headbands
EEG
Sociometric badges
Camera clips
Smartwatches
OXI
Sensors embedded in clothing
ALT
ECG
EMG
Accelerometer
Altimeter
Digital camera
Electrocardiogram
Electromyograph
Electroencephalogram
Electrodermograph
Location GPS
Microphone
Oximeter
Bluetooth proximity
Pressure
Thermometer


Non-Invasive Ambulatory BP, HRV
Mobile EEG
BC Air Pollution, Noise, Heat
3000
2500
2000
1500
1000
500
0
-500
-1000

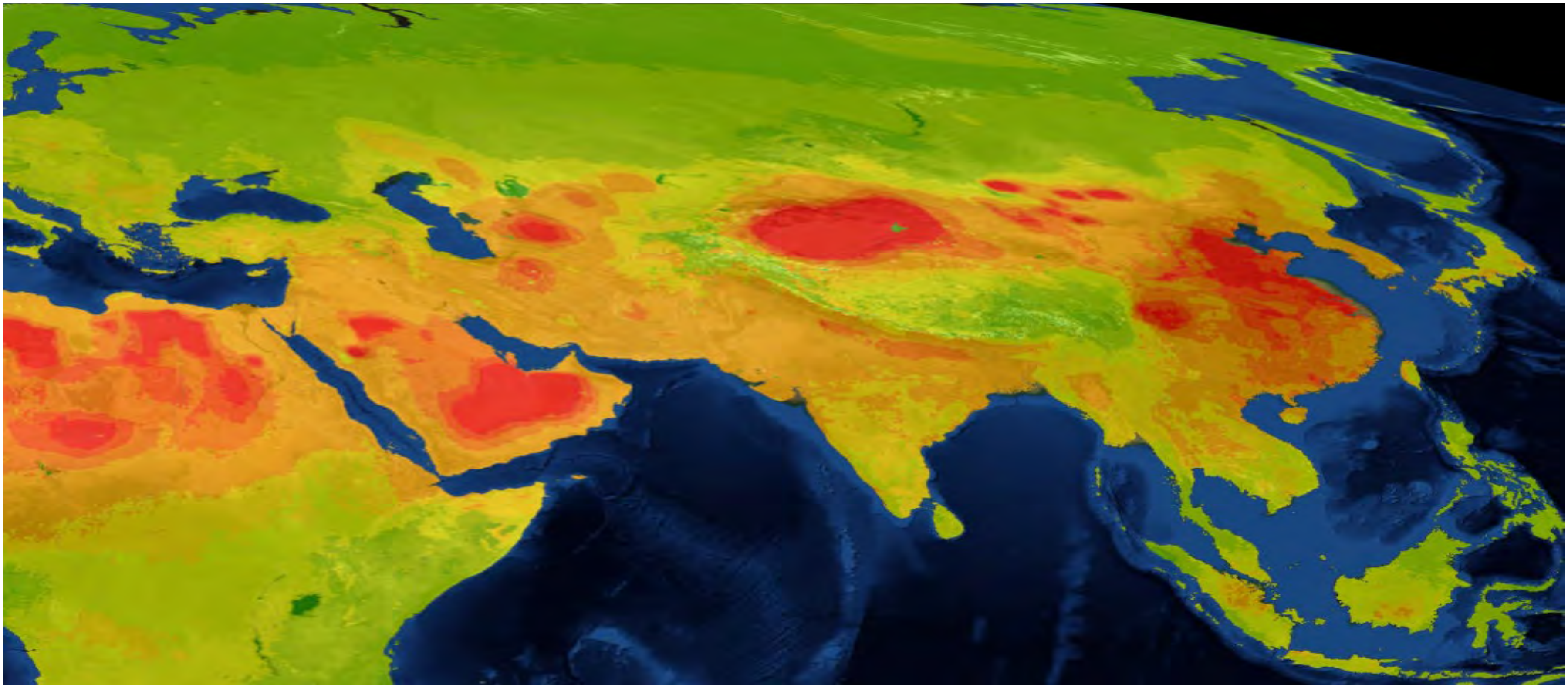
Not there yet… but sensors evolving rapidly

Pulling it all Together…



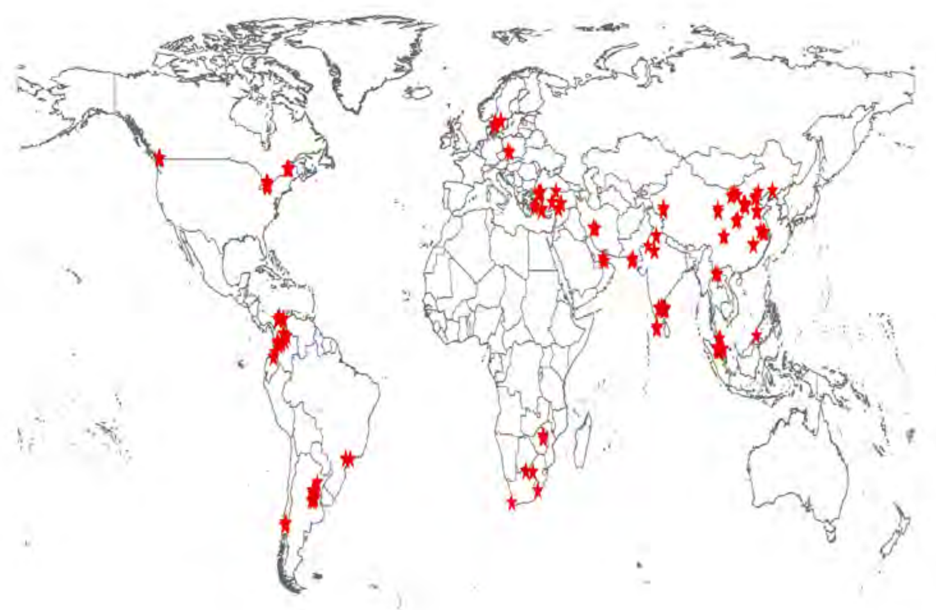
Closest I have Got ☺

PURE AIR: Global Assessment of Air Pollution and CVD



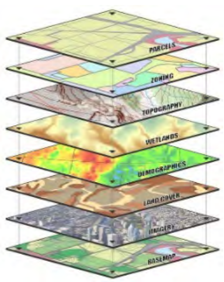
Prospective Urban and Rural Epidemiology (PURE) Study

- Prospective cohort study of 160,000 adults aged 35-70.
- Located in 750 communities in 21 countries.
- Comprehensive individuals survey data and medical information collected.
- Followed for 10 years to document incident health events.



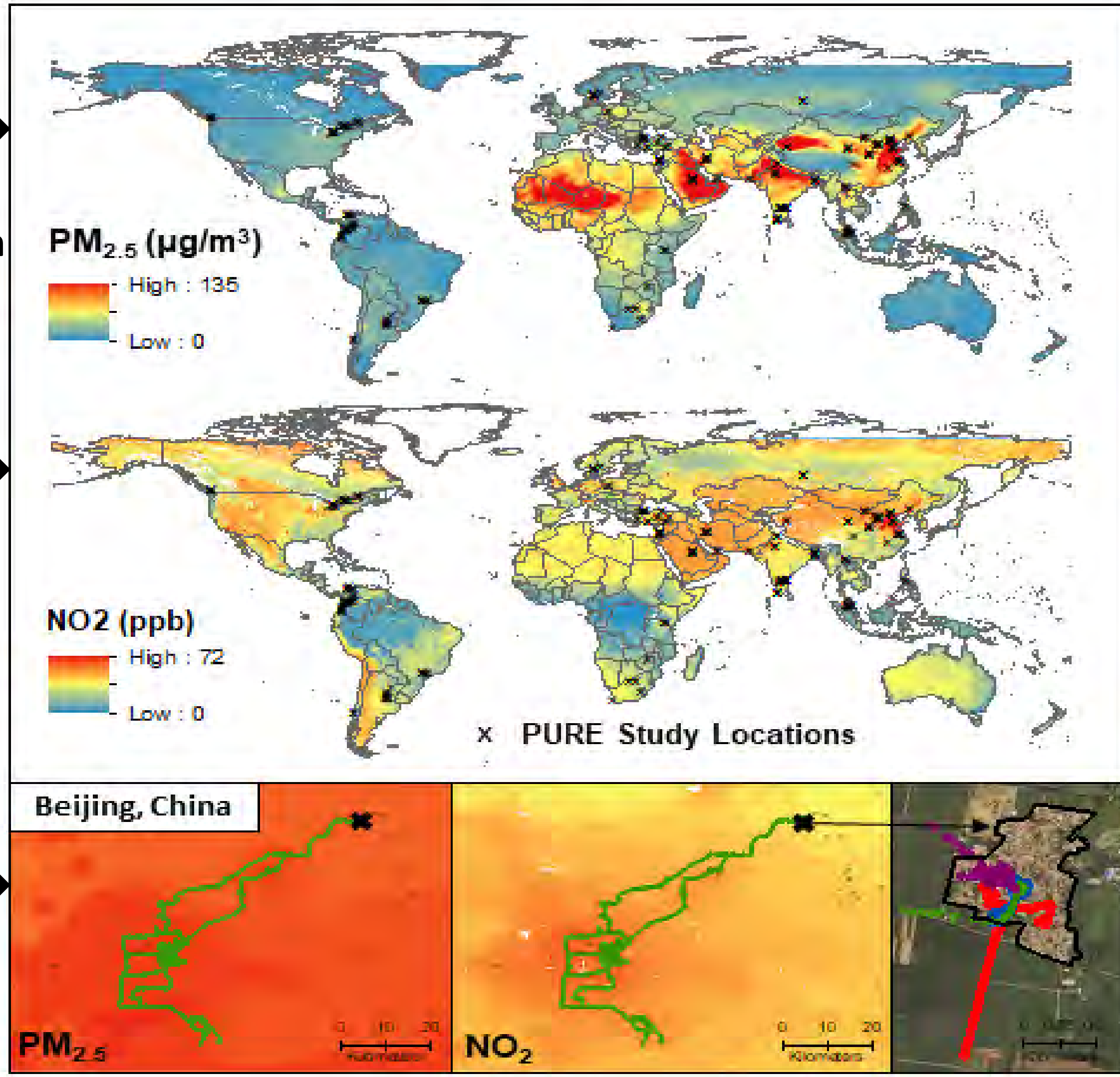
Air Pollution Exposure Information

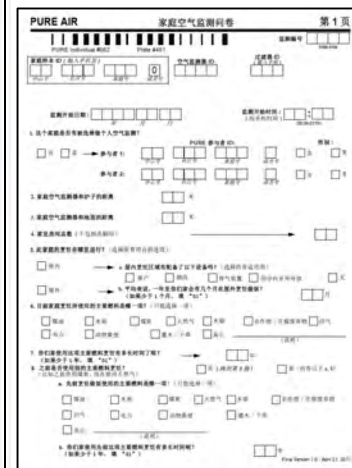
$PM_{2.5}$: 1 km Prediction



NO_2: 100 m Prediction

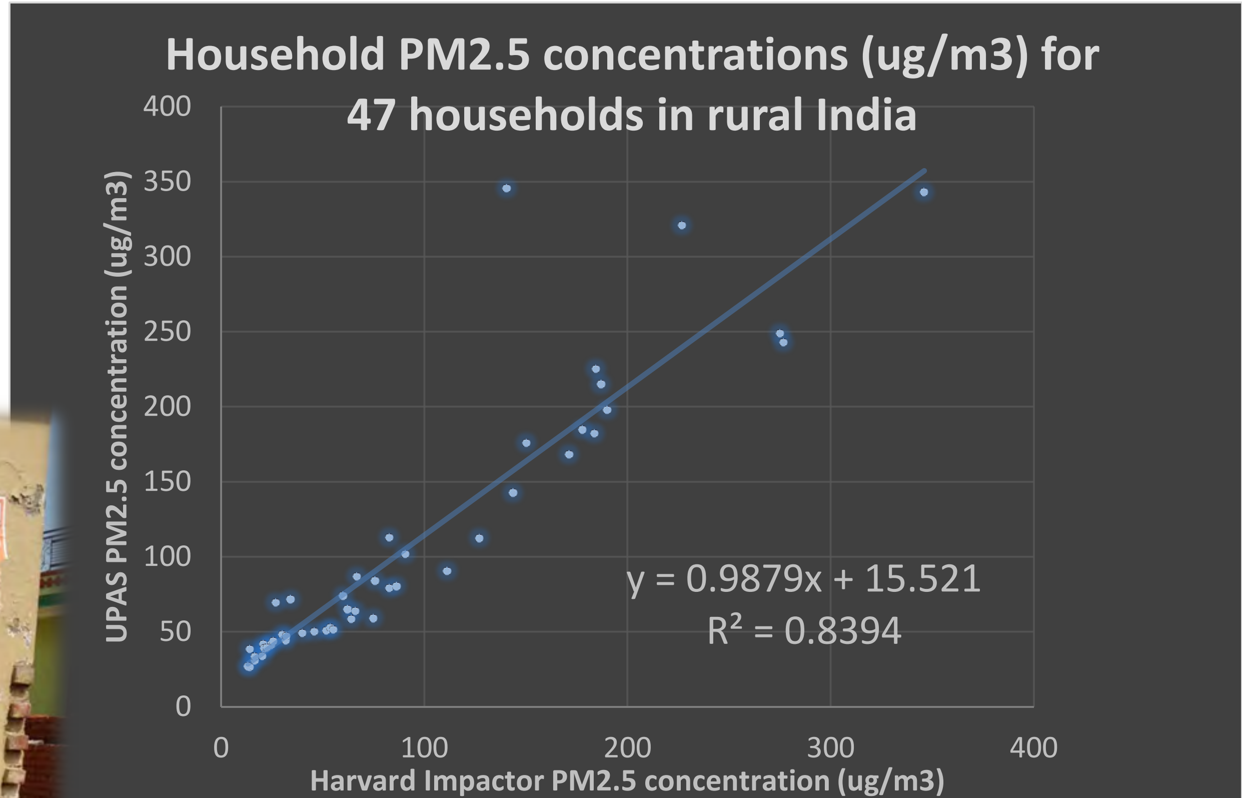
Air Monitoring & GPS (48 hrs)





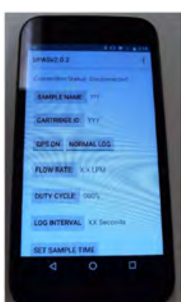
Household & Individual Characteristics

Testing Low-Cost Sensors

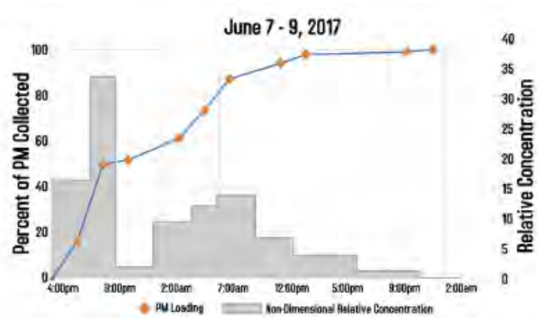


Air Monitoring

4,500 Households



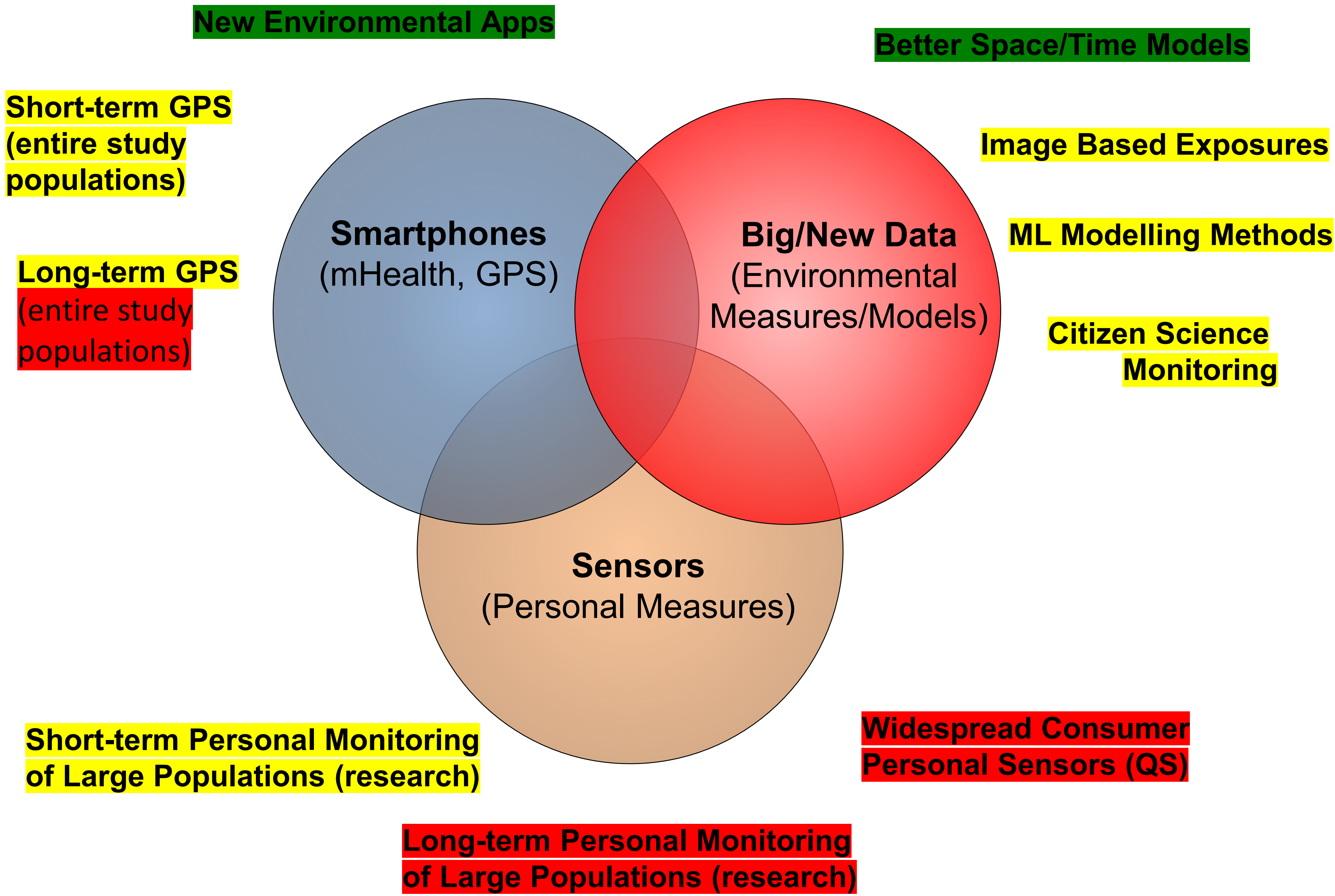
1,800 Personal Samples



1,000 Wrist Bands (1,500 chemicals)

Integrating Data For Health Analyses?

Work in Progress and Another Talk….



New Environmental Apps
Better Space/Time Models
Short-term GPS (entire study populations)
Image Based Exposures
Smartphones (mHealth, GPS)
Big/New Data (Environmental Measures/Models)
ML Modelling Methods
Long-term GPS (entire study populations)
Citizen Science Monitoring
Sensors (Personal Measures)
Short-term Personal Monitoring of Large Populations (research)
Widespread Consumer Personal Sensors (QS)
Long-term Personal Monitoring of Large Populations (research)

Acknowledgements

- Collaborators: To many to name but need to specifically recognize Andrew Larkin who leads the data science components of these studies.
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Thank You. Questions?

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