Emerging Health Impacts of Ambient Ultrafine Particles and Deep Learning for Air Pollution Exposure Science

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Outdoor Pollution Exposures and Health Risk Analysis

Environmental Health

1

EXPOSURE SCIENCE

Environmental Exposures

2

EPIDEMIOLOGY

New Population-Based Studies

People

Places

Populations

NOVEL EXPOSURE METRICS

- $PM_{2.5}$ Oxidative Potential
- Magnetite Nanoparticles
- ROS generation

ARTIFICIAL INTELLIGENCE

Deep learning Image Analysis

- Air Pollution
- Noise
- Heat

Cohort Studies

Panel Studies

Exposure Modeling

Personal Exposures

Regional Exposures

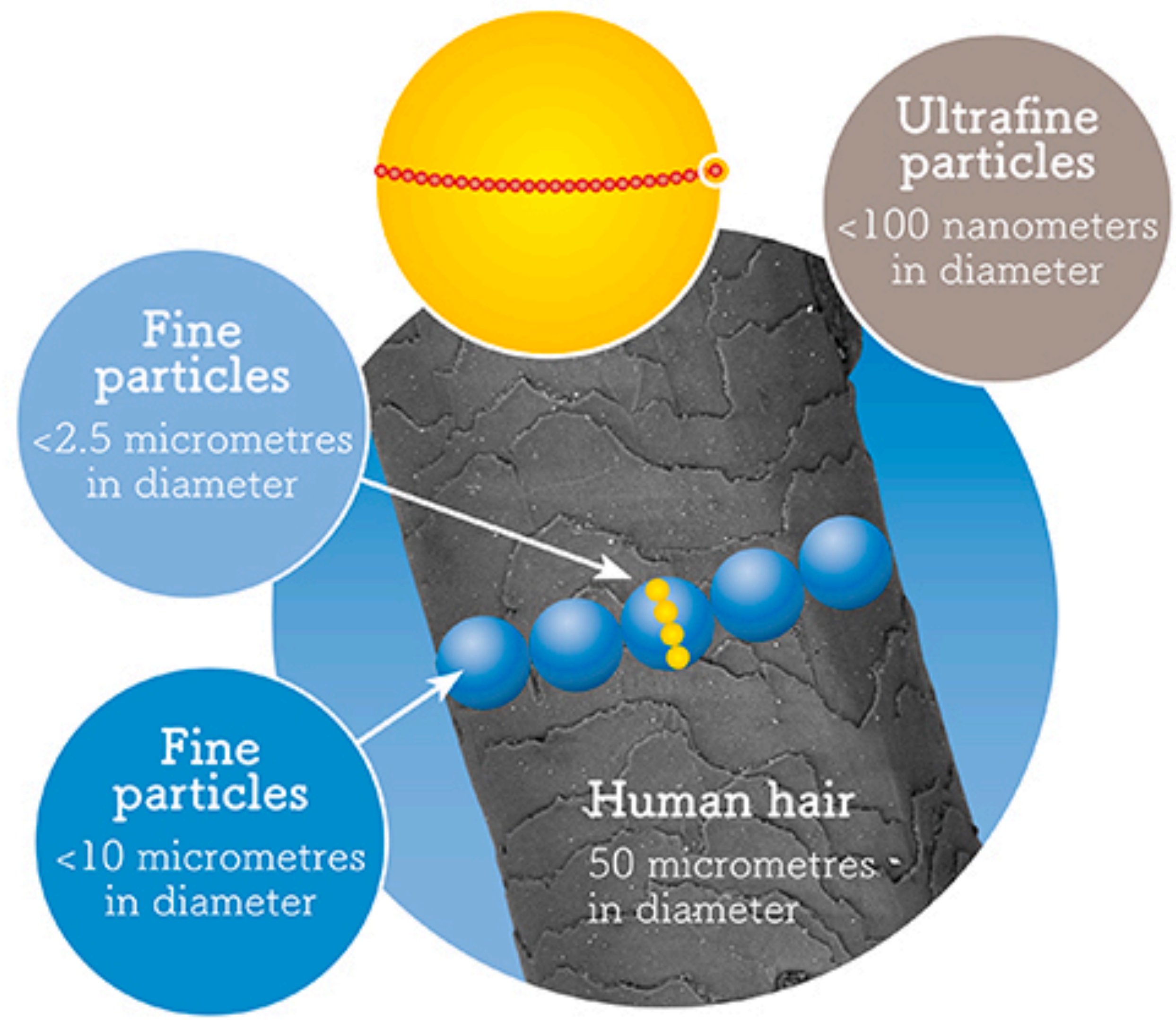
Predicting County-Level Disease Rates

Knowledge Translation

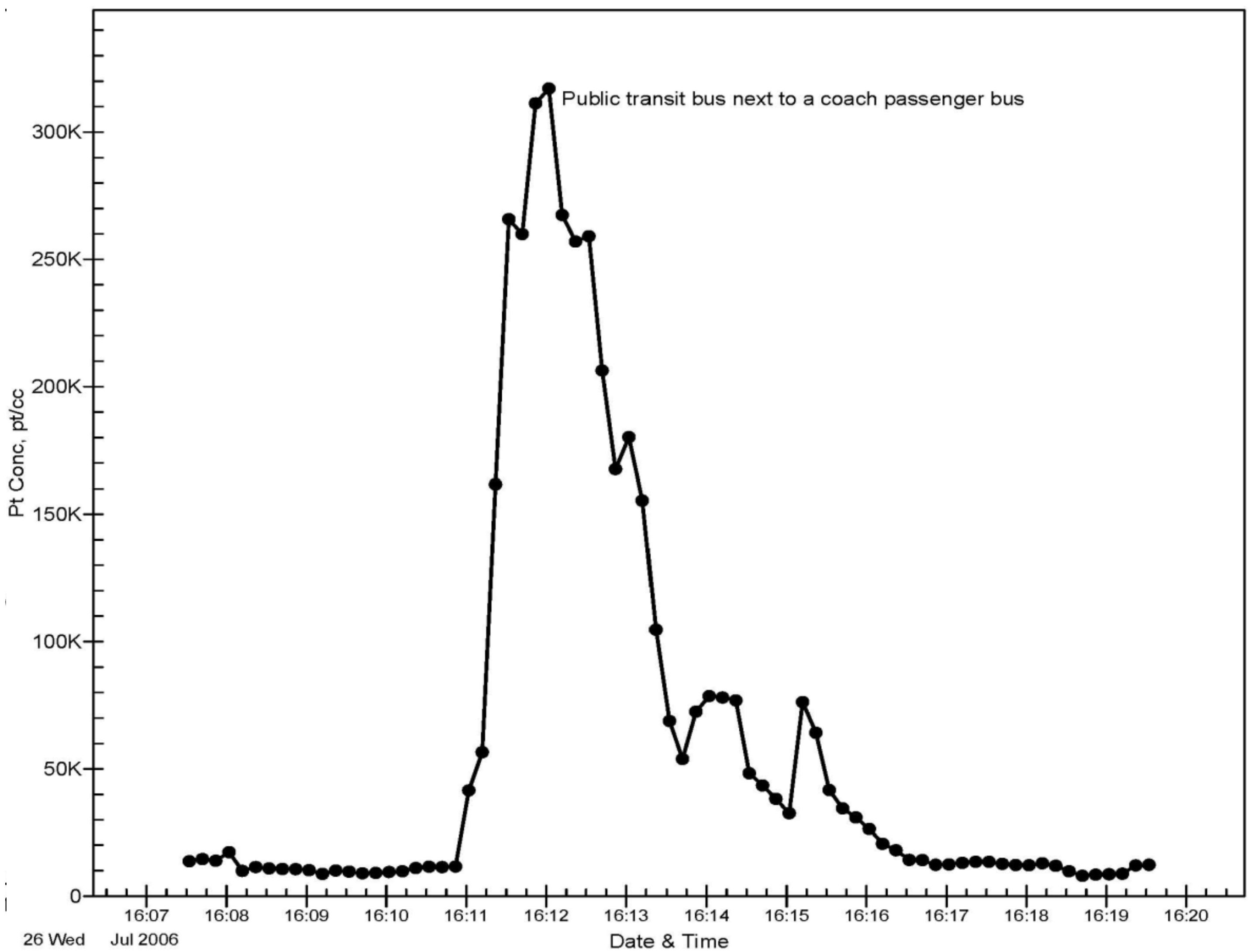
Part 1: Health Effects of Ultrafine Particles

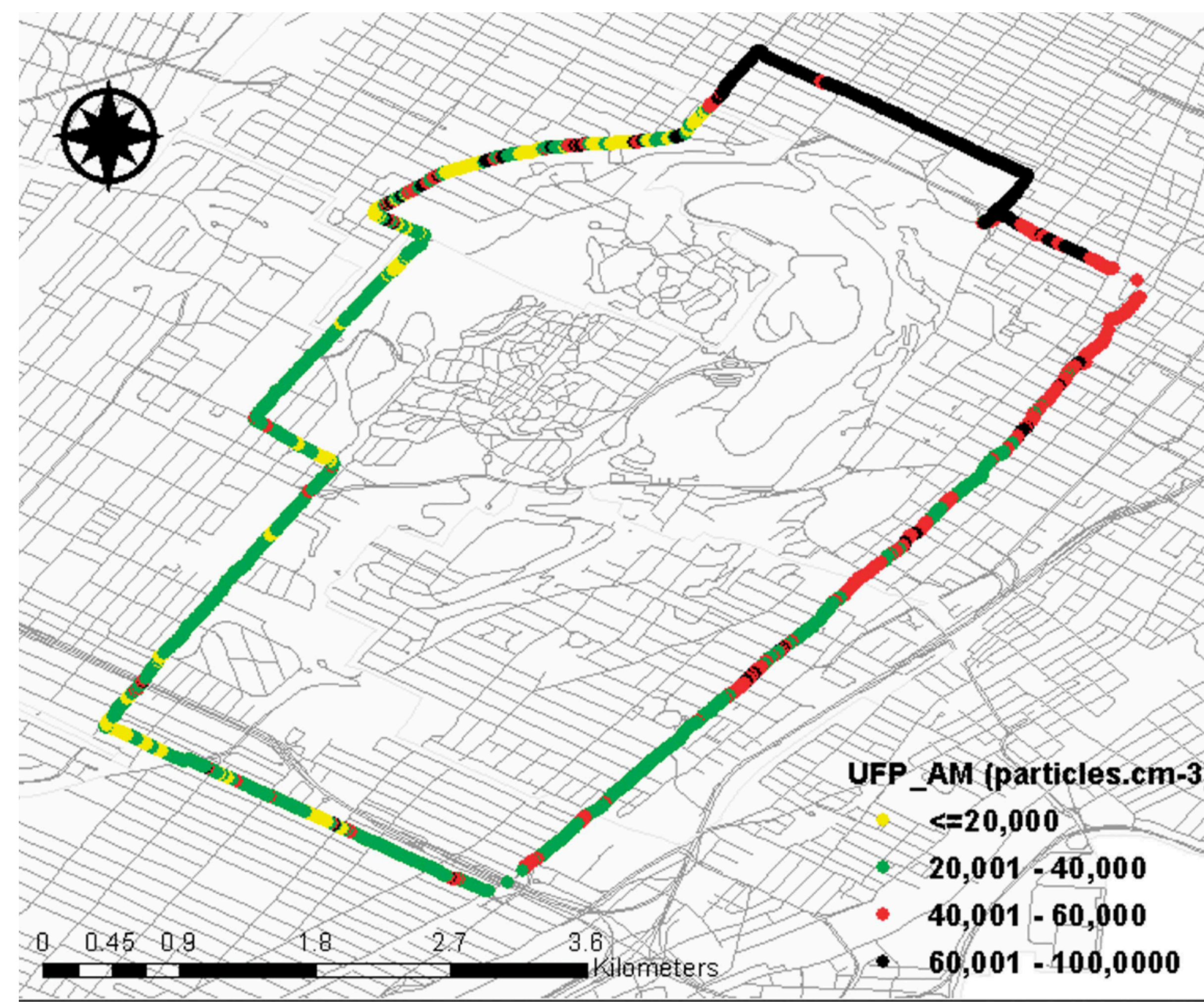
Part 2: Deep Learning for Air Pollution Exposure Science

Part 1: Health Impacts of Ultrafine Particles

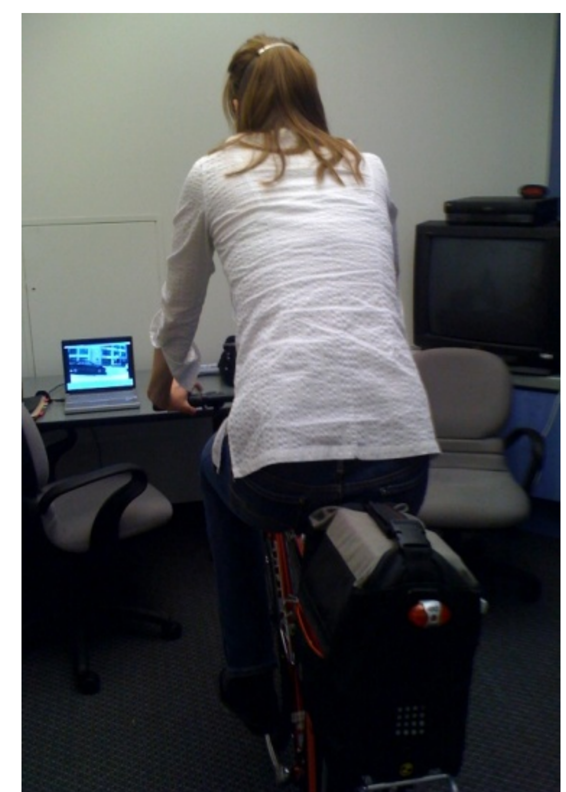


UFPs in Montreal, Canada
Spatial and Temporal Variability



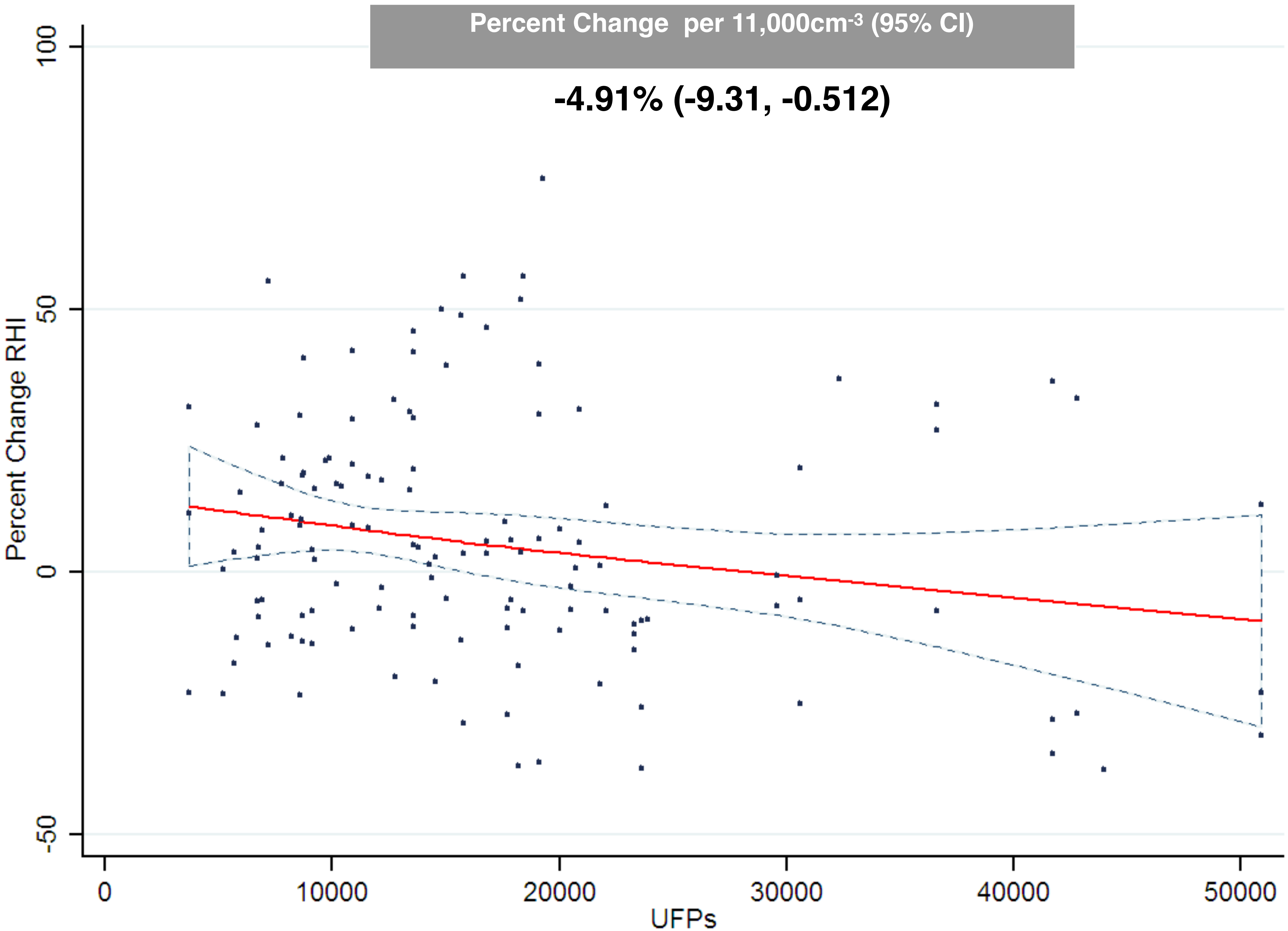


Studies of Short-Term UFP Exposures:
Acute Cardiovascular Effects among Cyclists



Studies of Short-Term UFP Exposures:
Scripted Cycling Routes

Studies of Short-Term UFP Exposures:
Decreased Endothelial Function



Particle and Fibre Toxicology 2014**11**:70

Studies of Short-Term UFP Exposures:
Decreased Heart Rate Variability

Exhaust-ing ride for cyclists: Air pollutants trigger heart risk

In big cities around the world, cyclists breathe an array of pollutants from exhaust-spewing cars. A new study has now found a link between cycling on high traffic roads and heart risks. Even healthy cyclists had harmful changes in their heart rates. Experts say cyclists should stick to their two-wheels, however, pointing to simple solutions to reduce exposure.

By Brett Israel
Environmental Health News

July 6, 2011

NEW YORK – Even by this c
standards, the Garment Distric
imposing place to ride a bike.

A never-ending parade of deliv
rumbles along 8th Avenue betw
and 42nd streets, leaving a wal
exhaust for cyclists to feel, sme
breathe.

"A very healthy person is like a Ferrari," said Arden Pope, an expert in the health effects of air pollution and professor at Brigham Young University in Provo, Utah. "Step on the gas and it really goes fast. Step on the brakes and it really slows down. The human heart, you want it to be like that too."

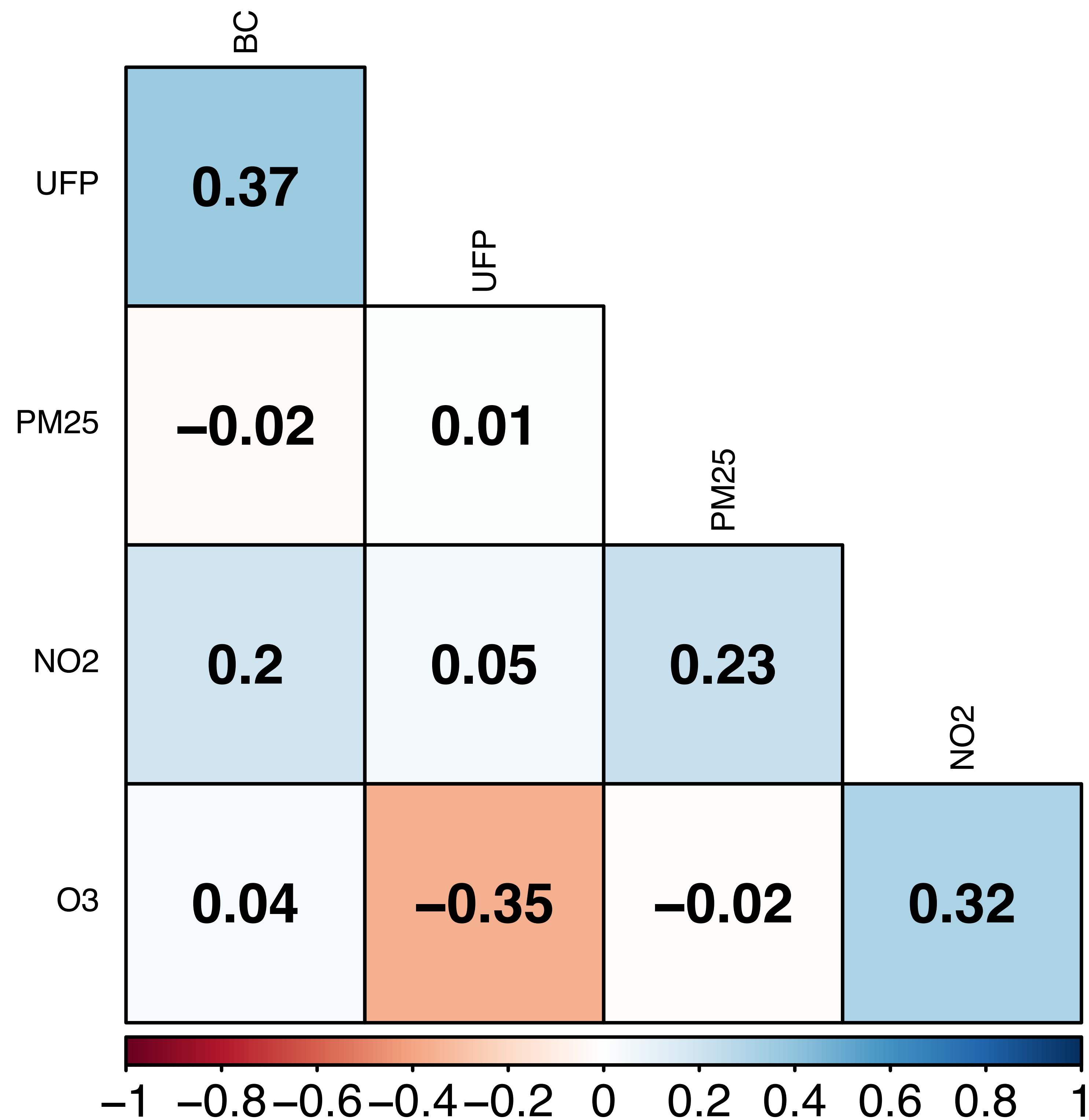
But with lower heart rate variability, the heart is behaving more like a minivan than a Ferrari, Pope said, meaning that it is less able to respond to stress.

Studies of Short-Term UFP Exposures
Correlations with Other Air Pollutants

- In Canada, UFPs tend to be weakly/moderately correlated with other pollutants (e.g. $PM_{2.5}$, black carbon, NO_2)
- **Values less than 0.4 are typical**
- This likely relates to the fact that Canada has **a low proportion of diesel vehicles**

Example: Pollutant Correlations

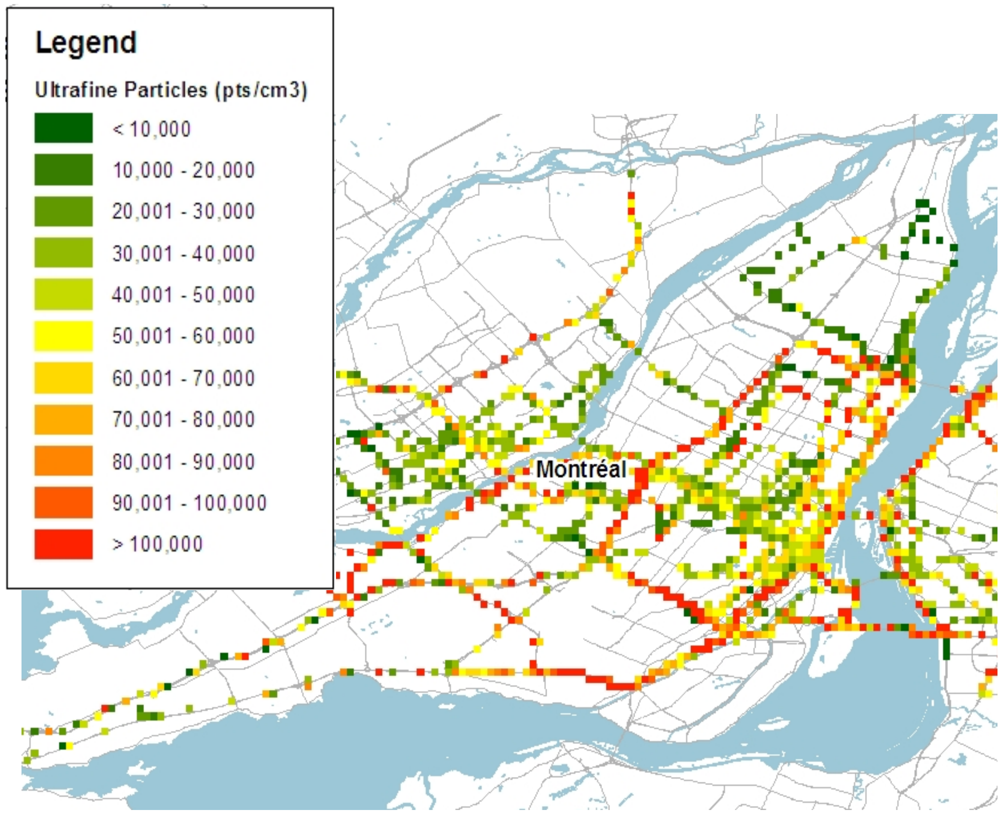
Personal Exposure Study in Montreal (n=93)

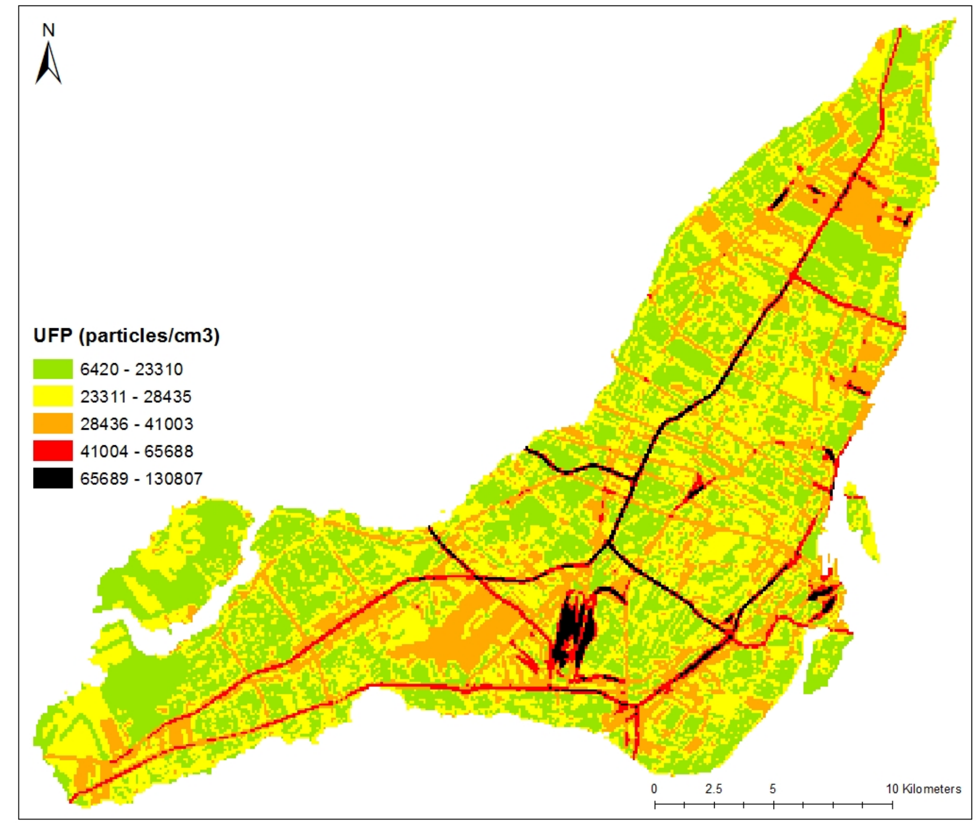


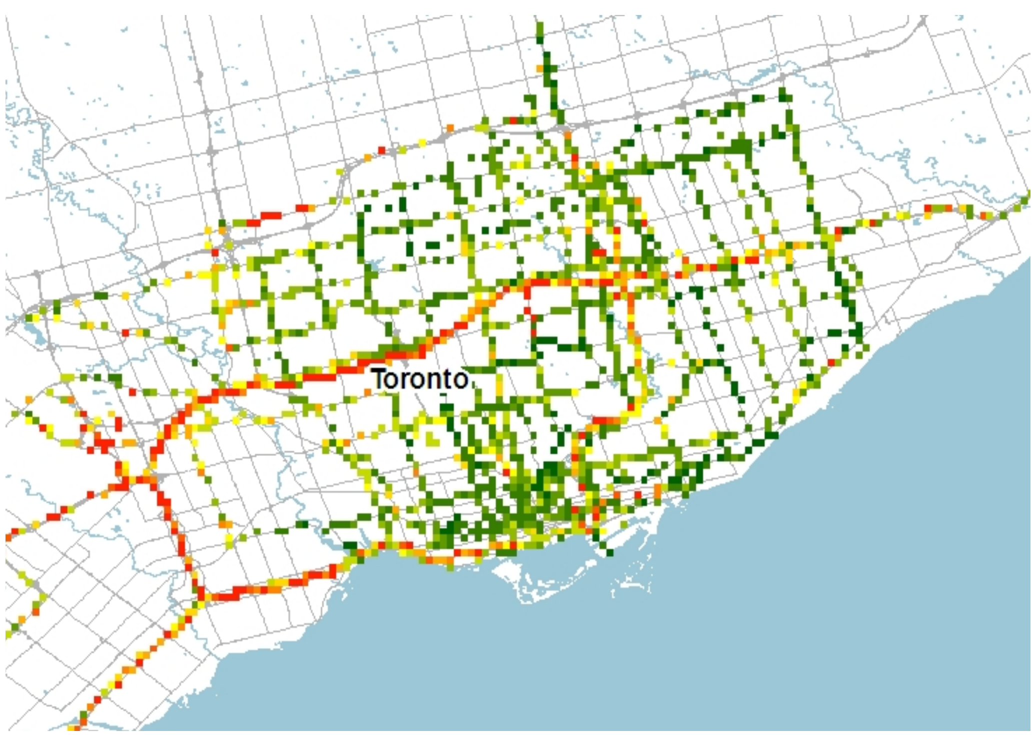
“What about Chronic Health Risks?”

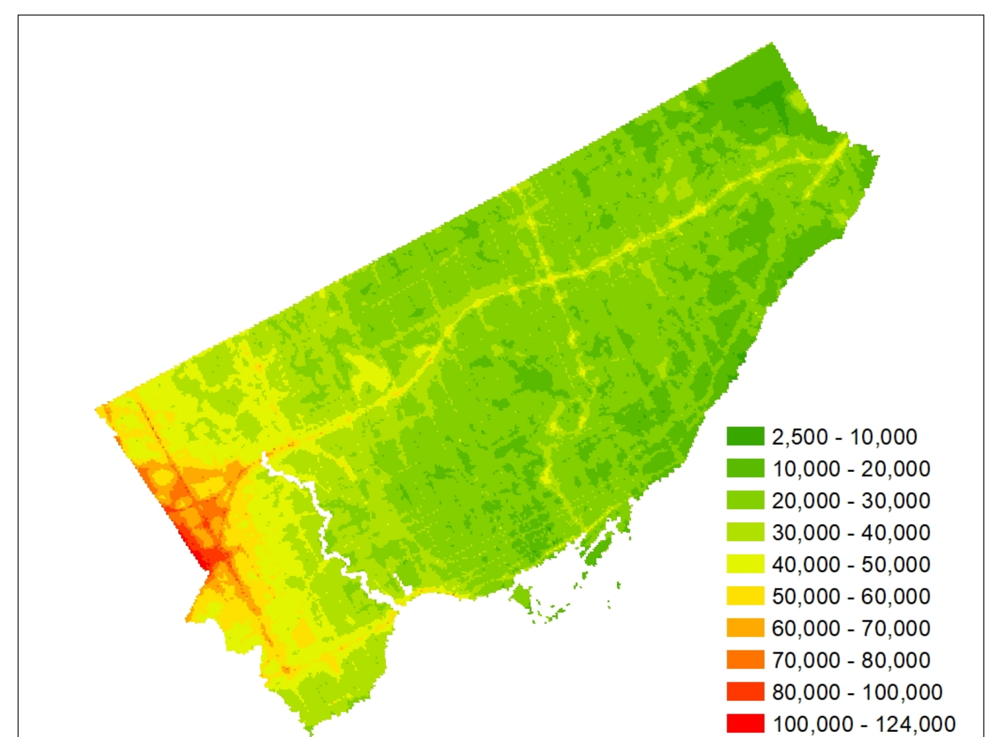
Estimating Spatial Variations in UFP Exposures

Land Use Regression Models









Cohort Studies of Long-Term Health Impacts

Ontario Population Health and Environment Cohort (OnPHEC)

All Ontario residents who on April 1, 1996, (1) were alive, (2) had a health card number, and (3) had recorded birth date and sex

(N = 10,768,635) **Ontario Residents**

- Exclude if not between 35 and 100 years of age, on April 1, 1996

(N = 5,291,074) **Remove <35 years**

All adult residents in Ontario on April 1, 1996

(N = 5,477,561)

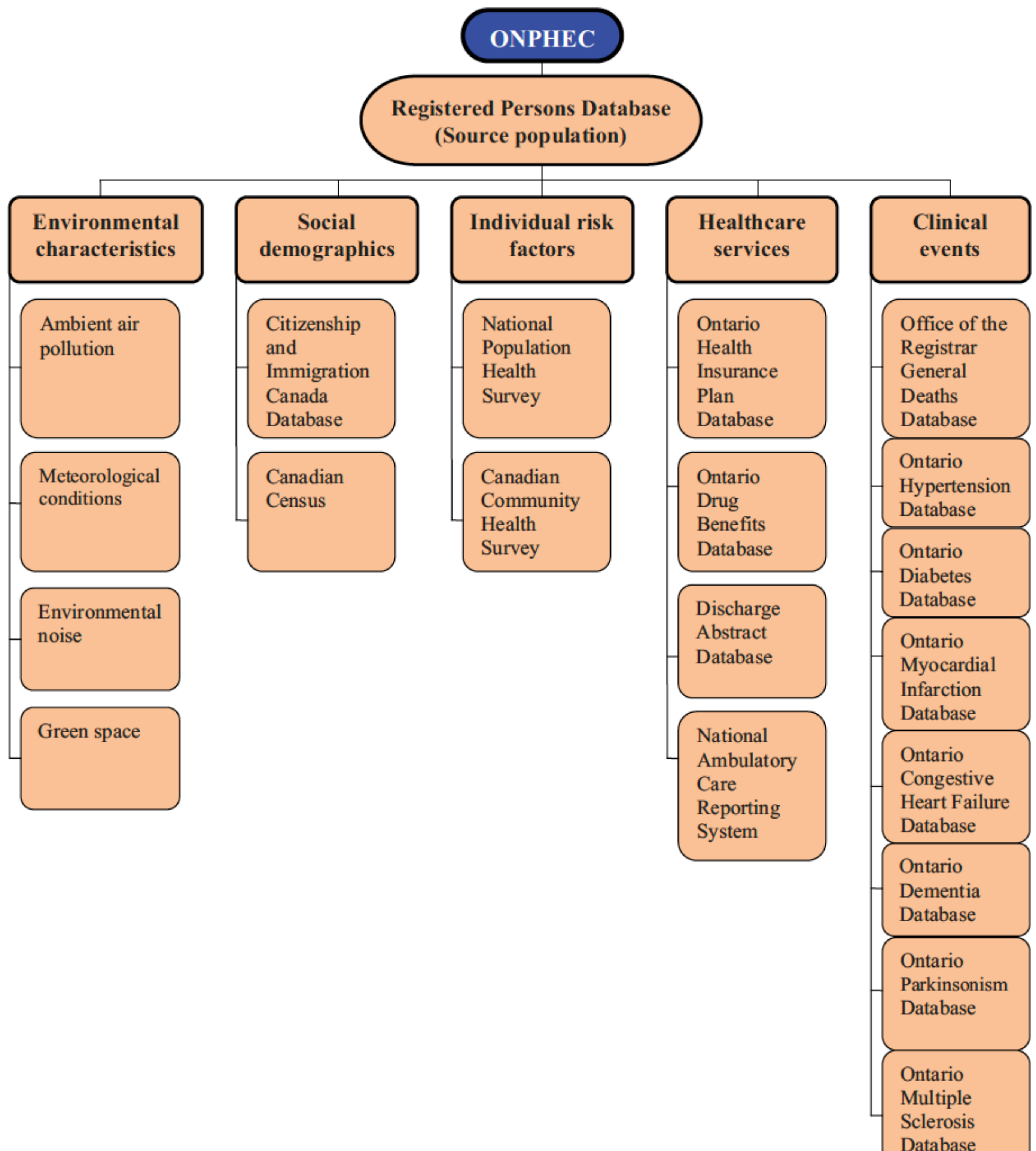
- Exclude landed immigrants
- Exclude if not had lived in Ontario between April 1, 1991 and March 31, 1996

(N = 535,255) **Remove Immigrants**

ONPHEC (N = 4,854,759)

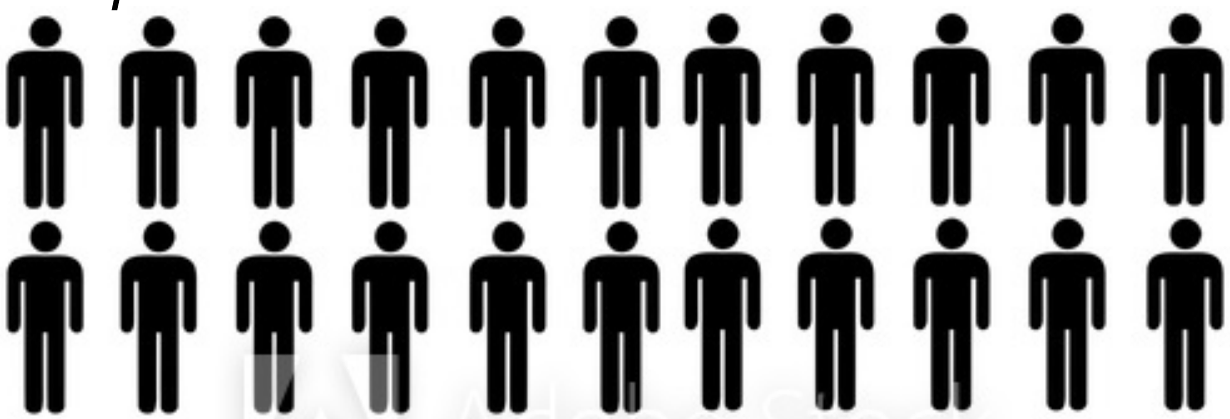
International Journal of Epidemiology, 2017, Vol. 46, No. 2

Cohort is linked to Environmental Exposure Data and Health Registry Data (Disease Incidence)

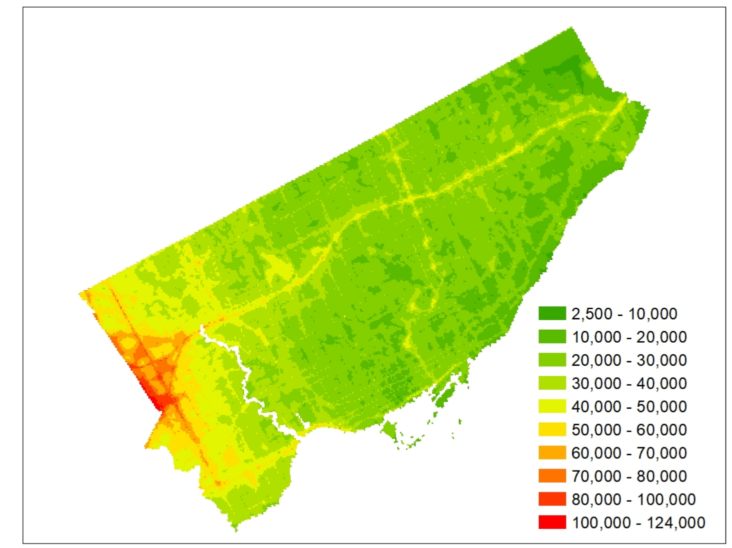


Simplified Cohort Study

Population Free of Disease

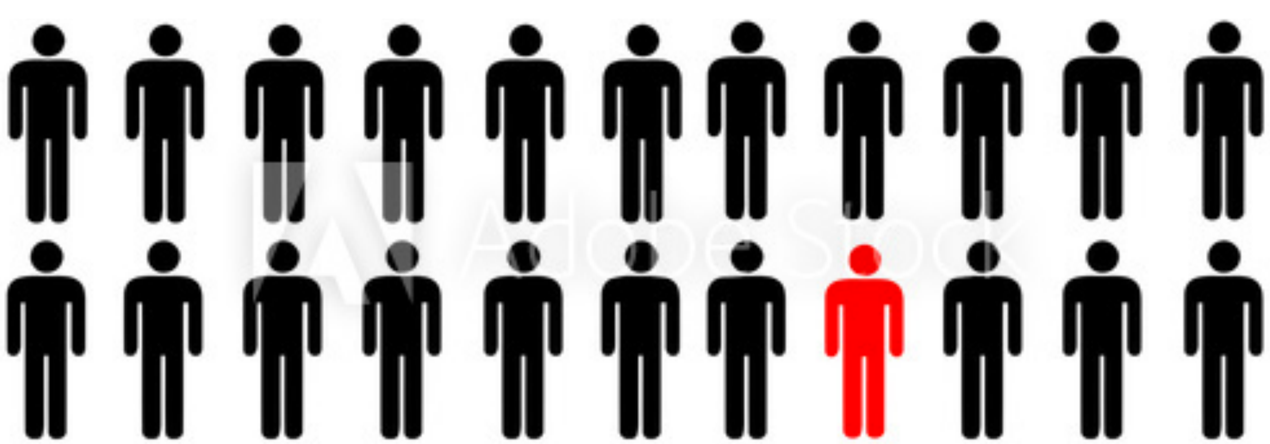


Assign Exposure



Time (1996-2012)

Follow for Disease Incidence



Long-Term Health Impacts
Heart Failure/Myocardial Infarction

- **ONPHEC Cohort (1.1 million adults, Toronto, Canada)**
  - **2-5% Increased risk per 10,000/cm³;** independent of $PM_{2.5}$ and NO_2

Table 3. Hazard Ratios for Incident Congestive Heart Failure and Acute Myocardial Infarction According to Long-Term Exposure to Ultrafine Particles and Nitrogen Dioxide, Toronto, Ontario, Canada, 1996–2012

Model[a]	Incident CHF		Incident AMI	
	HR	95% CI	HR	95% CI
UFPs				
Stratified by age and sex	1.06	1.04, 1.07	1.06	1.04, 1.08
Adjusted for neighborhood-level covariates[b]	1.04	1.02, 1.05	1.05	1.03, 1.07
Adjusted for comorbidity[c]	1.03	1.02, 1.05	1.05	1.02, 1.07
Adjusted for $PM_{2.5}$	1.03	1.02, 1.05	1.04	1.02, 1.06
Adjusted for nitrogen dioxide	1.02	1.00, 1.03	1.05	1.03, 1.07
Adjusted for $PM_{2.5}$ and nitrogen dioxide	1.02	1.00, 1.03	1.05	1.02, 1.07

Am J Epidemiol. 2019;188(1):151–159

Long-Term Health Impacts
Hypertension/Diabetes

- **ONPHEC Cohort (1.1 million adults, Toronto, Canada)**
  - **3-4% Increased risk per 10,000/cm³**; independent of $PM_{2.5}$ and NO_2

	Hypertension	Diabetes
Exposure	**HR (95% CI)**	**HR (95% CI)**
Ultrafine particles (per IQR_w)		
Stratified by age and sex	1.04 (1.03, 1.05)	1.09 (1.08, 1.11)
Adjusted for medical comorbidities[a]	1.04 (1.03, 1.05)	1.09 (1.07, 1.10)
Adjusted for neighborhood-level covariates[b]	1.03 (1.02, 1.04)	1.06 (1.05, 1.08)
Adjusted for $PM_{2.5}$	1.03 (1.02, 1.04)	1.06 (1.05, 1.08)
Adjusted for NO_2	1.03 (1.02, 1.04)	1.04 (1.02, 1.05)
Adjusted for $PM_{2.5}$ and NO_2	1.03 (1.02, 1.04)	1.04 (1.02, 1.05)

(*Epidemiology* 2018;29: 323–332)

Long-Term Health Impacts

Respiratory Outcomes in Adults

- **ONPHEC Cohort (1.1 million adults, Toronto, Canada)**
  - **Little evidence of increase risk in adults**

Table 4 Hazard ratios (HR) and 95% CIs for the incidence of chronic obstructive pulmonary disease (COPD), adult-onset asthma and lung cancer in relation to an IQR increases in each pollutant in Toronto, Canada

Exposure	Model	COPD (1996–2012)			Asthma (1996–2012)			Lung cancer [a] (2001–2012)		
		HR	95% CI		HR	95% CI		HR	95% CI	
UFPs	UFPs only [b]	0.96	0.95	0.97	1.02	1.01	1.02	0.97	0.95	0.99
	+ Neighborhood-level covariates [c]	0.95	0.94	0.96	1.00	0.99	1.01	0.97	0.95	0.99
	+ frailty term for neighborhoods	1.06	1.04	1.08	1.01	1.00	1.02	1.00	0.97	1.03
	+ Medical comorbidities [d]	1.06	1.04	1.08	1.00	1.00	1.01	1.00	0.97	1.04
	+ $PM_{2.5}$ [e]	1.07	1.05	1.09	1.01	1.00	1.02	1.00	0.97	1.04
	+ NO_2 [e]	1.01	0.98	1.03	1.00	0.99	1.01	0.98	0.94	1.01
	+ $PM_{2.5}$ and NO_2 [e]	1.01	0.98	1.03	1.00	0.99	1.01	0.98	0.95	1.01

- But, we recently reported evidence of a relationship between UFPs and **incidence of childhood asthma** (*Am J Crit Care Med*, Lavigne E)

- HR =1.05 (95% CI: 1.01, 1.09) after adjusting for $PM_{2.5}$ and NO_2.

Long-Term Health Impacts

Incident Brain Tumours (2001-2016)

- **Canadian Census Cohort (1.9 million adults, Toronto/Montreal)**
  - **10-13% Increased risk per 10,000/cm³**; independent of $PM_{2.5}$ and NO_2

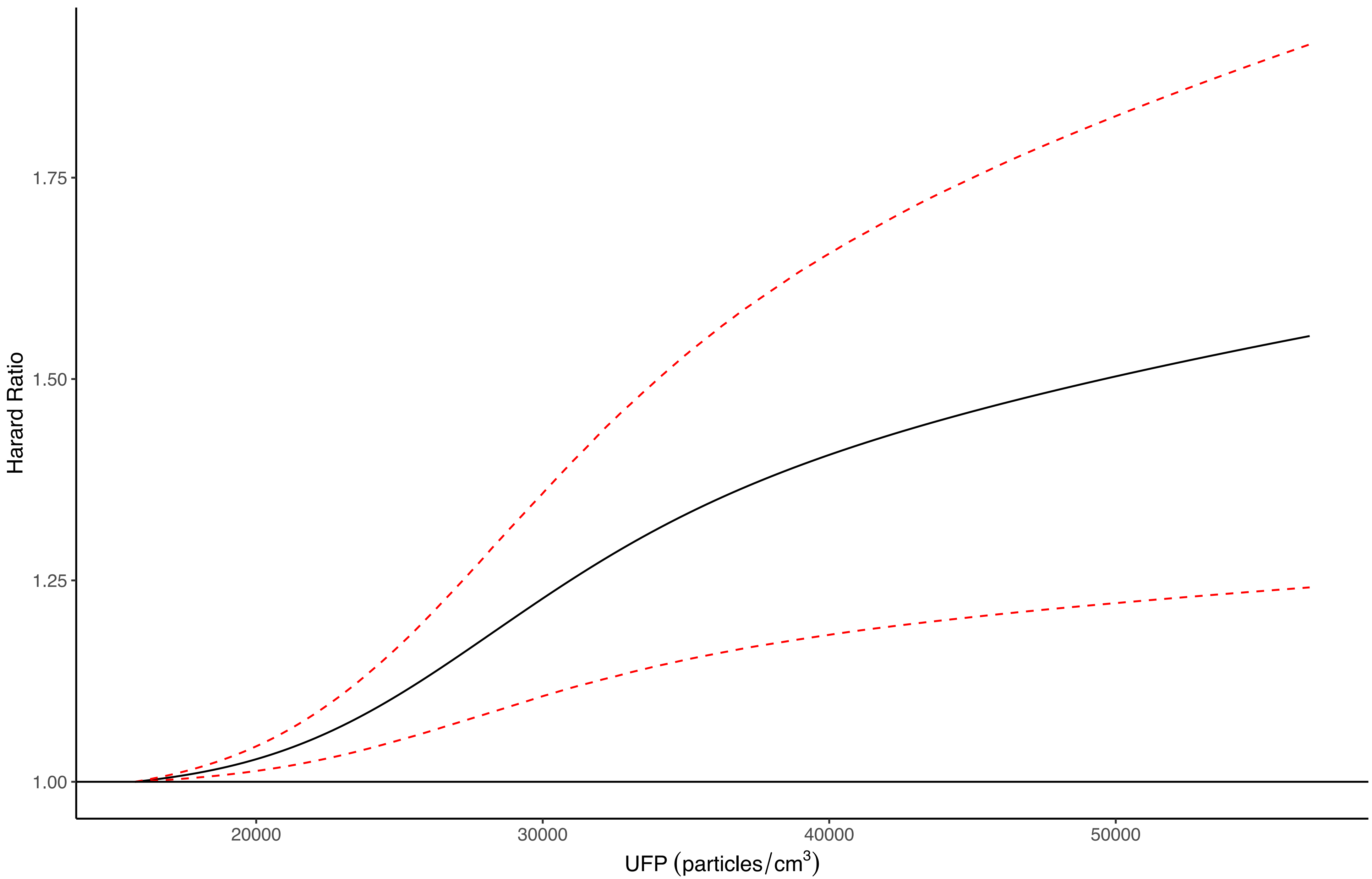
Model	HR (95% CI)
Base Model[a]	1.10 (1.03, 1.17)
Fully Adjusted Multi-Pollutant Models	
All SES	**1.09 (1.03, 1.16)**
All SES + NO_2	**1.10 (1.03, 1.18)**
All SES + $PM_{2.5}$	**1.10 (1.04, 1.18)**
All SES + $PM_{2.5}$ + NO_2	**1.11 (1.04, 1.19)**
All SES + $PM_{2.5}$ + NO_2 + Indirect Adjustment for Smoking and BMI	**1.13 (1.03, 1.24)**

- On an absolute level: **1 new brain tumour case per 100,000 population per 10,000/cm³ increase in UFPs**

Cohort Studies of Long-Term Health Impacts

UFPs and Incident Brain Tumours

- **Canadian Census Cohort (1.9 million people, Toronto/Montreal)**



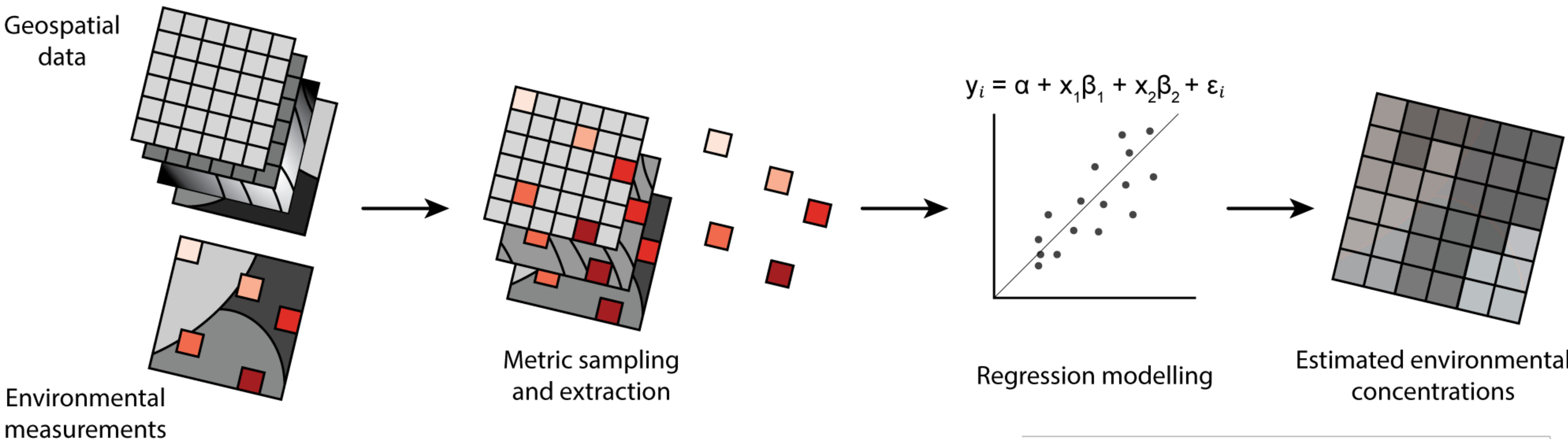
Summary

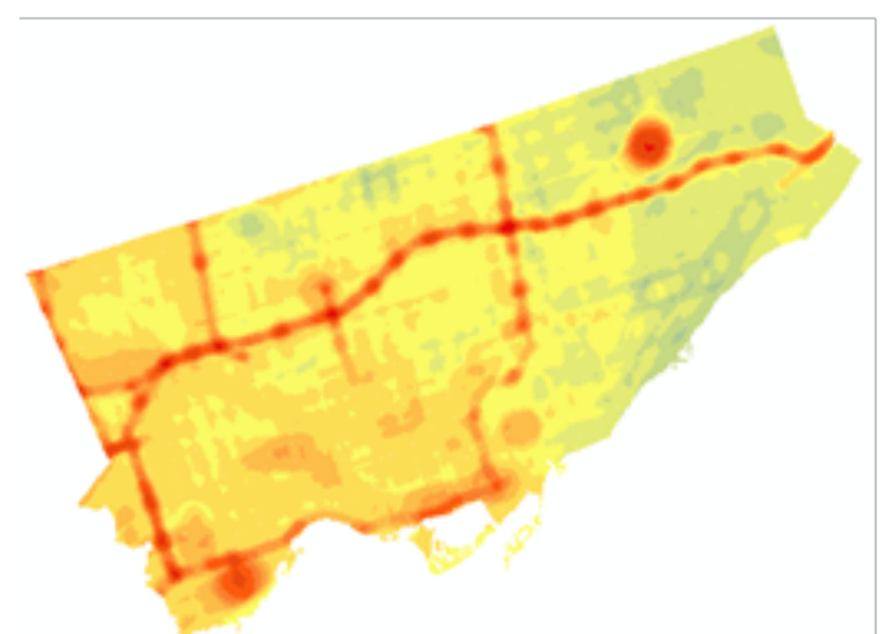
- UFP exposures appear to have important public health impacts **independent of $PM_{2.5}$ and NO_2**.
- **Cardiovascular health effects** are most consistent to date
- New evidence related to **brain tumours** is concerning: we know that UFPs can reach the human brain

Part 2: Deep Learning for Air Pollution Exposure Science

Traditional Approach to Modelling Spatial Variations in Environmental Pollutants

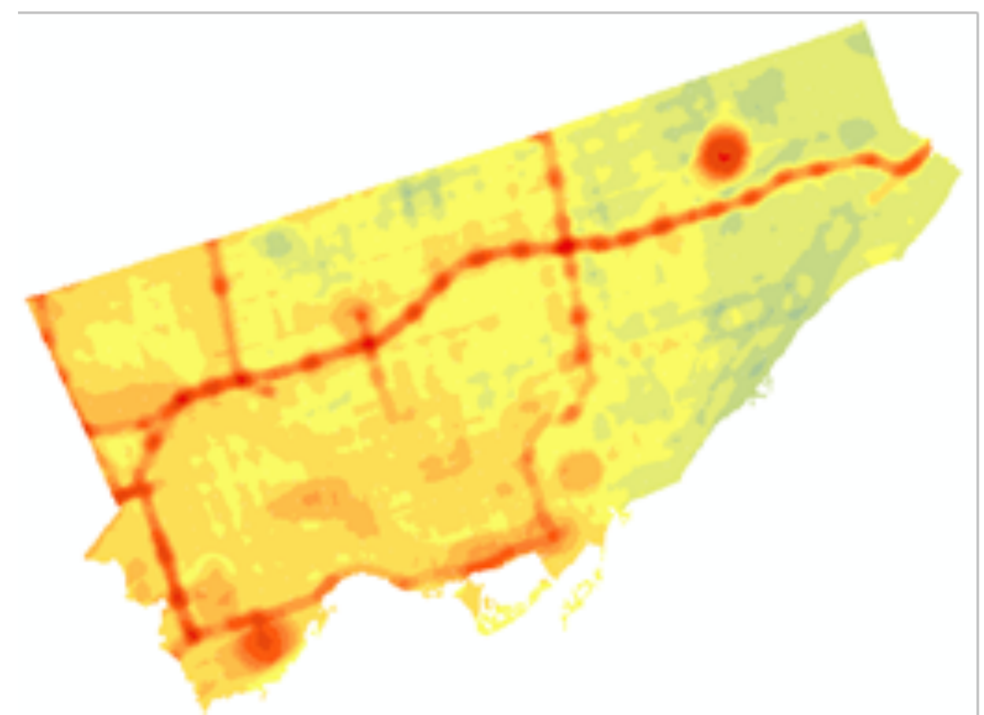
Geostatistical models





Traditional Approach to Modelling Spatial Variations in Environmental Pollutants

- **But…**
  - GIS data are available on a **limited spatial scale**
  - Predict **one pollutant at a time**
  - Difficult to evaluate interactions
  - **GIS data does not reflect the environment as we experience it**



A Picture Tells a Thousands…Exposures?

Local Level

A Picture Tells a Thousands…Exposures?

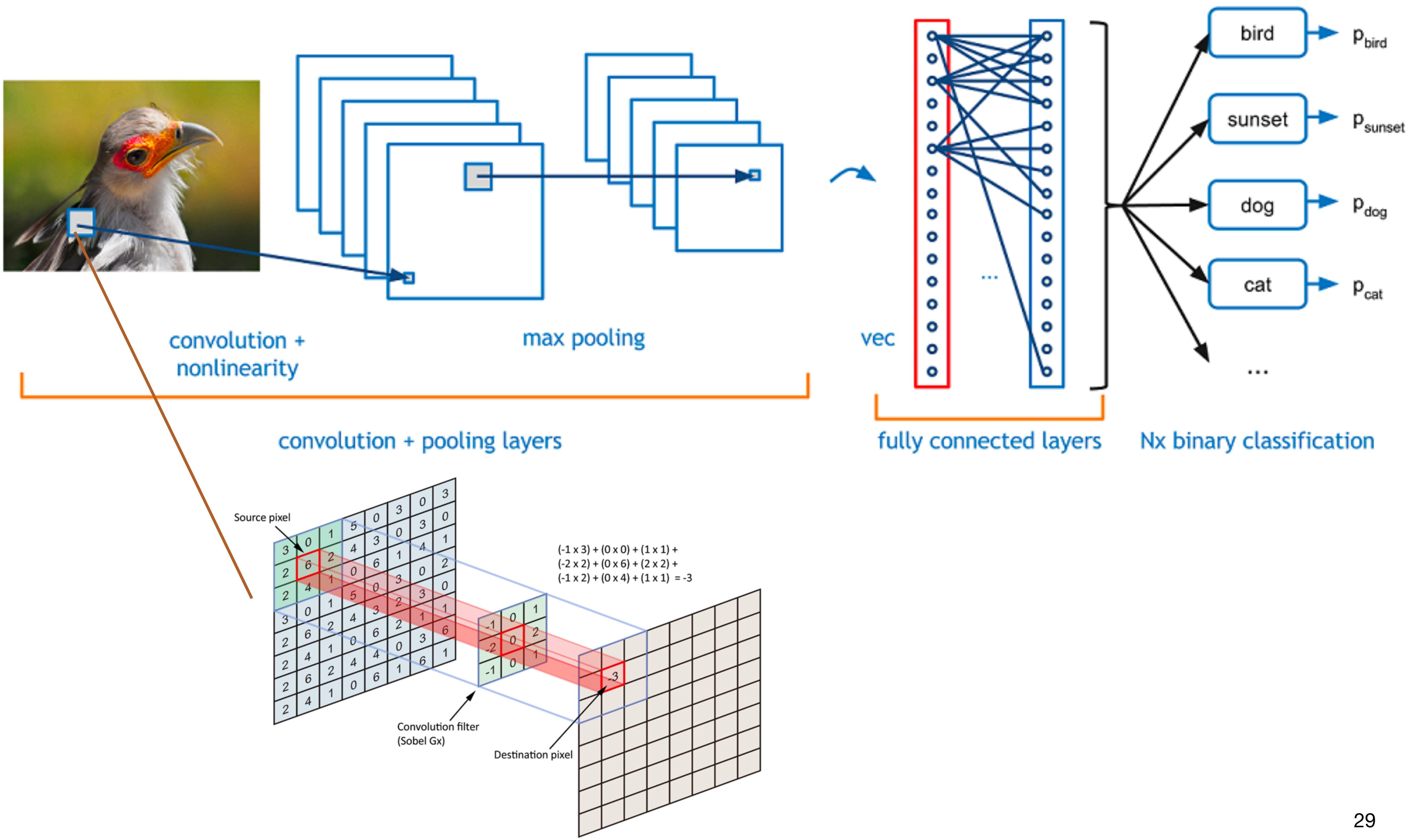
Regional Level

~Scott thinking at his desk, Spring 2018

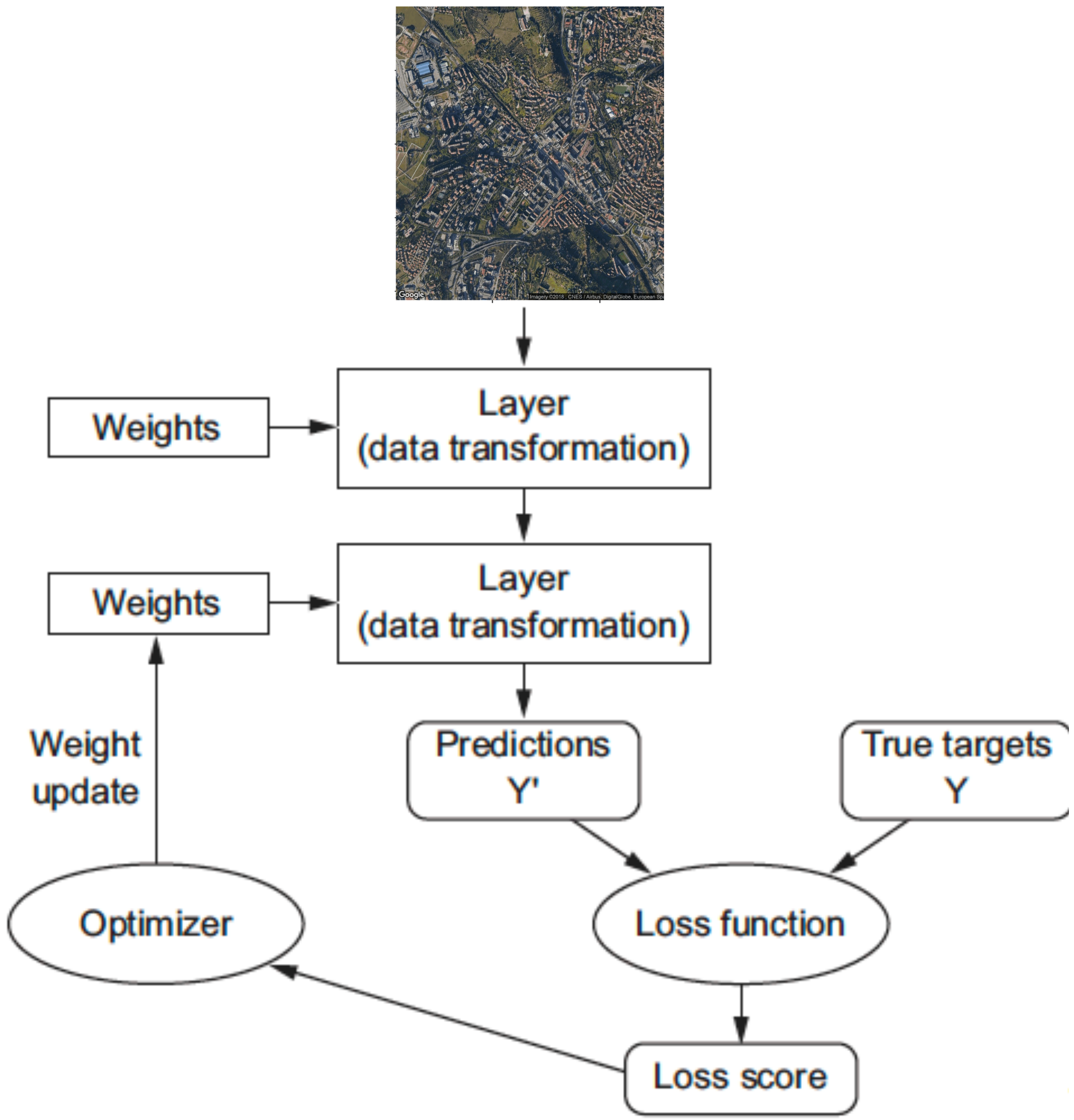
“Can we use large databases of paired image/pollutant data to predict environmental exposures? ”

“What on earth is convolutional neural network? ”

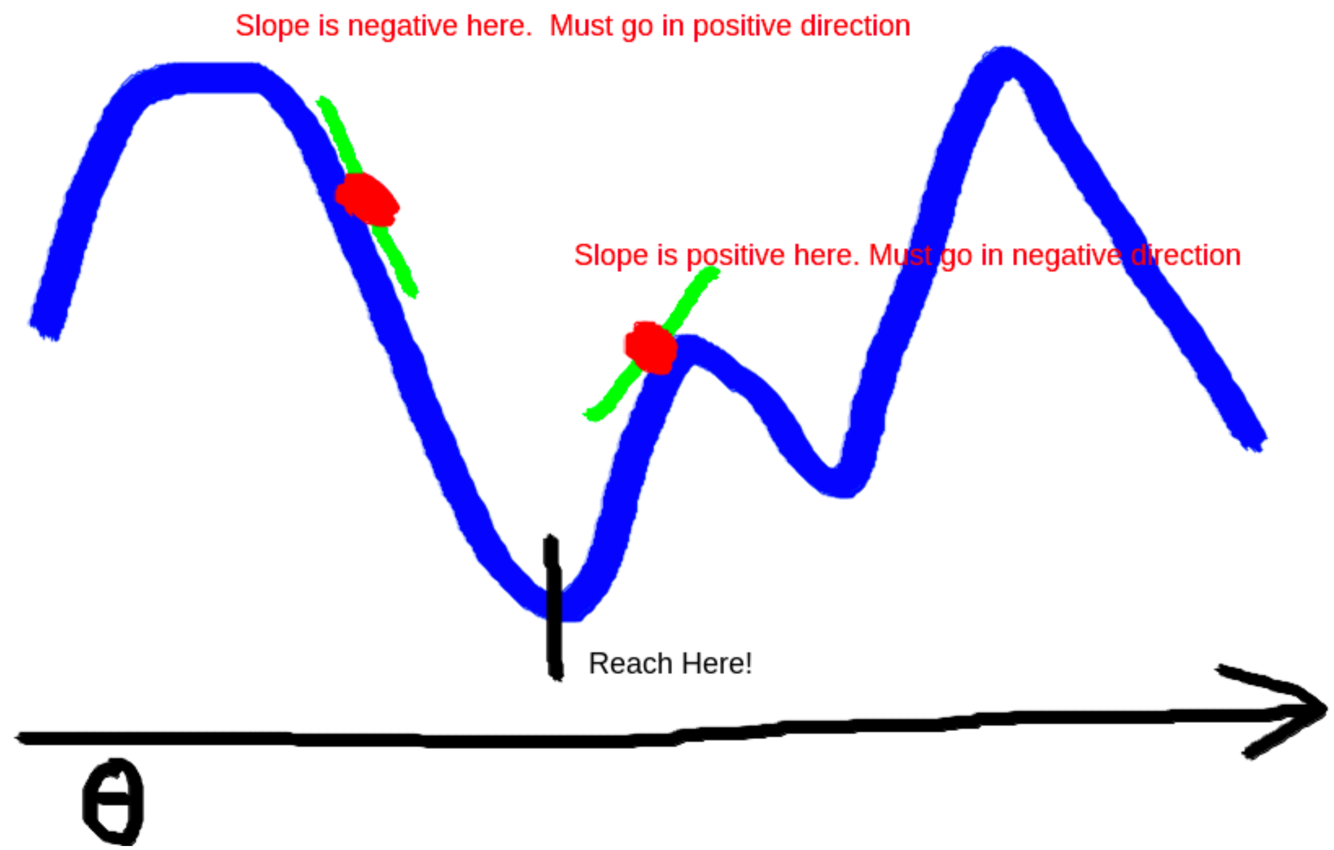
Deep Convolutional Neural Networks



How Does Learning Happen?



from *Deep Learning with R*



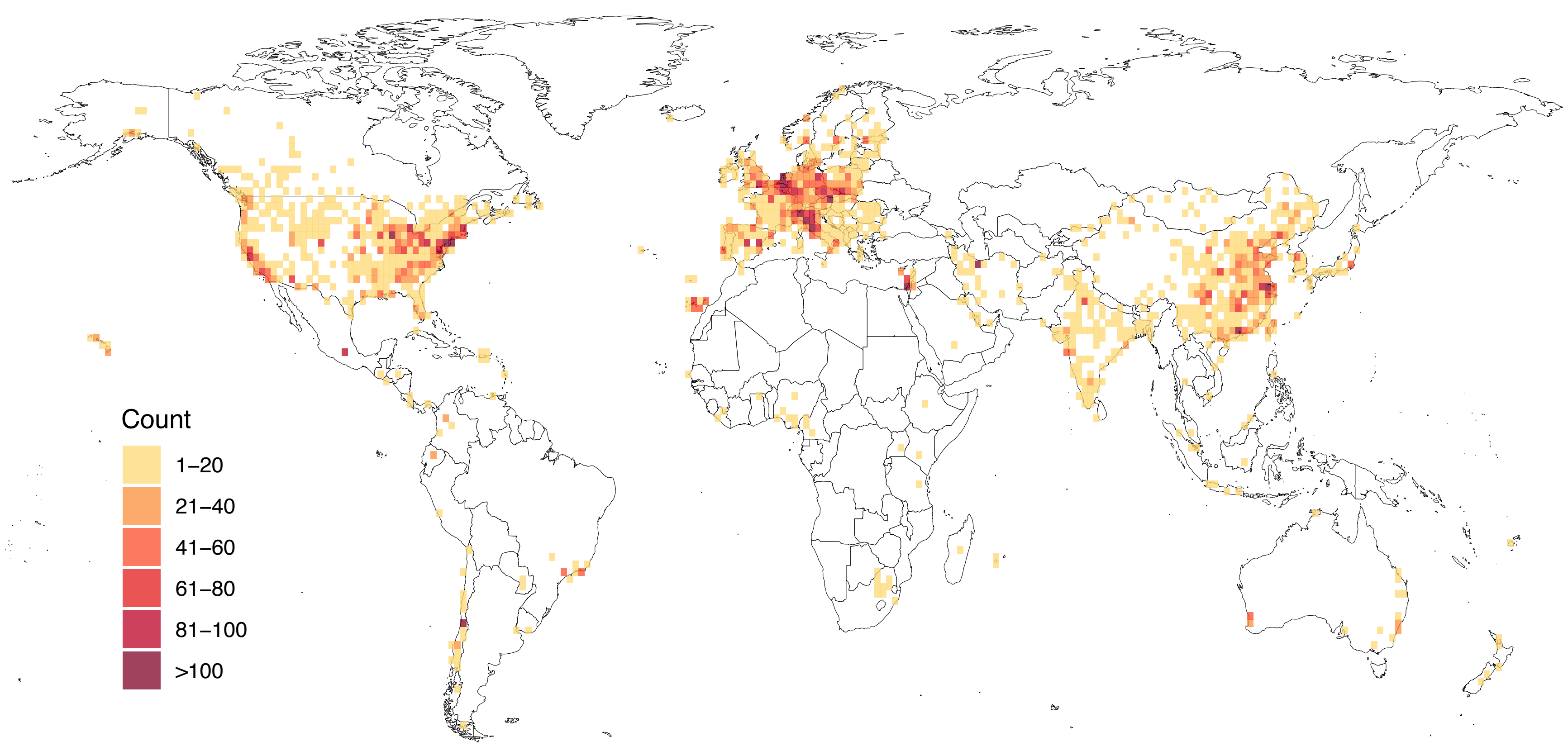
https://vatsalbits.wordpress.com/2017/04/09/stochastic-

Repeat this process many times!

Predicting Annual Average $PM_{2.5}$ using Satellite Images

We created **two large databases** to train our models:

- ~20,000 images/ground measurements from ~6000 sites (available from the WHO)
- >100,000 images/ground estimate for North America based on remote sensing data



http://arxiv.org/abs/1906.03975

Predicting Annual Average $PM_{2.5}$ using Satellite Images

- For each location, download **Satellite images** using *ggmap* in R (two different zoom levels)

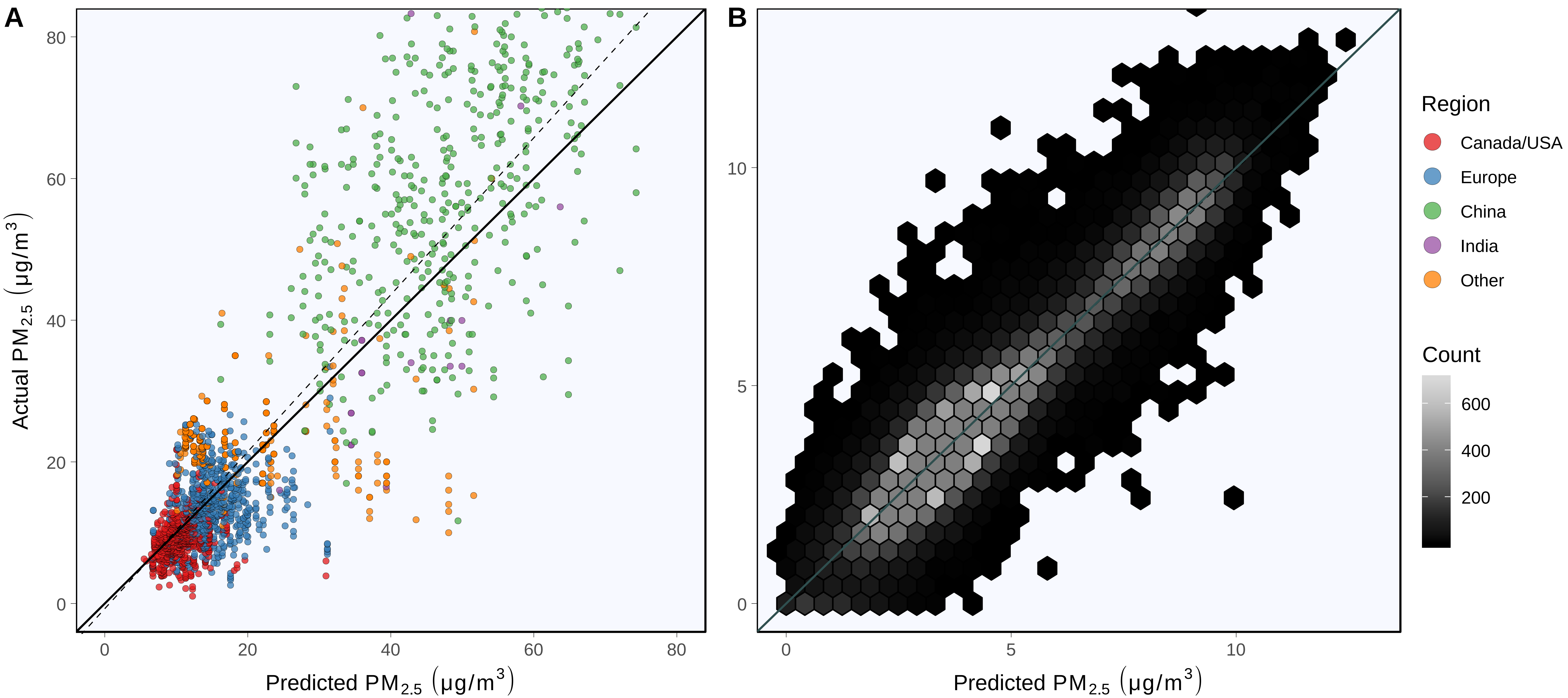
- Created disjoint **training** (80%), **validation** (10%), and **test sets** (10%)

- Evaluated several **model architectures** (*Inception V3*, *Xception*, *VGG16)*.

- Run models using the *keras package* in R and Python

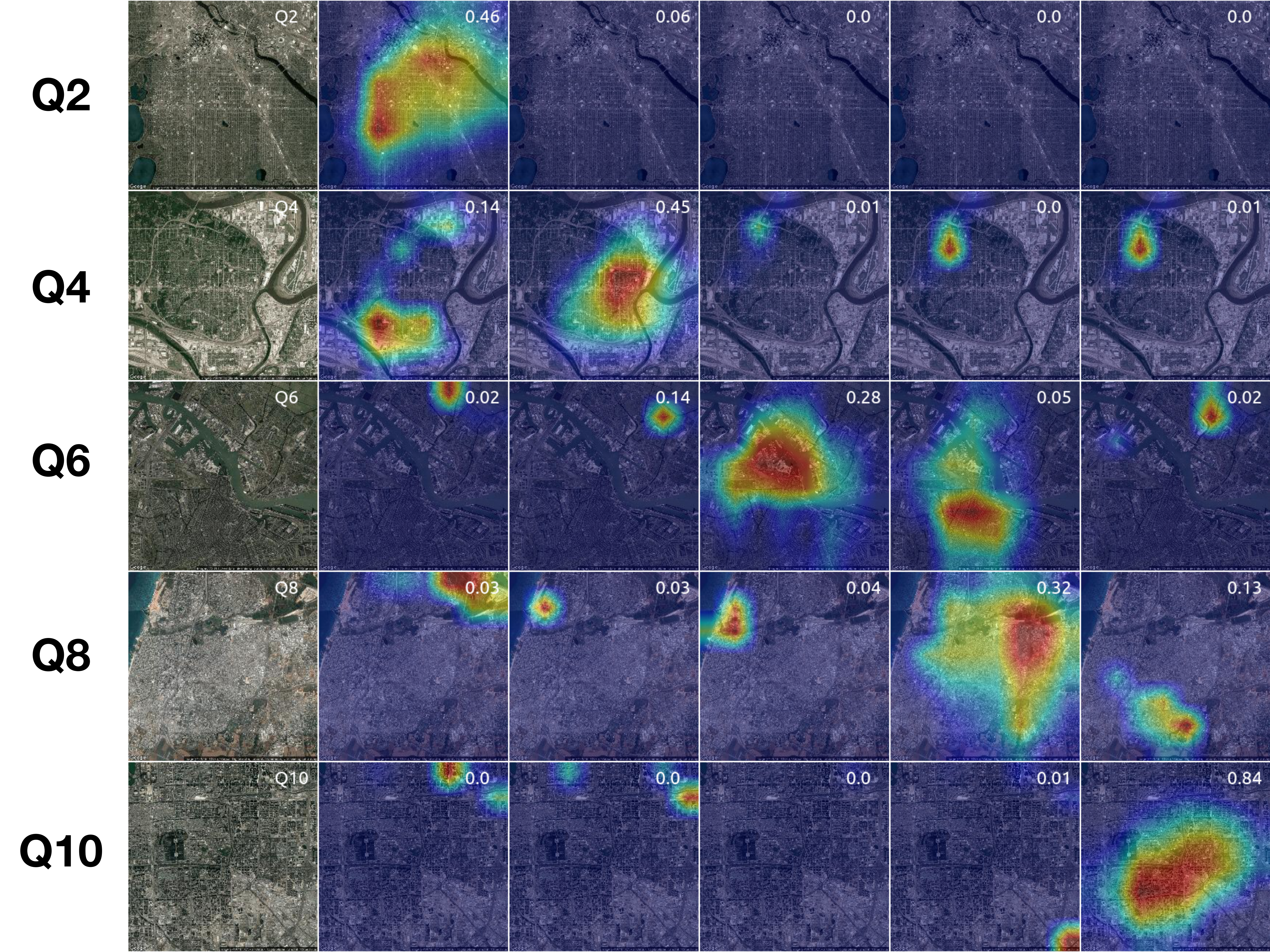
Continuous $PM_{2.5}$ Predictions

Figure 1. Measured versus predicted $PM_{2.5}$ concentrations Globally (A) and in North American (B).

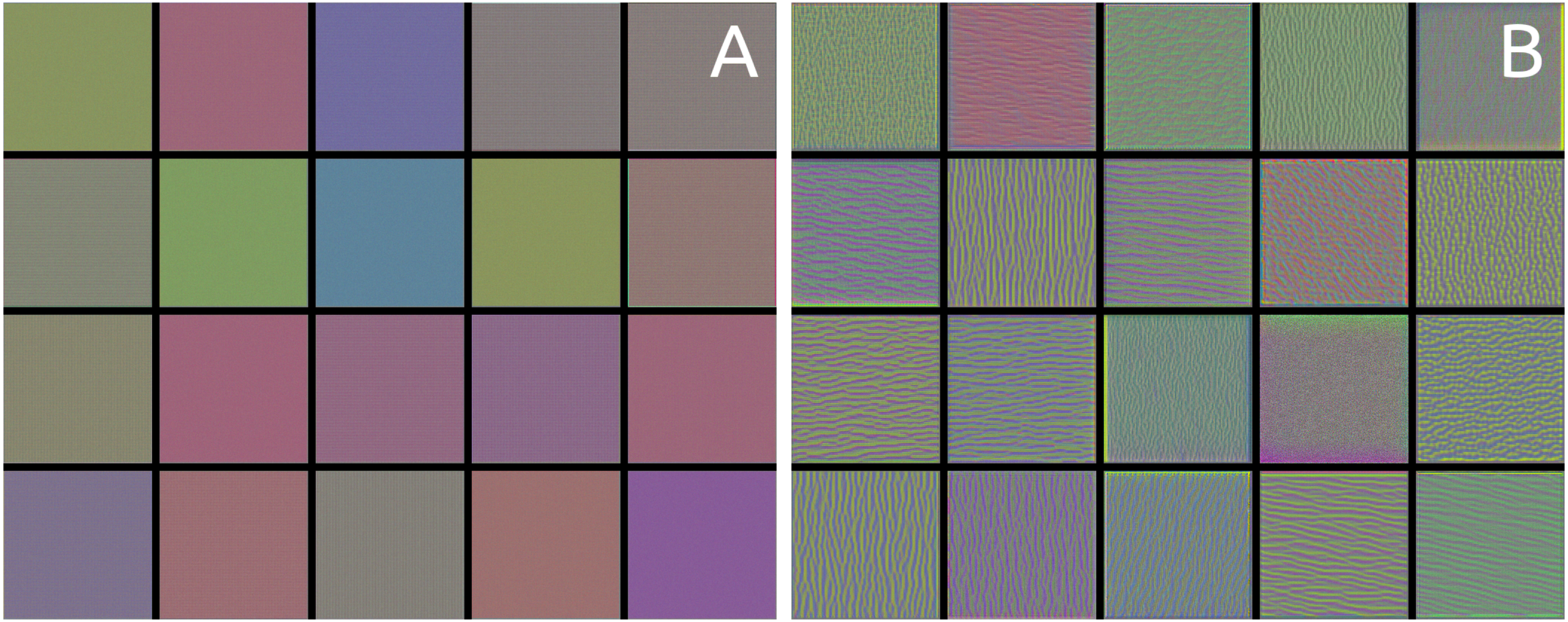


Global: R^2=0.75

North America: R^2=0.89


Q2
Q2
0.46
0.06
0.0
0.0
0.0
Q4
Q4
0.14
0.45
0.01
0.0
0.01
Q6
Q6
0.02
0.14
0.28
0.05
0.02
Q8
Q8
0.03
0.03
0.04
0.32
0.13
Q10
Q10
0.0
0.0
0.0
0.01
0.84

Visualizing Filters (Early Layers)



How Does Our IMAGE-$PM_{2.5}$ Model Compare to the Current “Gold Standard”?

Global $PM_{2.5}$ Range: ~1 - 400 ug/m^3

Best in the World (GBD Model)

RMSE

= 12.10 ug/m^3

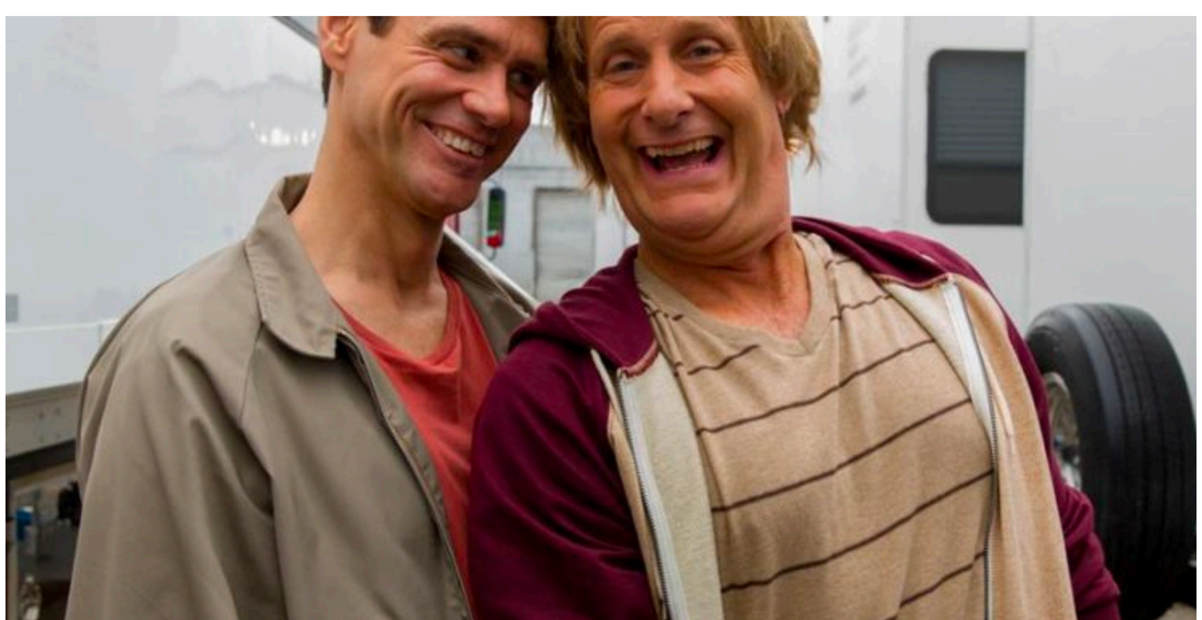
Global $PM_{2.5}$ Range: ~1 - 400 ug/m^3

Best in the World (GBD Model)

RMSE

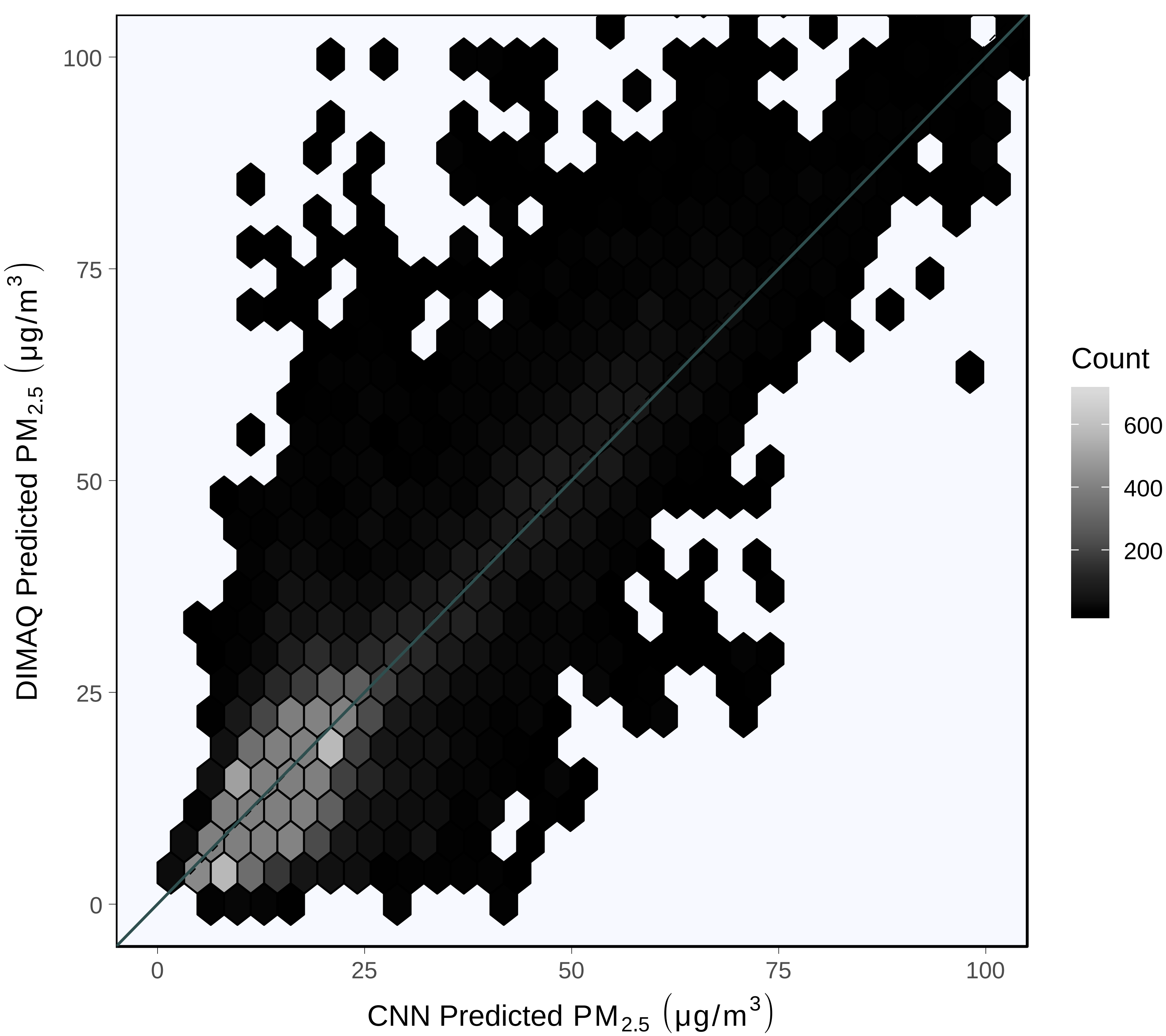
= 12.10 ug/m^3

Us



= 13.01 ug/m^3

Direct Comparison: GBD vs. IMAGE-$PM_{2.5}$



R^2= 0.79
Slope= 1.019,
(95% CI: 1.014, 1.025)

And Still Improving….Two Input Model

+

IMAGE-PM$_{2.5}$
RMSE (as of last week)

= 12.43 ug/m^3

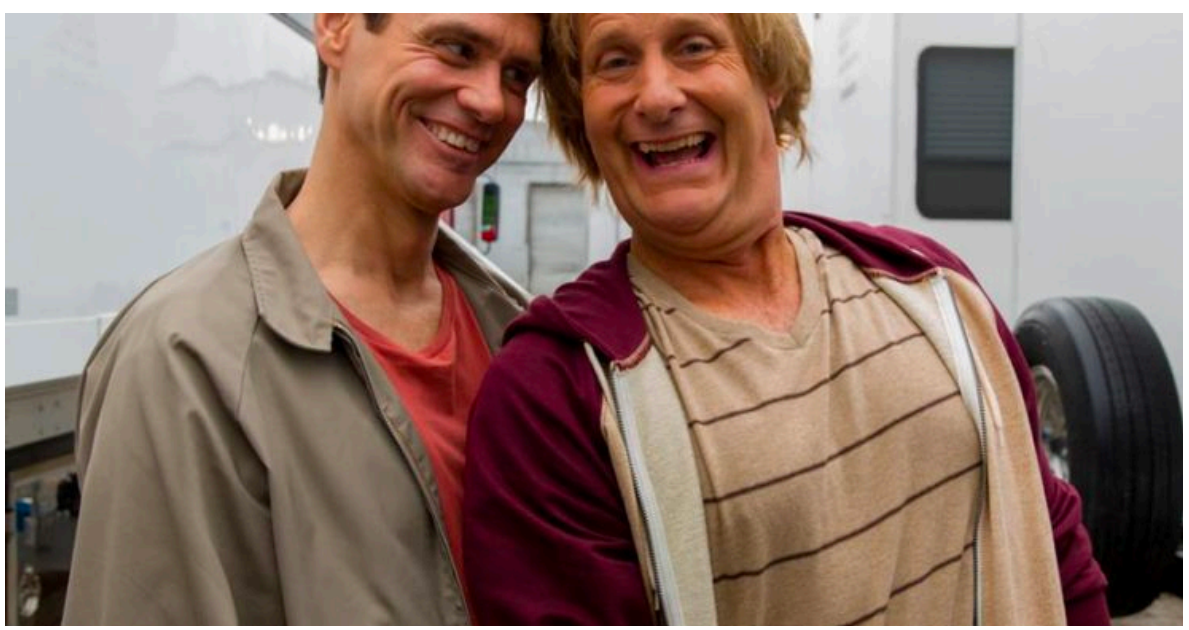
Best in the World

=

Model Input

- Satellite Remote sensing (AOD)
- Chemical transport models
- Elevation data
- Land use information
- Bayesian Hierarchical model
- Lots of greek letters

Us



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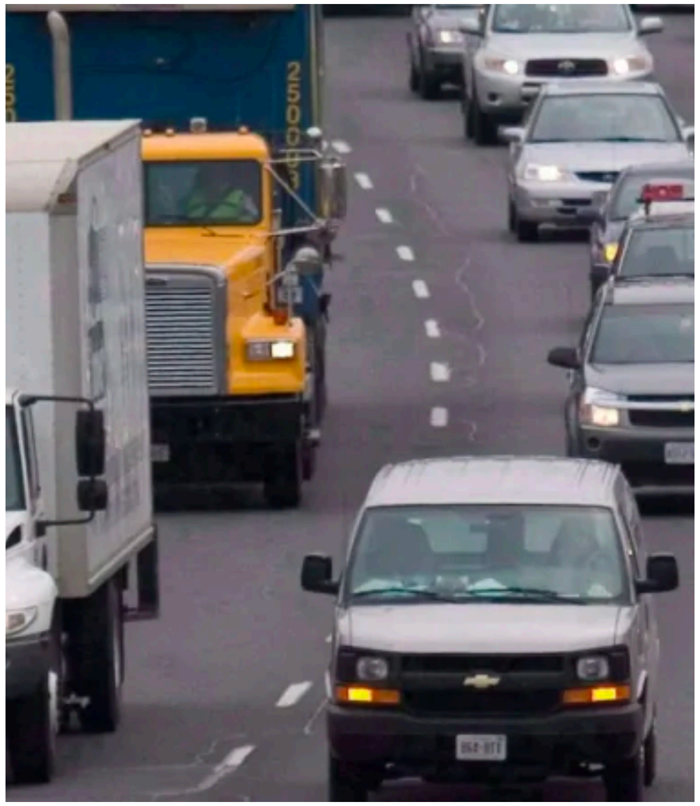
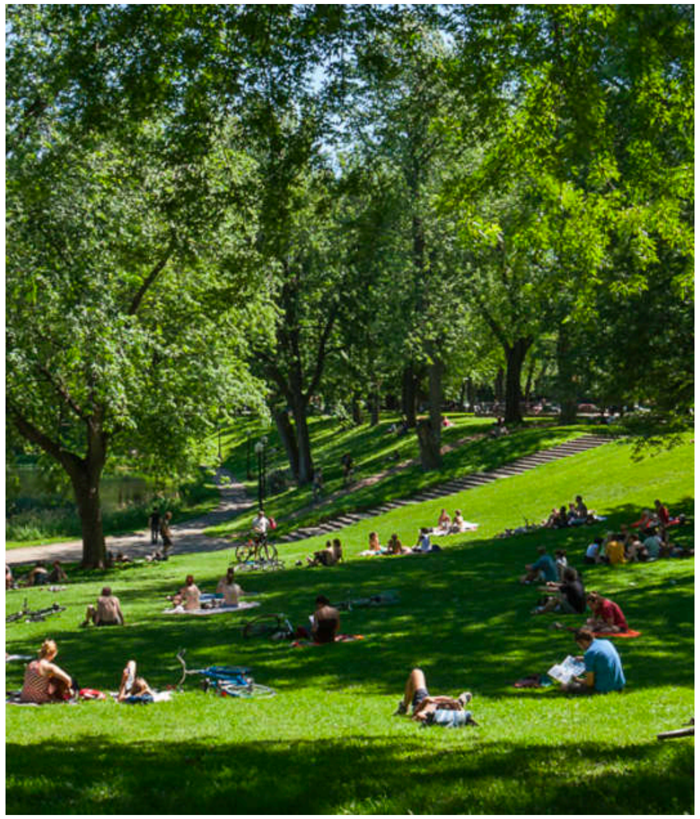
But no temporal component…yet!

What is Next?





Audio Data

Classifying Acoustic Scenes

- **"Machine Listening"**
- Classification accuracy of 83% across 15 acoustic scenes
- **Sound provides information about location**
- **Location is important for exposure!**
- There is exposure information in audio data
- We hope to find it!

JOURNAL OF LaTeX CLASS FILES, VOL. 14, NO. 8, AUGUST 2015

Acoustic scene classification using convolutional neural network and multiple-width frequency-delta data augmentation

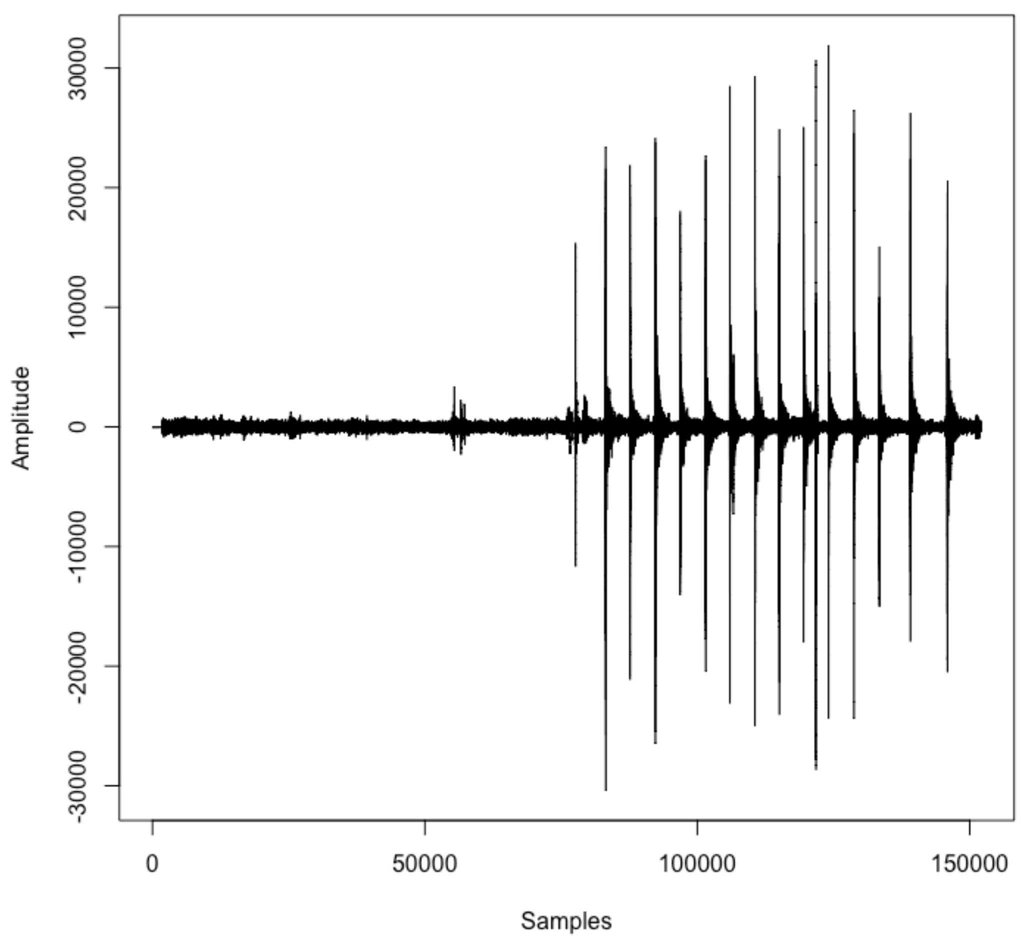
Yoonchang Han and Kyogu Lee, *Senior Member, IEEE*

	beac.	bus	cafe	car	city.	fore.	groc.	home	libr.	metr.	offi.	park	resi.	trai.	tram
beac.	0.87	0.0	0.0	0.01	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.12	0.0	0.0
bus	0.0	0.88	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.02	0.1
cafe	0.0	0.0	0.73	0.0	0.0	0.0	0.0	0.07	0.0	0.18	0.0	0.0	0.0	0.0	0.01
car	0.0	0.01	0.0	0.93	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.0
city.	0.0	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.02	0.0	0.0	0.08	0.0	0.0
fore.	0.0	0.0	0.0	0.0	0.0	0.99	0.0	0.0	0.0	0.0	0.0	0.0	0.01	0.0	0.0
groc.	0.0	0.0	0.0	0.0	0.0	0.0	0.81	0.0	0.07	0.13	0.0	0.0	0.0	0.0	0.0
home	0.0	0.0	0.01	0.0	0.0	0.0	0.0	0.81	0.04	0.0	0.12	0.0	0.0	0.0	0.01
libr.	0.0	0.0	0.02	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.06	0.0	0.02
metr.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
offi.	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.04	0.0	0.0	0.96	0.0	0.0	0.0	0.0
park	0.04	0.0	0.0	0.0	0.03	0.0	0.0	0.0	0.04	0.0	0.0	0.33	0.56	0.0	0.0
resi.	0.03	0.0	0.0	0.0	0.01	0.02	0.0	0.0	0.01	0.0	0.0	0.09	0.84	0.0	0.0
trai.	0.0	0.1	0.08	0.0	0.0	0.0	0.0	0.0	0.04	0.01	0.0	0.0	0.0	0.66	0.11
tram	0.0	0.0	0.03	0.0	0.05	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.02	0.9

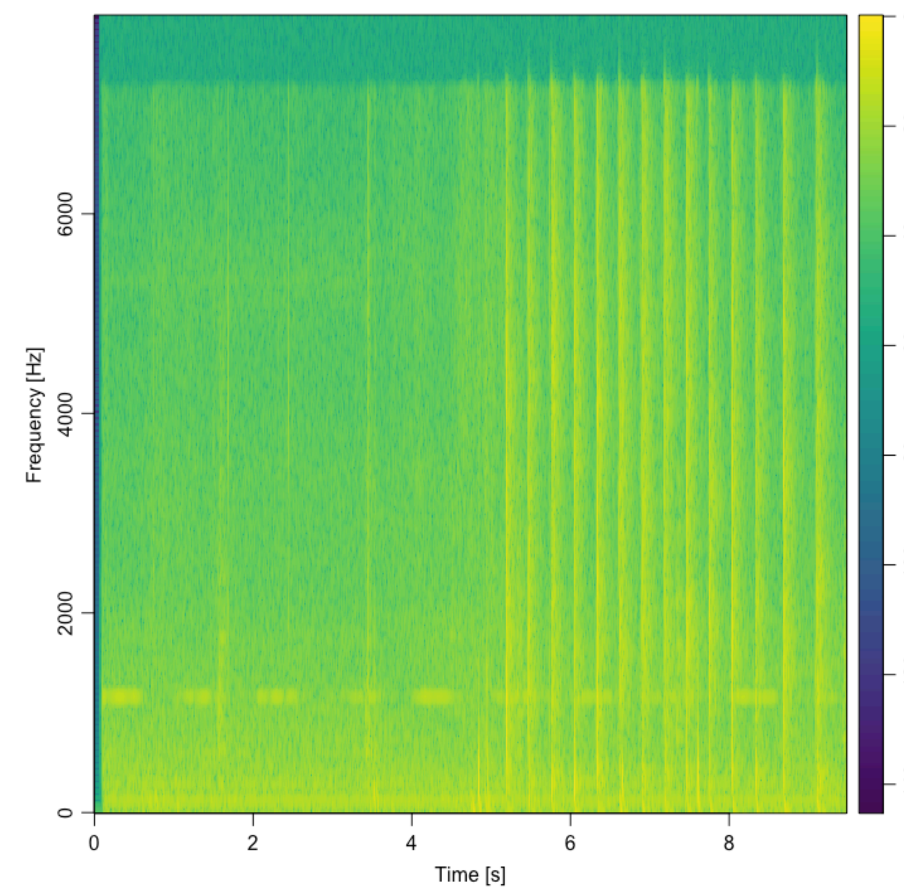
Fig. 3. Confusion matrix of the proposed ConvNet system with MWFD data augmentation, extracted from the four-fold cross-validation mean accuracy of the ensemble model with aggregation strategy *S2*, which achieved the best classification result. The scene labels are abbreviated. The original names of the scenes are beach, bus, cafe/restaurant, car, city center, forest path, grocery store, home, library, metro station, office, park, residential area, train, and tram. The x-axis is the predicted label; the y-axis is the true label.

Audio Data

Audio Data (.wav file)



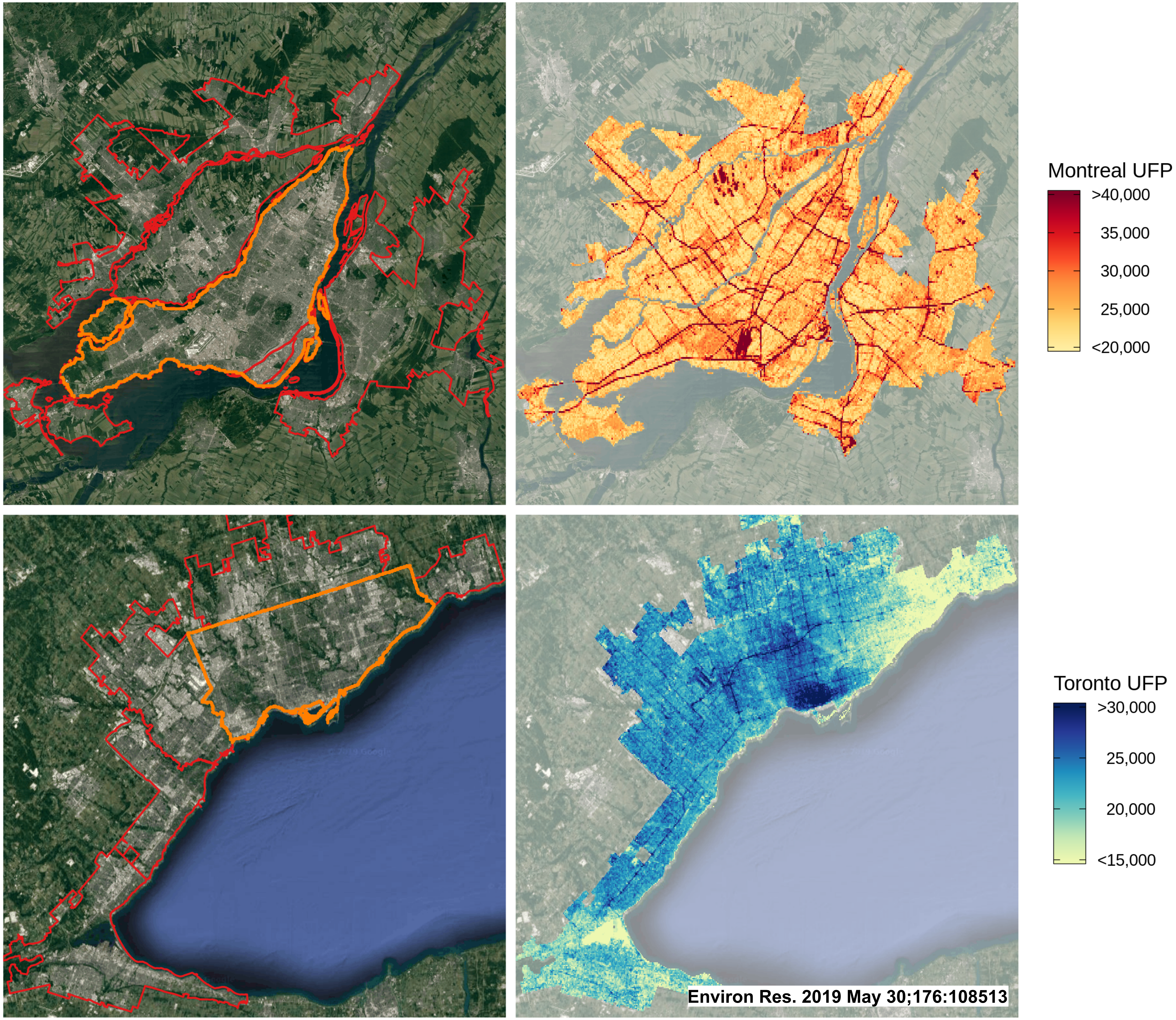
Convert Audio file to Spectrogram Image

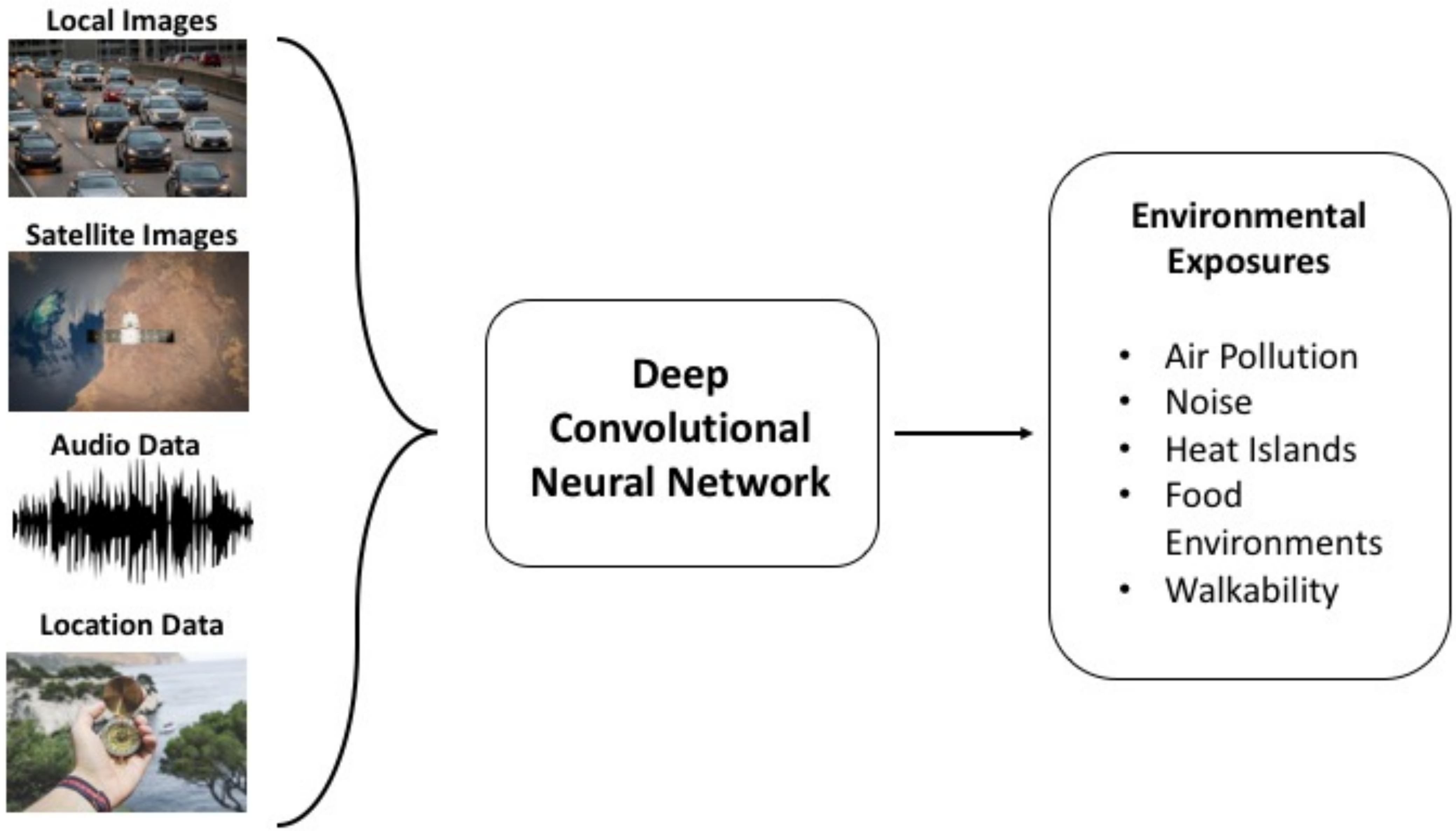


Use Image as Input in CNN

Predict Environmental Expoures

Expanding the Spatial Scale of UFP Models





- Combine Multiple Inputs to estimate exposures to Multiple Pollutants

- We want to understand the <u>**collective**</u> impact of the urban built environment on exposures and disease

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A picture tells a thousand…exposures: Opportunities and challenges of deep learning image analyses in exposure science and environmental epidemiology

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Thank You!

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M[i]4 Interdisciplinary Initiative in Infection and Immunity

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