Taking a wider view of NO_2 pollution: Estimating NO_2's health impacts from local to global scales

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Michael Brauer (Institute for Health Metrics and Evaluation)

Additional support from the Health Effects Institute

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HAQAST2020
WEBINAR SERIES

Speakers

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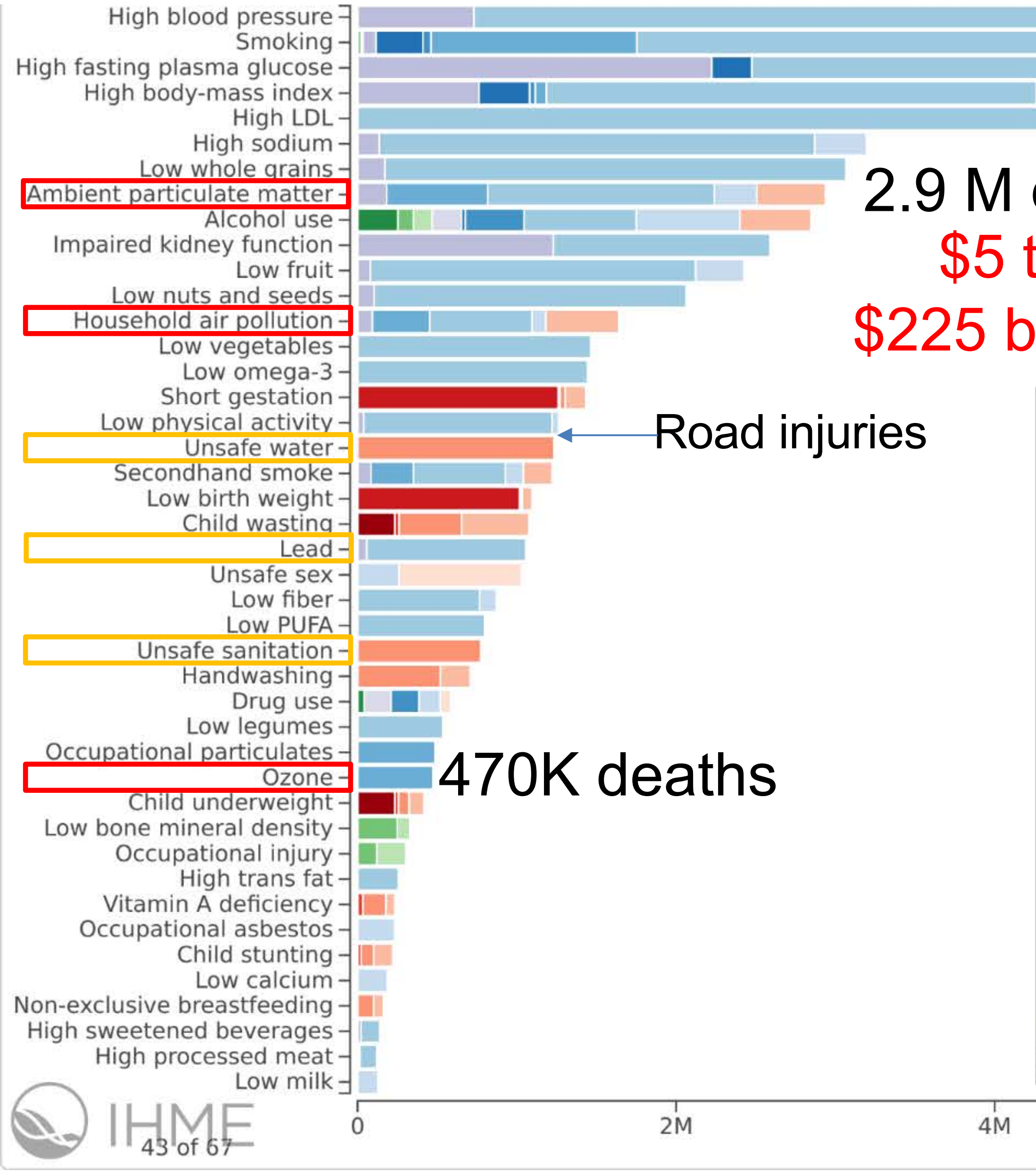
Argonne National Laboratory

Agenda

- Overview of the Global Burden of Disease and air pollution
- Estimating NO_2 disease burdens from local to global scales
- Satellite remote sensing of NO_2 using OMI and TROPOMI
- Questions

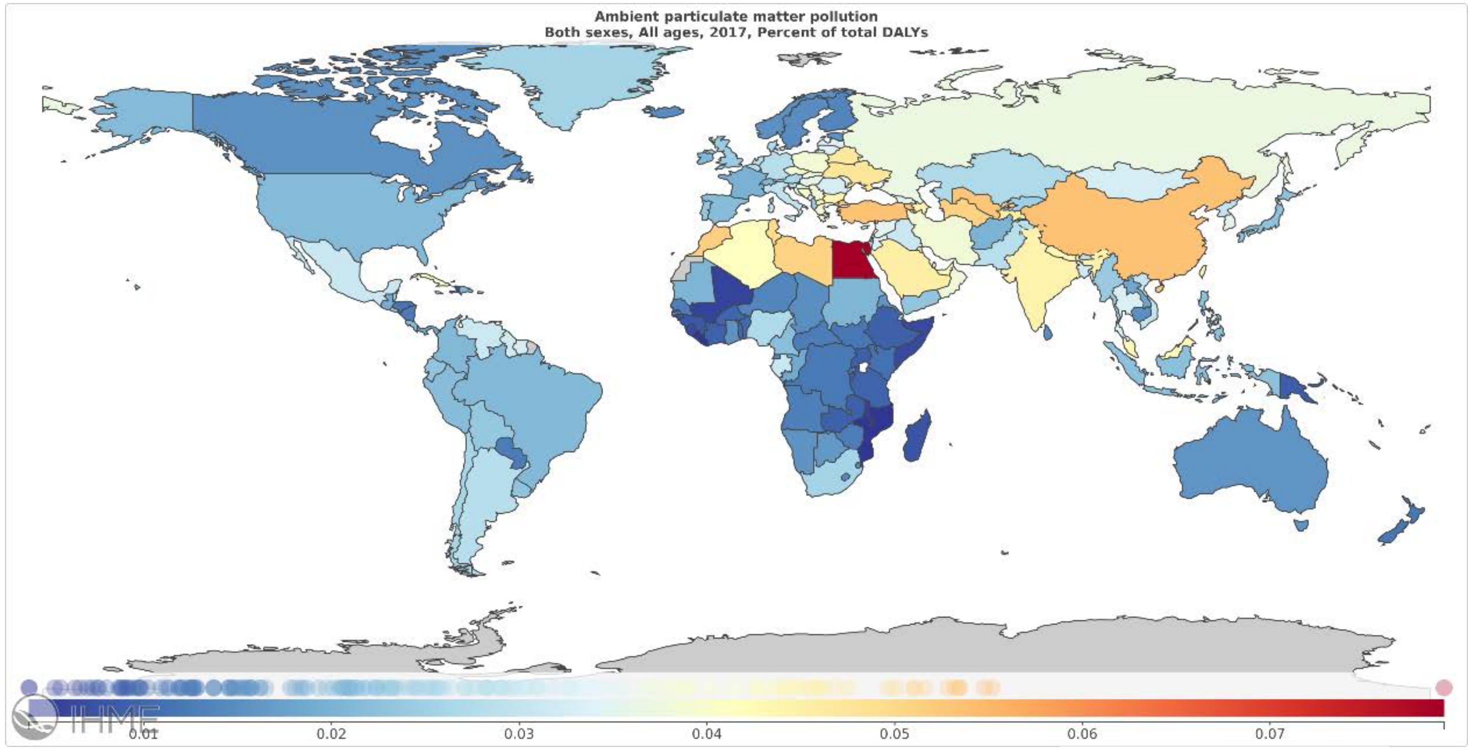
Air pollution is a major risk factor for global health



2.9 M deaths ~9% of all deaths

$5 trillion/yr welfare losses

$225 billion/yr lost labour income



2017

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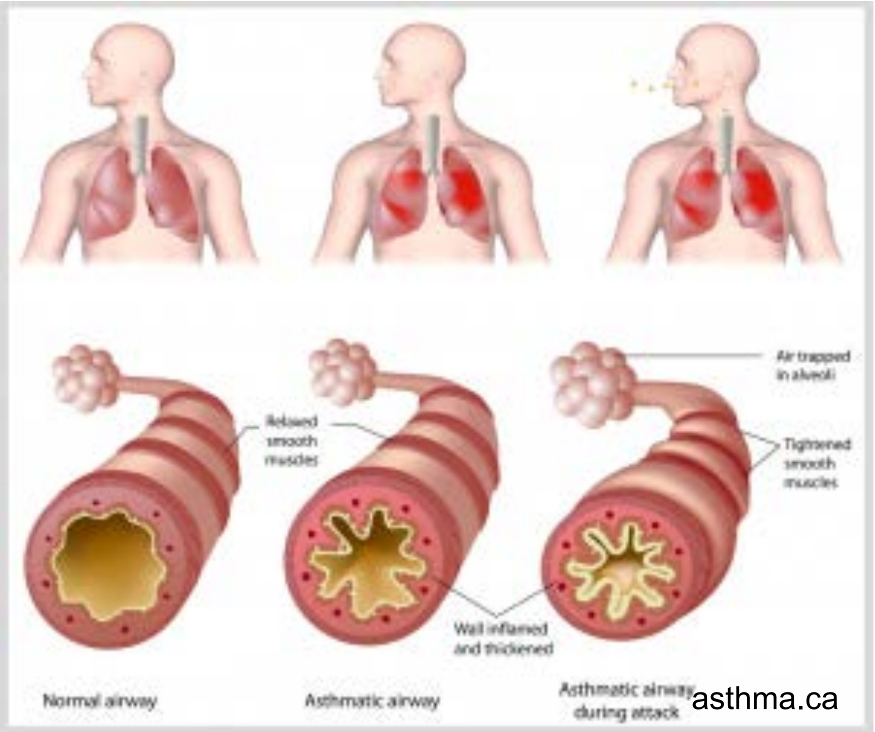
https://vizhub.healthdata.org/gbd-compare/

World Bank. 2016. *The cost of air pollution : strengthening the economic case for action*

What's missing?

- Current air pollution risks ($PM_{2.5}$, O_3) don't fully characterize urban air pollution (especially related to motor vehicle exhaust)
- Currently, no accounting for impacts on asthma

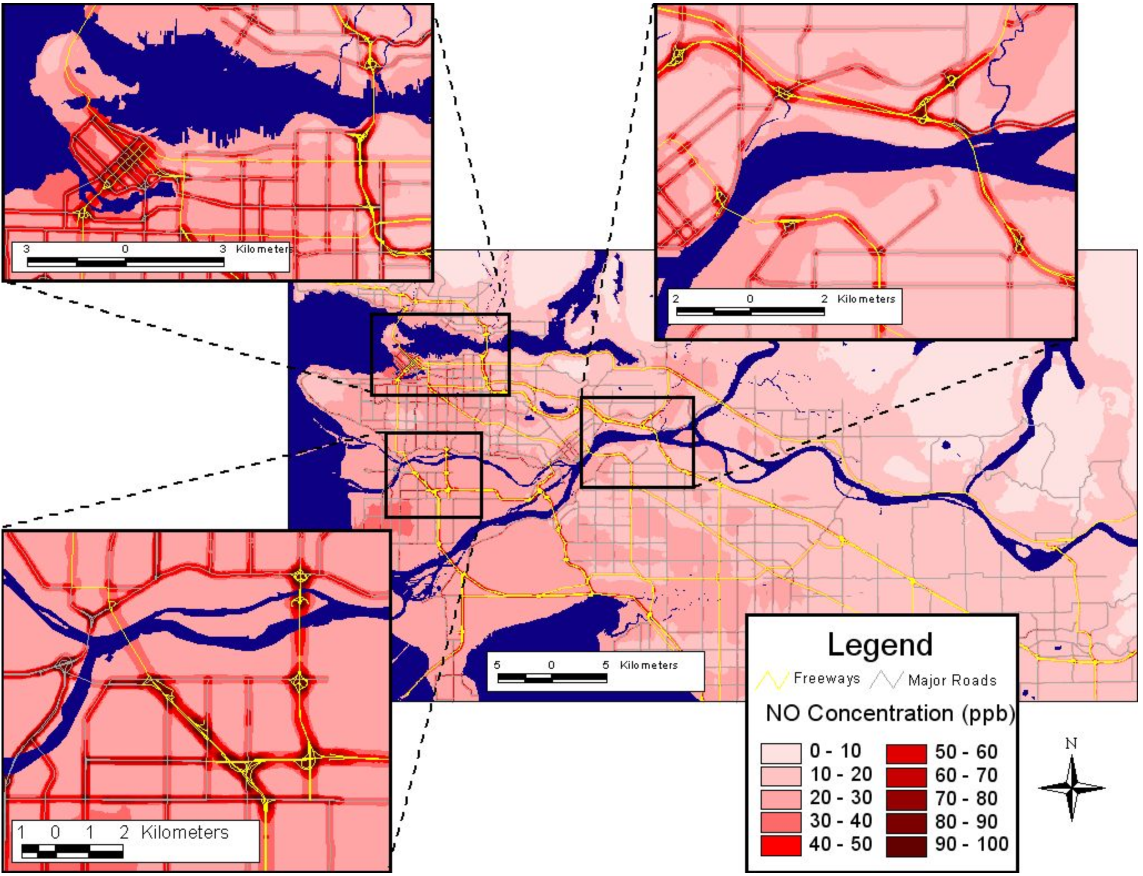


Four of world's biggest cities to ban diesel cars from their centres

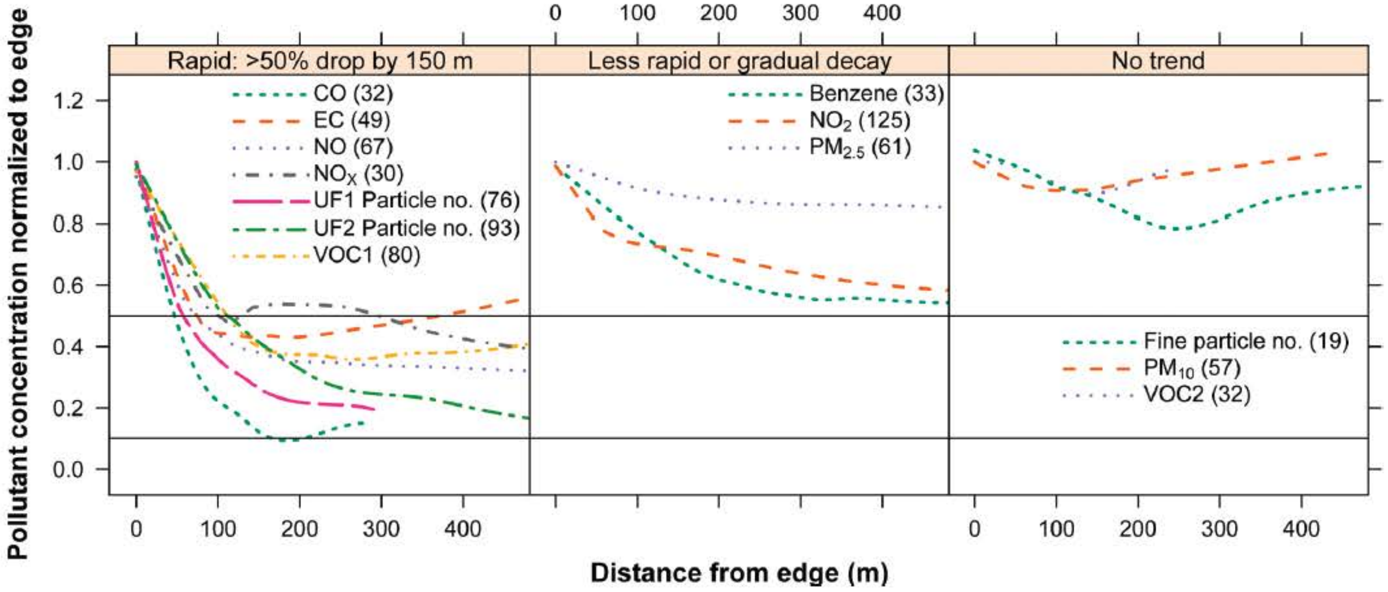
Paris, Madrid, Athens and Mexico City will ban the most polluting cars and vans by 2025 to tackle air pollution

Cars sit in traffic in Mexico City, Mexico. Photograph: Brett Gundlock/Getty Images

Traffic-related air pollution (TRAP)



Henderson SB et al. Environmental Science and Technology. 2007; 41 (7):2422 -2428



Karner *et al.* (2010) Environ. Sci. Technol. 44, 5334

Traffic influence zones (<500m from highway or <100m from major road)

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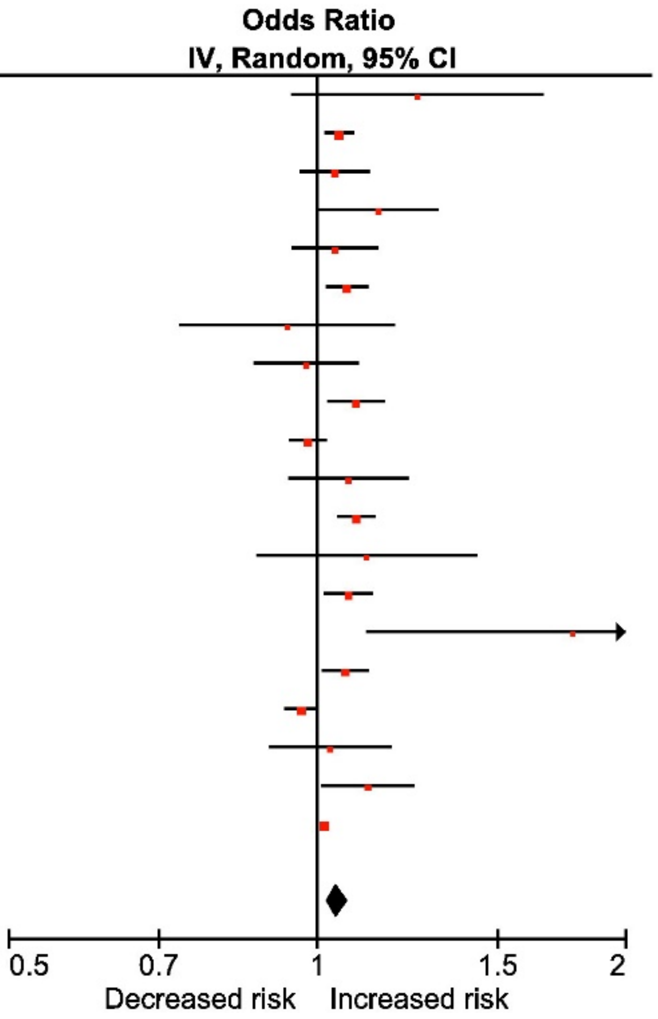
Background

- Multiple meta analyses indicate associations between TRAP exposure, as characterized by high resolution nitrogen dioxide (NO_2), and pediatric asthma.

NO_2 and asthma

Study or Subgroup	log[Odds Ratio]	SE	Weight	Odds Ratio IV, Random, 95% CI
Carlsten et al. 2010 - at 7 y.o.	0.2253	0.1448	0.6%	1.25 [0.94, 1.66]
Clark et al. 2010 LUR - at mean age of 4 y.o.	0.0489	0.0171	9.5%	1.05 [1.02, 1.09]
Dell et al. 2014 LUR - 5 to 9 y.o.	0.039	0.04	5.0%	1.04 [0.96, 1.12]
Deng et al. 2016 - 3 to 6 y.o.	0.1374	0.0689	2.4%	1.15 [1.00, 1.31]
Gehring et al. 2015 b - BAMSE birth to 16 y.o.	0.0397	0.0498	3.8%	1.04 [0.94, 1.15]
Gehring et al. 2015 b - PIAMA birth to 14 y.o.	0.0665	0.0246	7.8%	1.07 [1.02, 1.12]
Gehring et al. 2015b - GINI&LISA North birth to 15	-0.0679	0.1235	0.8%	0.93 [0.73, 1.19]
Gehring et al. 2015b - GINI&LISA South birth to 15	-0.0252	0.0602	2.9%	0.98 [0.87, 1.10]
Jerret et al. 2008 - 10 to 18 y.o.	0.0874	0.033	6.1%	1.09 [1.02, 1.16]
Kim et al. 2016 - 6 to 7 y.o.	-0.0214	0.0219	8.4%	0.98 [0.94, 1.02]
Krämer et al. 2009 - 4 to 6 y.o.	0.0698	0.069	2.3%	1.07 [0.94, 1.23]
Liu et al. 2016 - 4 to 6 years old	0.0877	0.0215	8.5%	1.09 [1.05, 1.14]
MacIntyre et al. 2014 - CAPPS&SAGE only birth to 8	0.1111	0.1268	0.8%	1.12 [0.87, 1.43]
McConnell et al. 2010 - 4th to 6th grade	0.0698	0.0281	7.1%	1.07 [1.01, 1.13]
Mölter et al. 2014 b - MAAS only birth to 8 y.o.	0.574	0.2374	0.2%	1.78 [1.11, 2.83]
Nishimura et al. 2013 - 8 to 21 y.o.	0.0632	0.0269	7.3%	1.07 [1.01, 1.12]
Oftedal et al. 2009 - birth to 10 y.o.	-0.0359	0.0196	8.9%	0.96 [0.93, 1.00]
Ranzi et al. 2014 - birth to 7 y.o.	0.0289	0.0701	2.3%	1.03 [0.90, 1.18]
Shima et al. 2002 - 6 to 12 y.o.	0.1136	0.0534	3.5%	1.12 [1.01, 1.24]
Tétreault et al. 2016 - birth to 12 y.o.	0.0153	0.0048	11.6%	1.02 [1.01, 1.03]
Total (95% CI)			**100.0%**	**1.05 [1.02, 1.07]**

Heterogeneity: Tau² = 0.00; Chi² = 54.38, df = 19 (P < 0.0001); I² = 65%
Test for overall effect: Z = 3.76 (P = 0.0002)



(per 4 μg/m³; birth – 21 yrs)

Khreis H, et al. Environ Int. 2017. doi: 10.1016/j.envint.2016.11.012;

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Background

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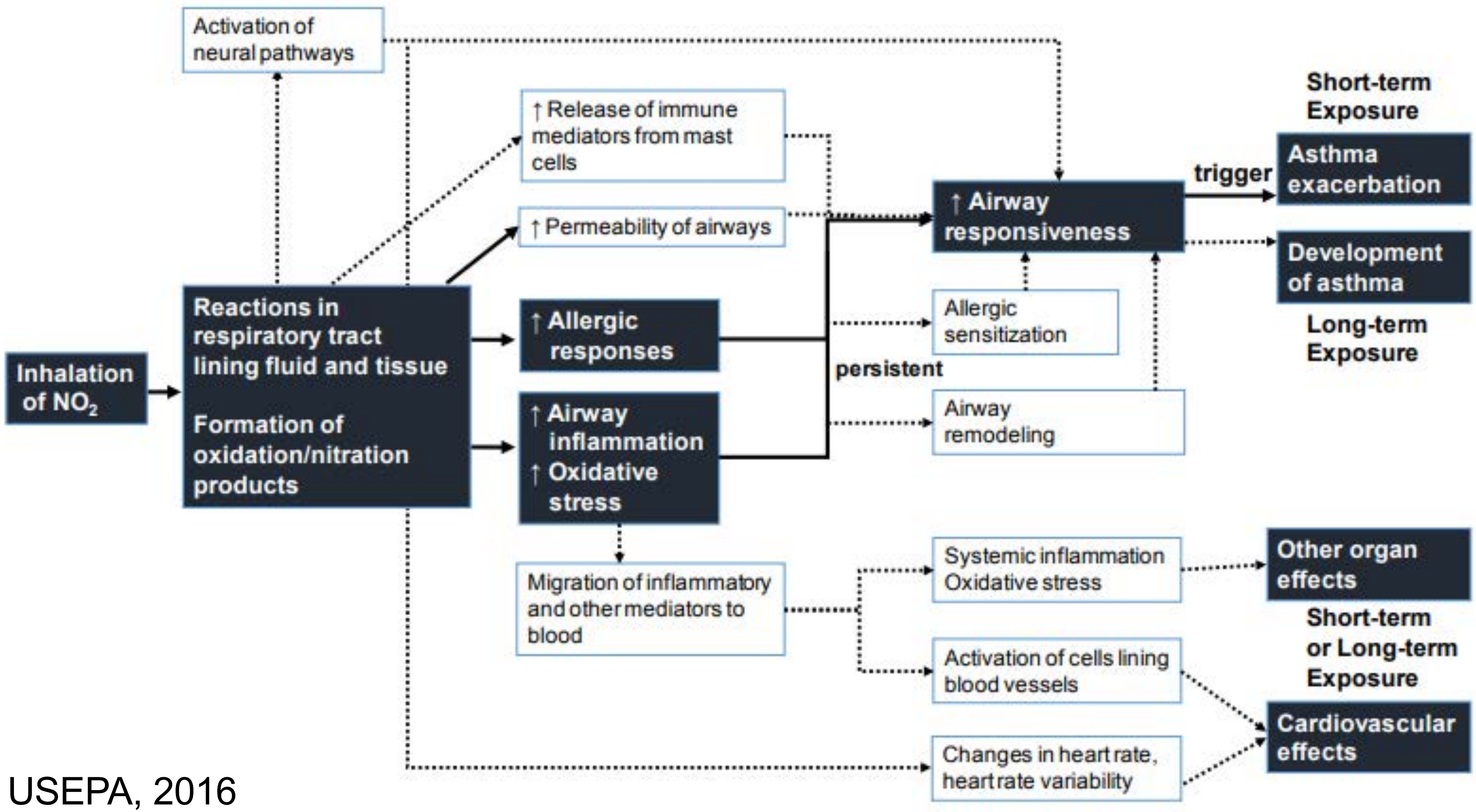
  - Biological plausibility

Biological Pathways



USEPA, 2016

Background

- Multiple meta analyses indicate associations between TRAP exposure, as characterized by high resolution nitrogen dioxide (NO_2), and pediatric asthma.
  - Biological plausibility
  - US EPA, 2016; Health Canada, 2016: **Likely a causal** relationship between long-term NO_2 exposure and pediatric asthma development.
- Global exposure estimation at required spatial resolution

Background

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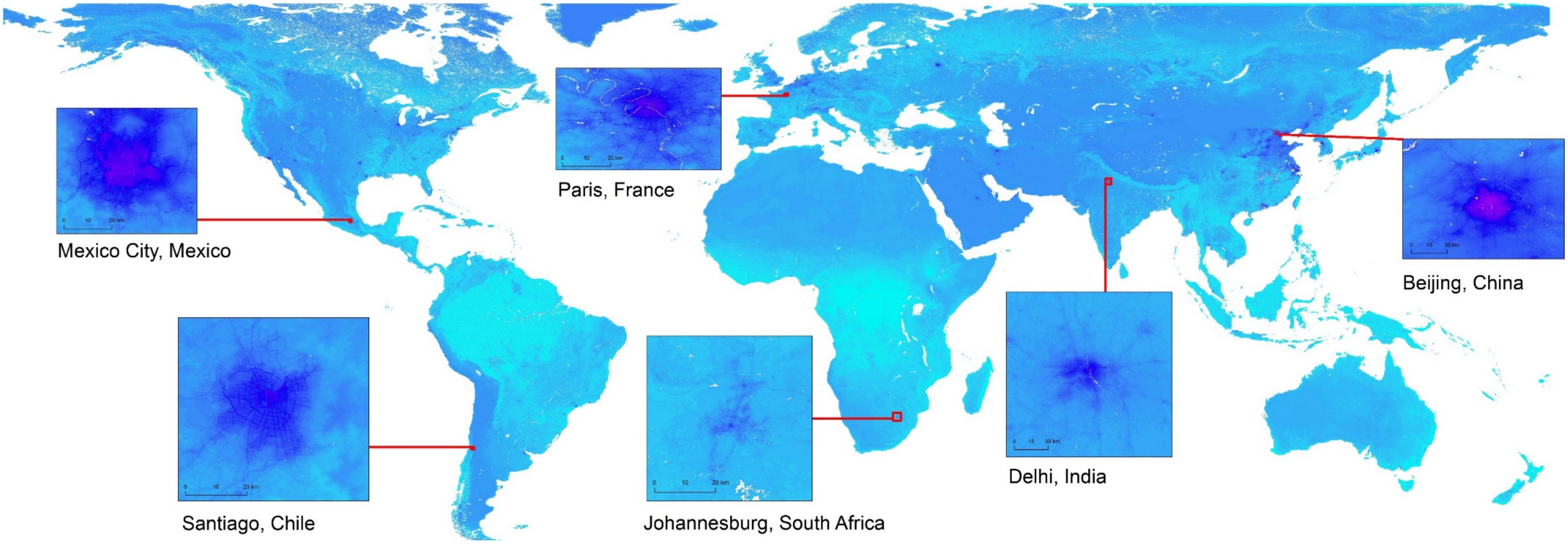
Exposure: Global high resolution (100m) NO_2 model



Larkin A, Geddes J, Martin RV, Xiao Q, Liu Y, Marshall JD, Brauer M, Hystad P. A Global Land Use Regression Model for Nitrogen Dioxide Air Pollution. Environmental Science & Technology. 2017

Estimating global NO_2 disease burdens

Research

Estimates of the Global Burden of Ambient $PM_{2.5}$, Ozone, and NO_2 on Asthma Incidence and Emergency Room Visits

Surface NO_2 from OMI satellite retrieval plus GMI-Replay model

- 0.1° resolution
- 1:45pm → 24hr avg

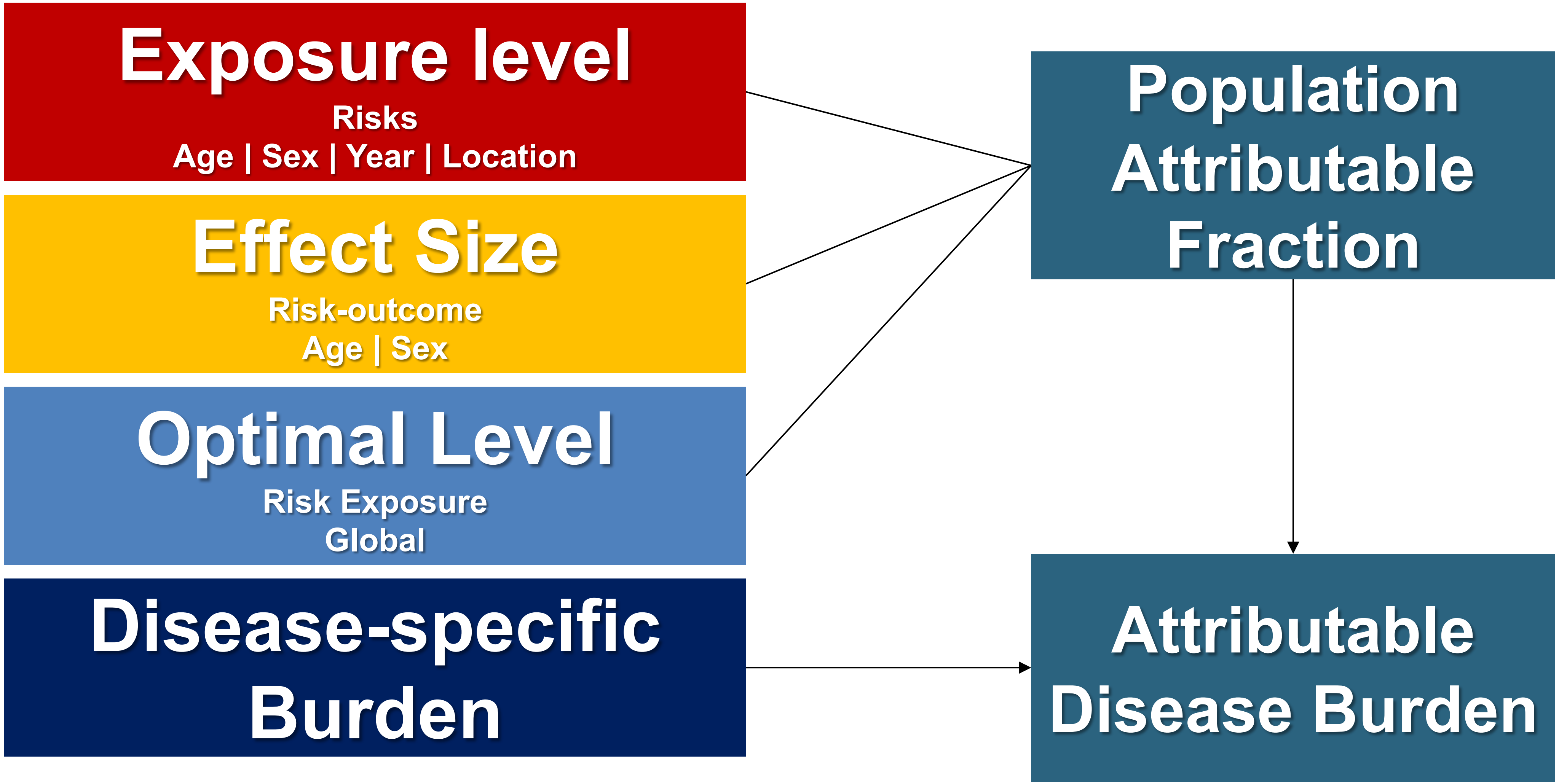
Articles

Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: estimates from global datasets

Surface NO_2 from land use regression

- 100m resolution
- Average 2010-2012
- GOME2 and SCIAMACHY satellite retrievals

Estimating (global) disease burden from air pollution



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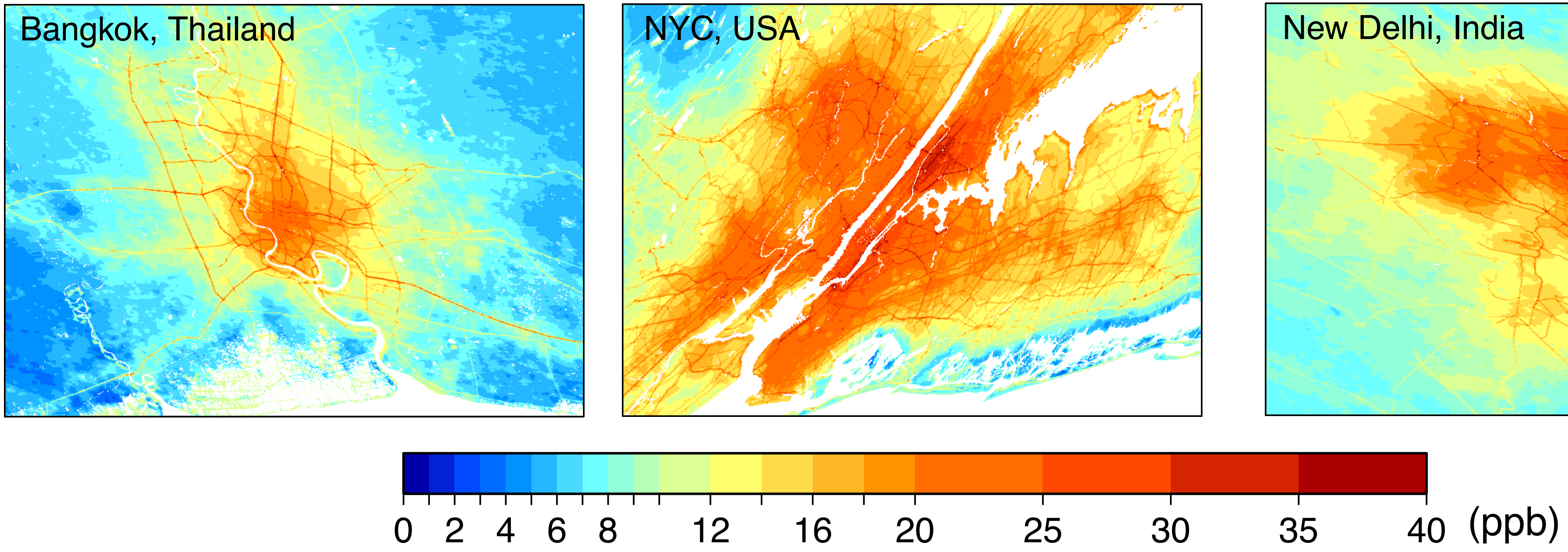
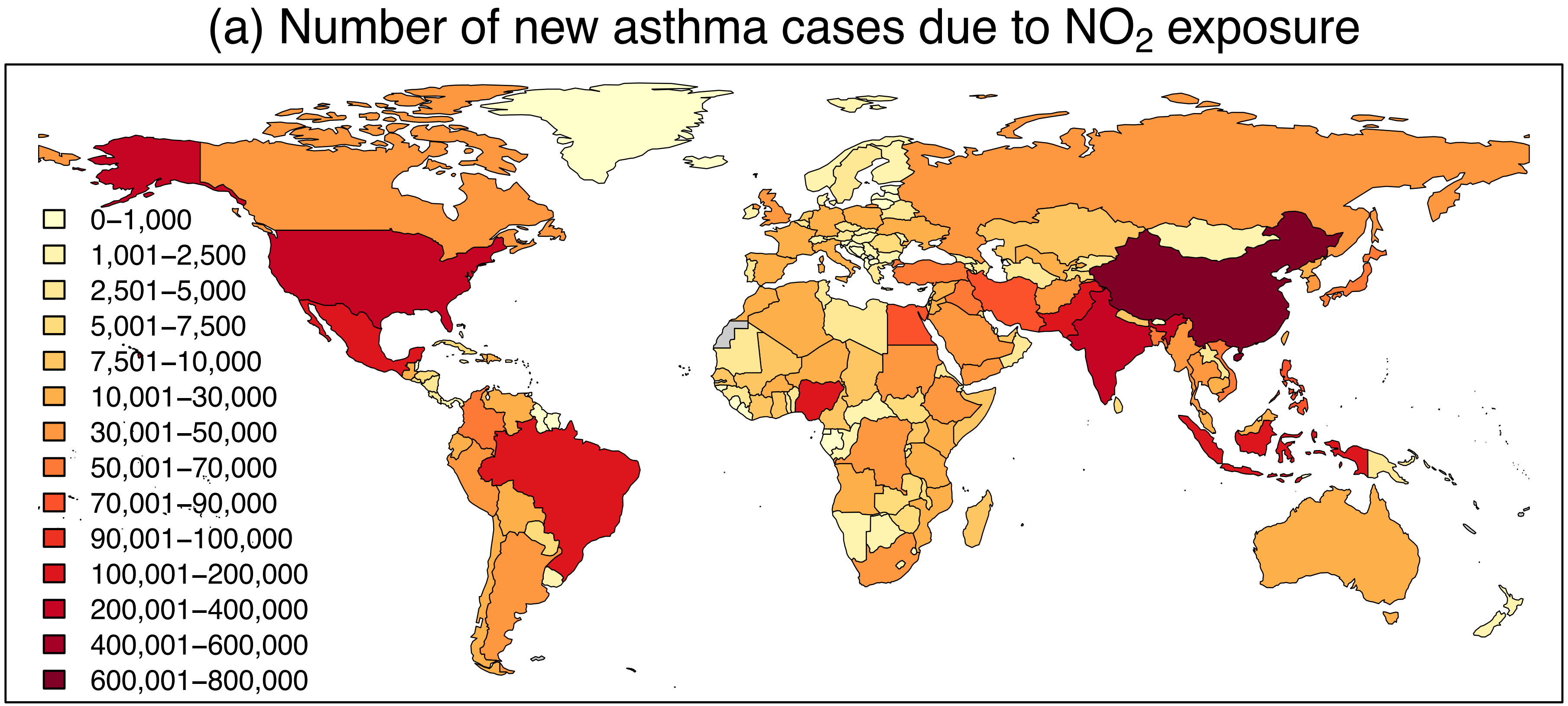
Methods: Finding global datasets that can resolve intra-city and near-roadway exposures

2010-2012 global surface NO_2 modeled by land-use regression at 100m x 100m (Larkin et al., 2017)



Traffic-related NO_2 generally declines to urban background levels at a distance beyond 300-500 m from roadways (HEI, 2010).

Each year, 4 million (95% UI 1.8-5.2) children developed asthma due to NO_2 pollution, accounting for 13% (6-16) of the global annual burden (2010-2015)



- Top national burdens (attributable cases/year): China (760,000), India (350,000), USA (240,000), Indonesia (160,000)
- We estimate that ~97% of children lived, and ~92% of NO_2-attributable pediatric asthma incidence occurred, in areas below the current WHO guideline of 21 ppb for annual average NO_2.

Achakulwisut et al., 2019, *Lancet Planetary Health (2019)*

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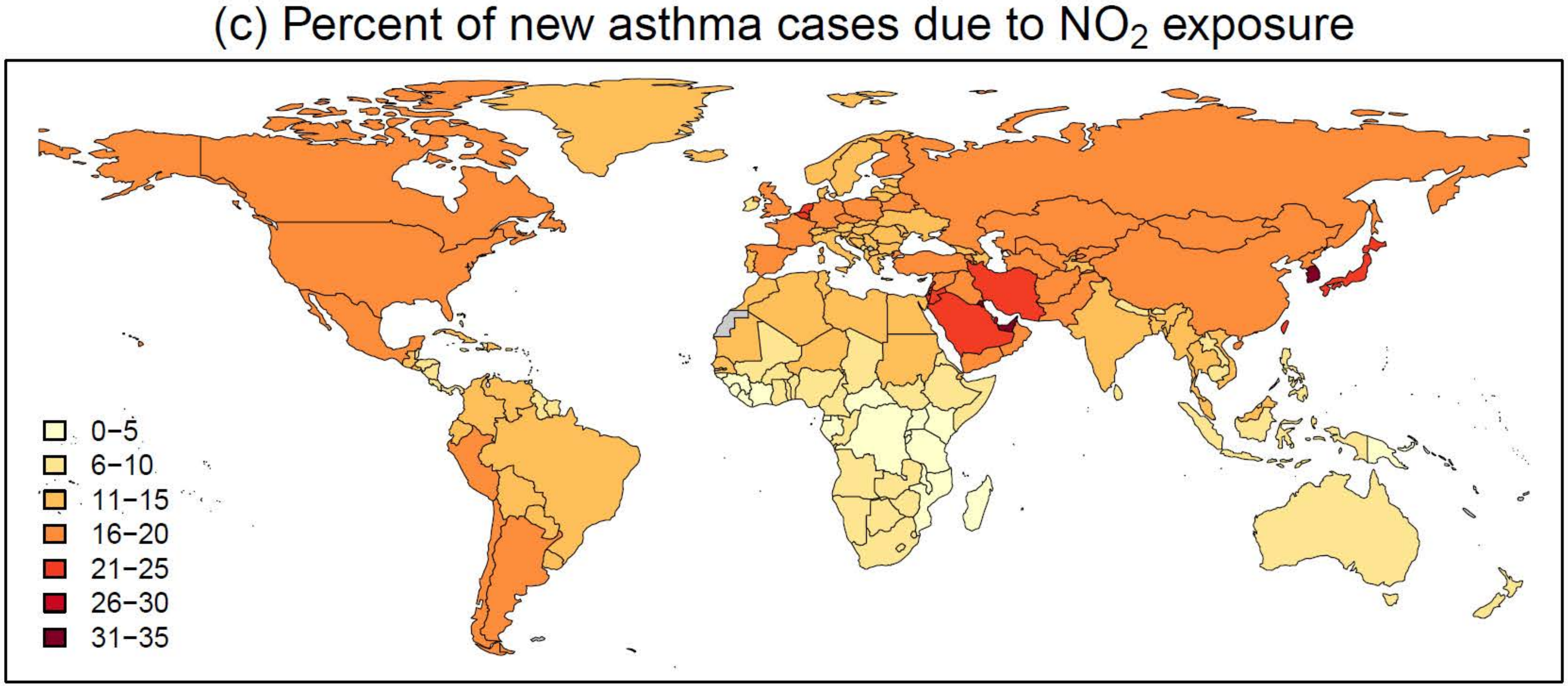
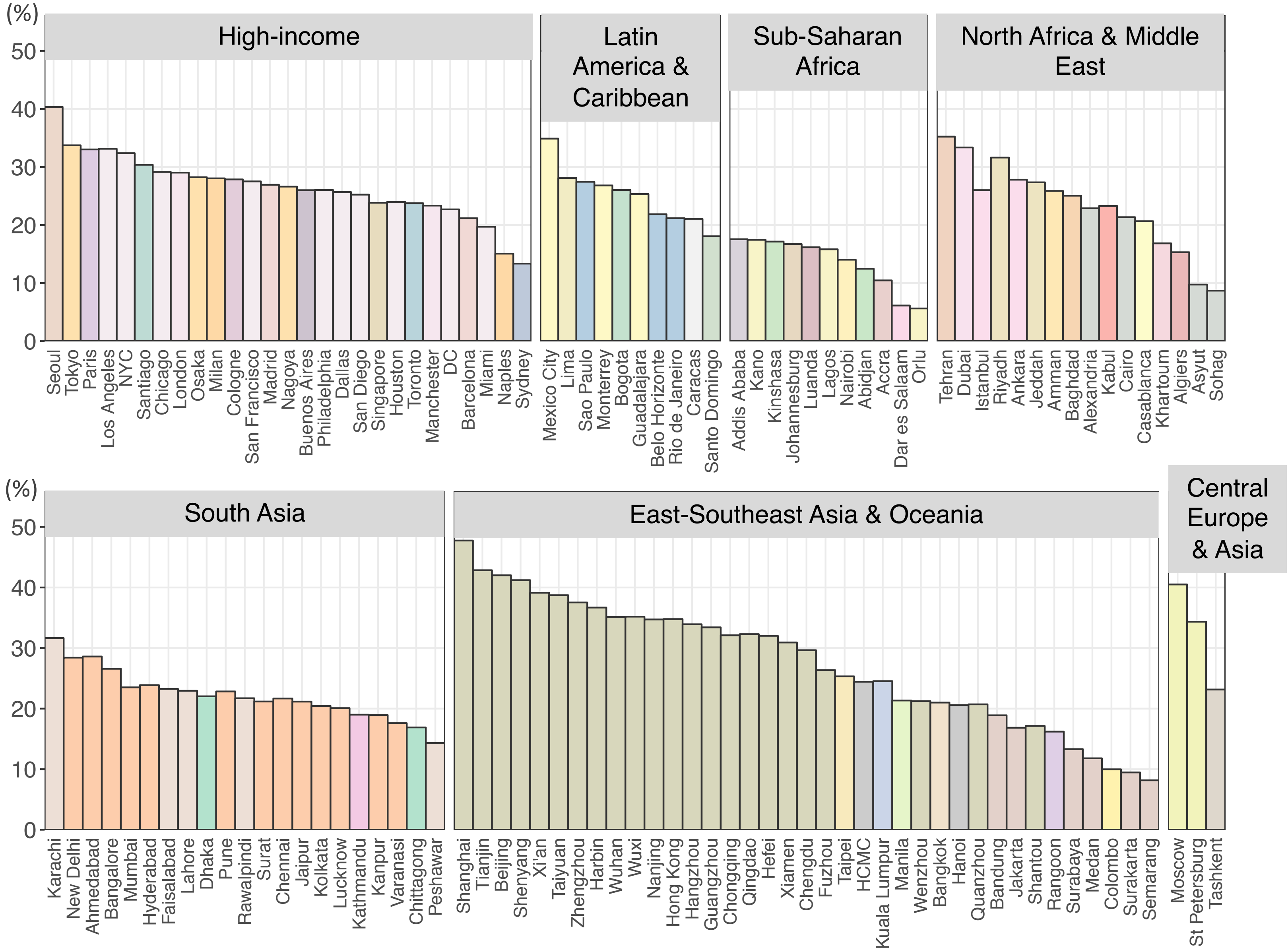
Spatial pattern of NO_2-attributable asthma impacts differs from $PM_{2.5}$ mortality



Achakulwisut et al., 2019, *Lancet Planetary Health (2019)*

In both developed and developing cities, NO_2 pollution is an important risk factor for pediatric asthma incidence



Globally, 90% of NO_2-attributable pediatric asthma incidence occurred in urban centers (including suburban areas)

In 125 major cities, the percent of new pediatric asthma cases attributable to NO_2:

- Ranged from 6% (Orlu, Nigeria) to 48% (Shanghai, China).
- Exceeded 20% in 92 cities, located in both developed and developing countries.

Achakulwisut et al., 2019, *Lancet Planetary Health (2019)*

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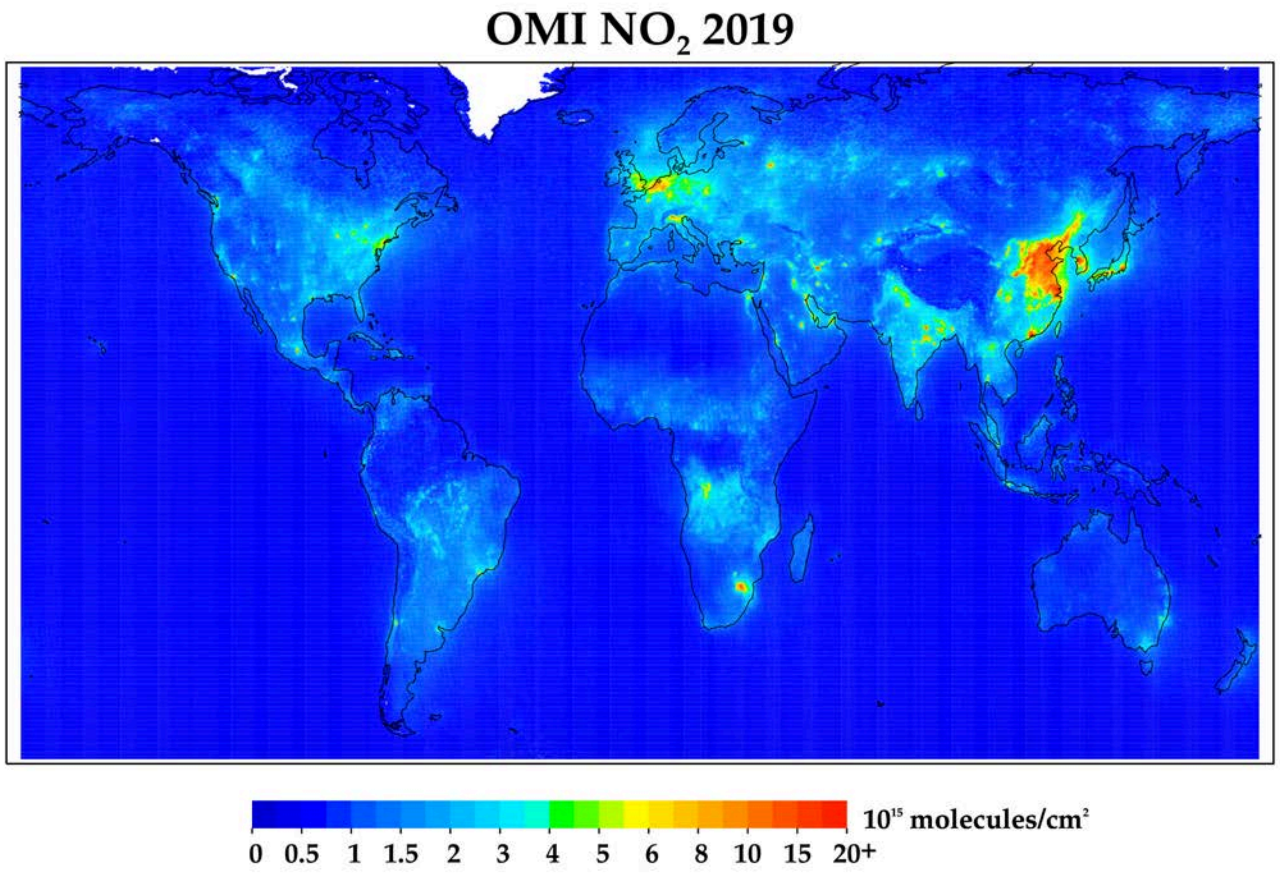
How can satellites help us improve estimates of the global burden of NO_2 on asthma?

- Consistency with GBD comparative framework
  - – Full global coverage
  - – Temporal trends

- High spatial resolution
  - Urban vs rural
  - Capture near roadway concentrations



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Number of AQ monitors globally are sparse

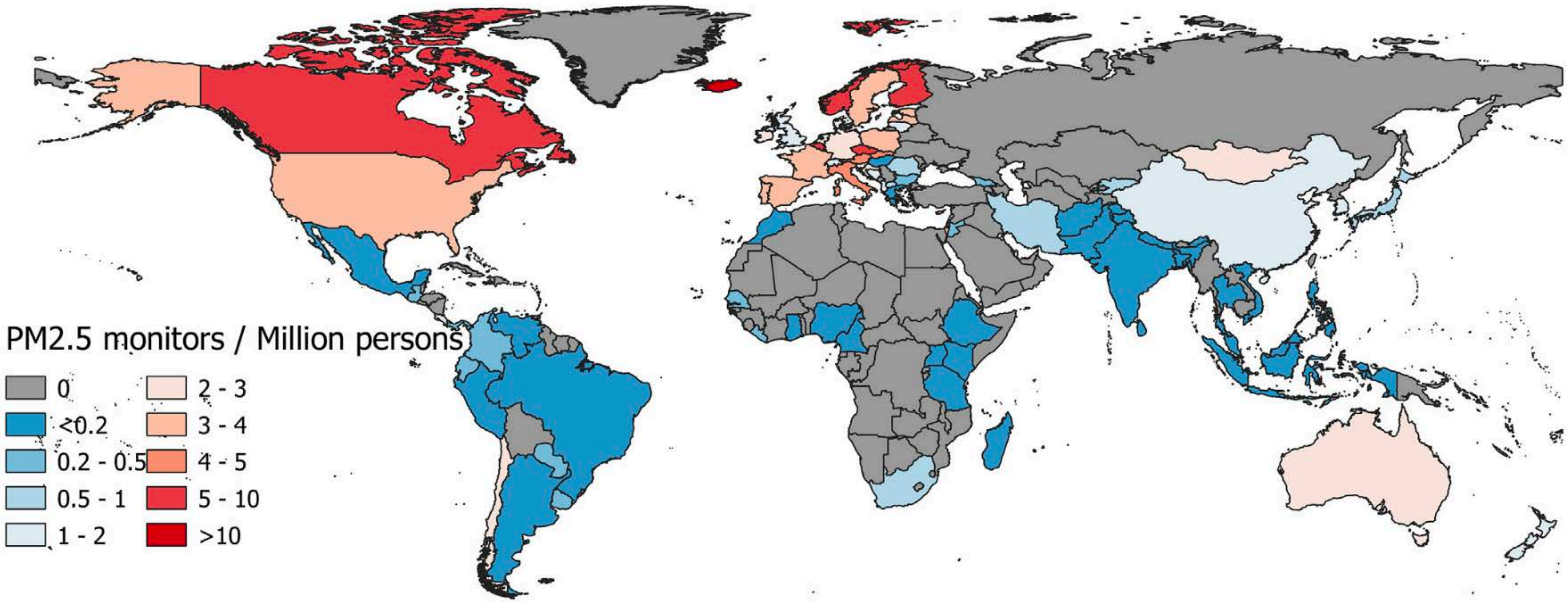


Fig. 1. Number of $PM_{2.5}$ monitors per million inhabitants by country for any of the years 2010–2016.

From Martin et al., 2019: "No one knows which city has the highest concentration of fine particulate matter"

NO_2 from satellite instruments: 101

Names of the satellite instruments:

- **OMI** (Ozone Monitoring Instrument) (pixels are ~13 × 24 km^2)
- **TROPOMI** (Tropospheric Monitoring Instrument) (pixels are ~3.5 × 5.5 km^2)

Key points:

- Polar-orbiting; global coverage once per day
- Quantities reported are ***column contents*** between surface and ~12 km in altitude
- Units: molecules per cm^2
- Measures during the mid-afternoon only (~1:30 PM local time)

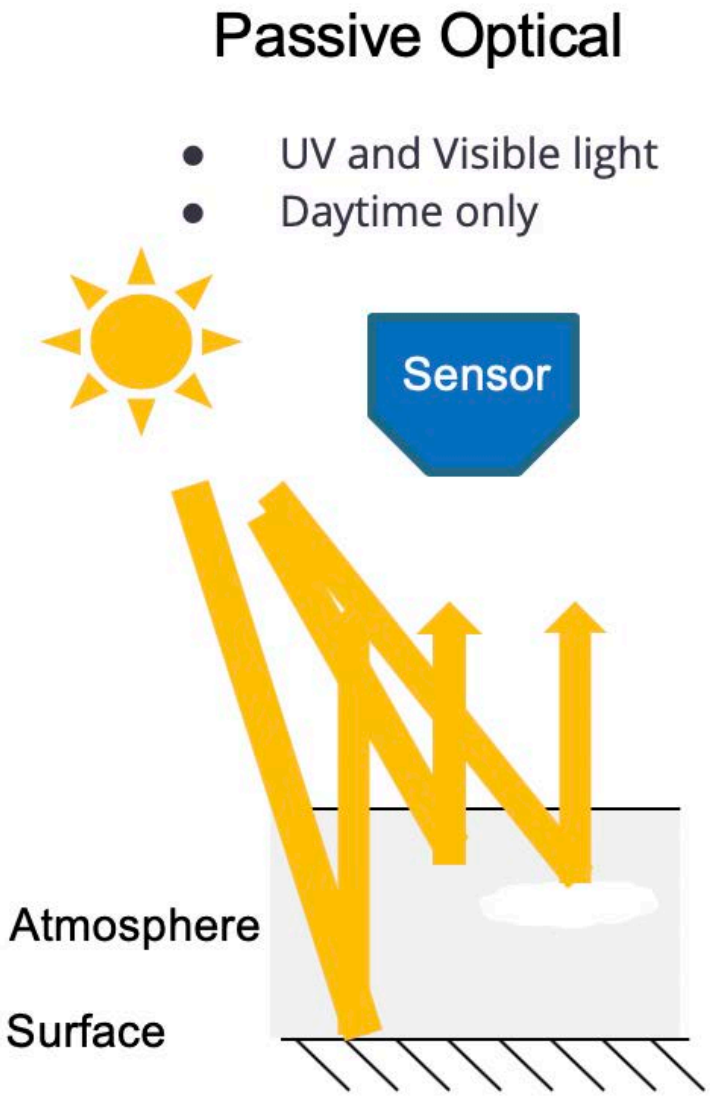
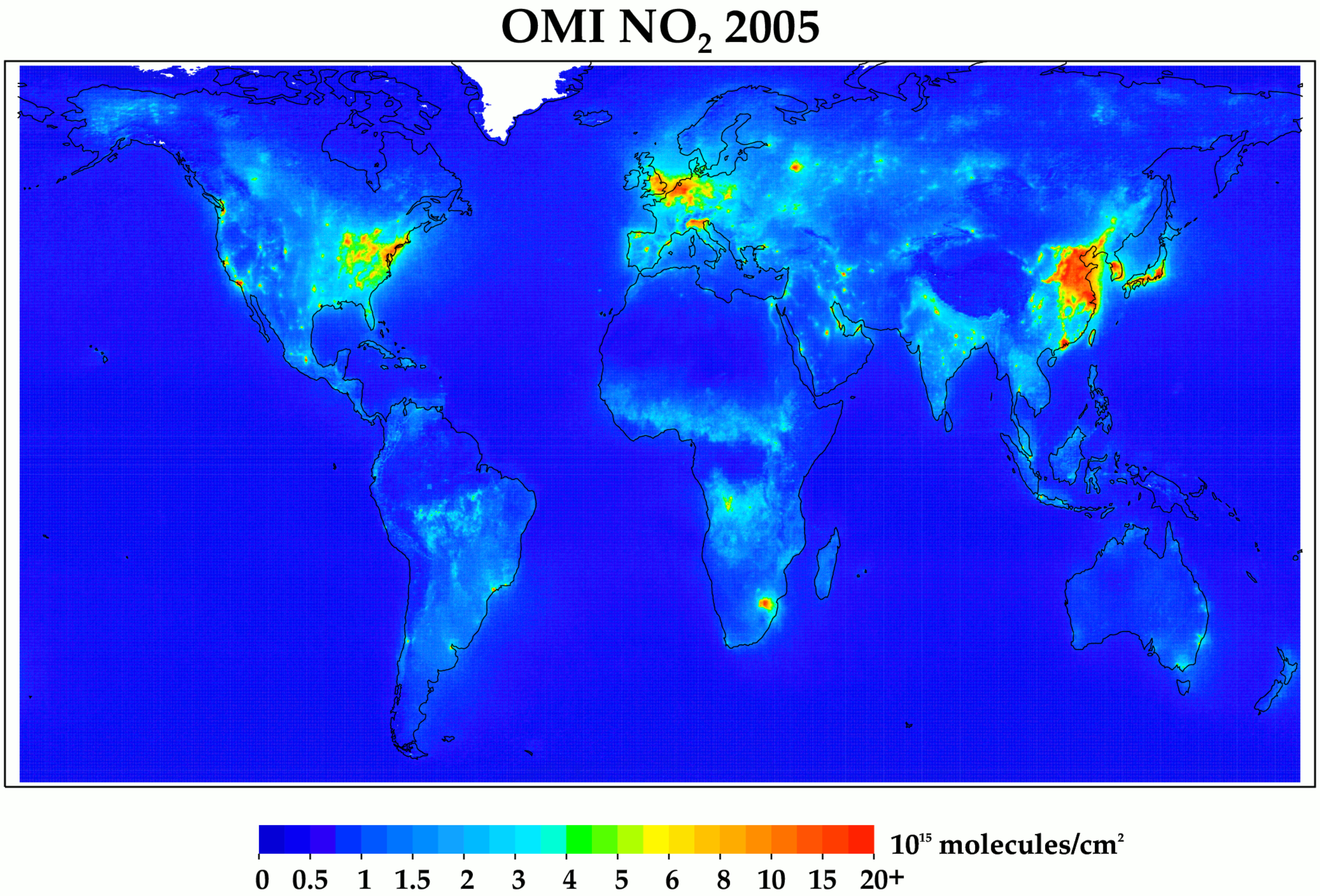


Figure from: Dr. John Kerekes, RIT

Trends of NO_2 using satellite (OMI) data



OMI = Ozone Monitoring Instrument, launched July 2004

- Largest regional decreases since 2005 are in the United States
- Moderate decreases in Europe
- Increase in China between 2005 and 2012, then decrease since then
- General increases in India (with the exception of Delhi itself)

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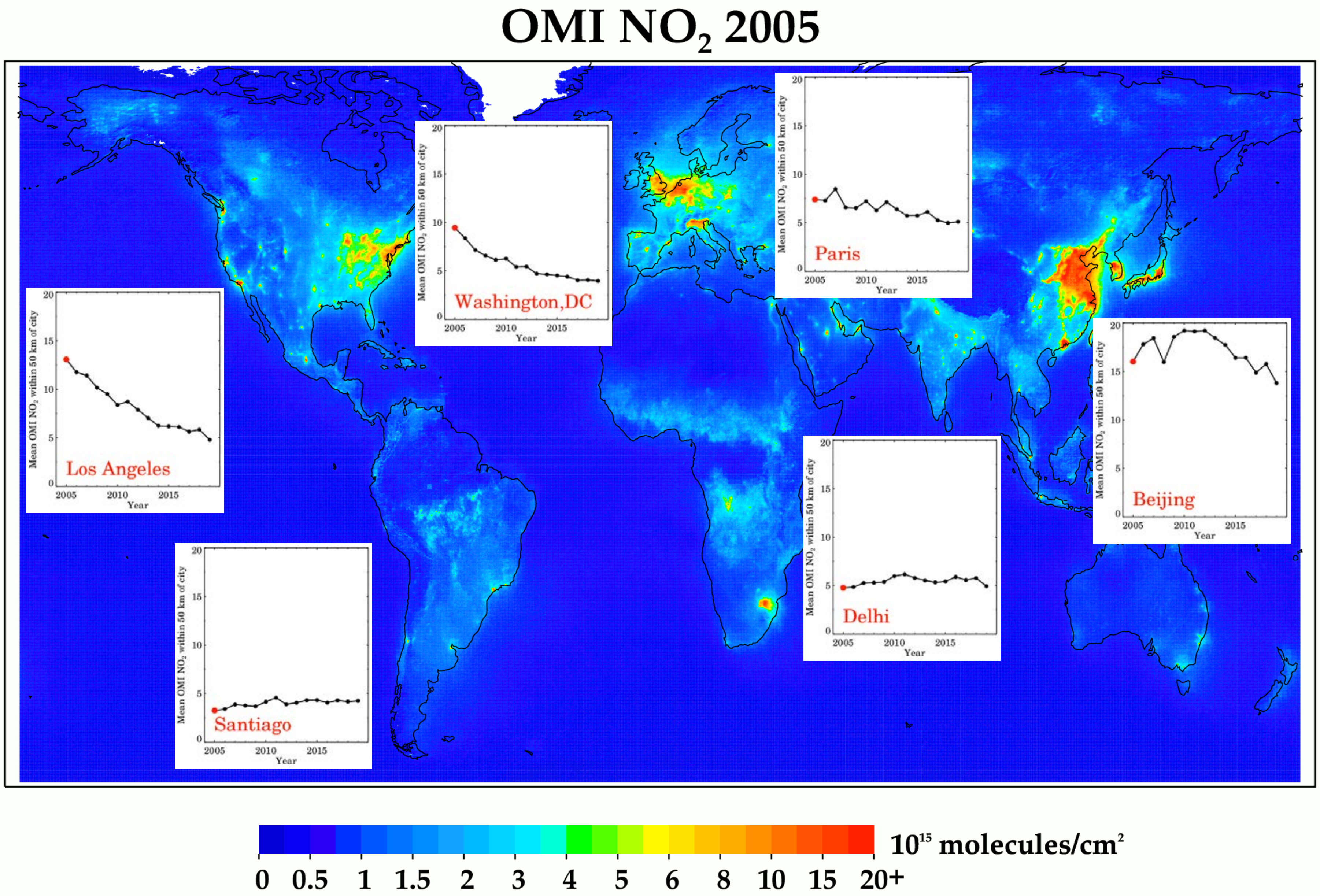

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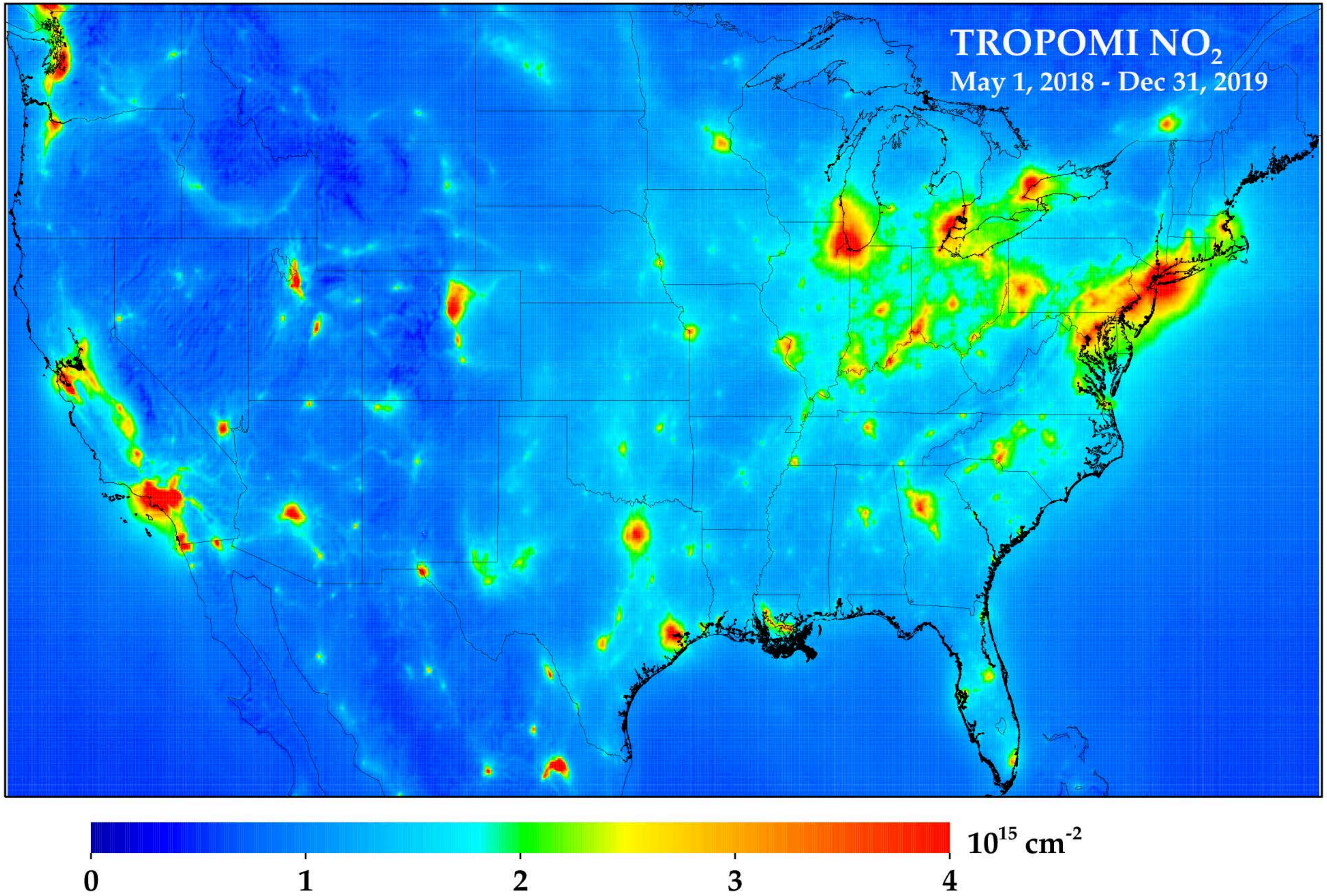
Using TROPOMI NO_2 to quantify urban/rural gradients



Largest values encompass cities, but other small scale features can be seen:

- Power plants in Ohio River Valley and rural western US
- Roadway networks (e.g., Idaho and Montana)
- Oil & gas operations including Permian basin (Texas), Uintah Basin (Utah), Bakken (North Dakota)
- Airports (e.g., Dulles)
- Cement kilns (e.g., Mexico)
- Copper mining operations (Utah & Arizona)
- Steel mills (e.g., E Chicago)

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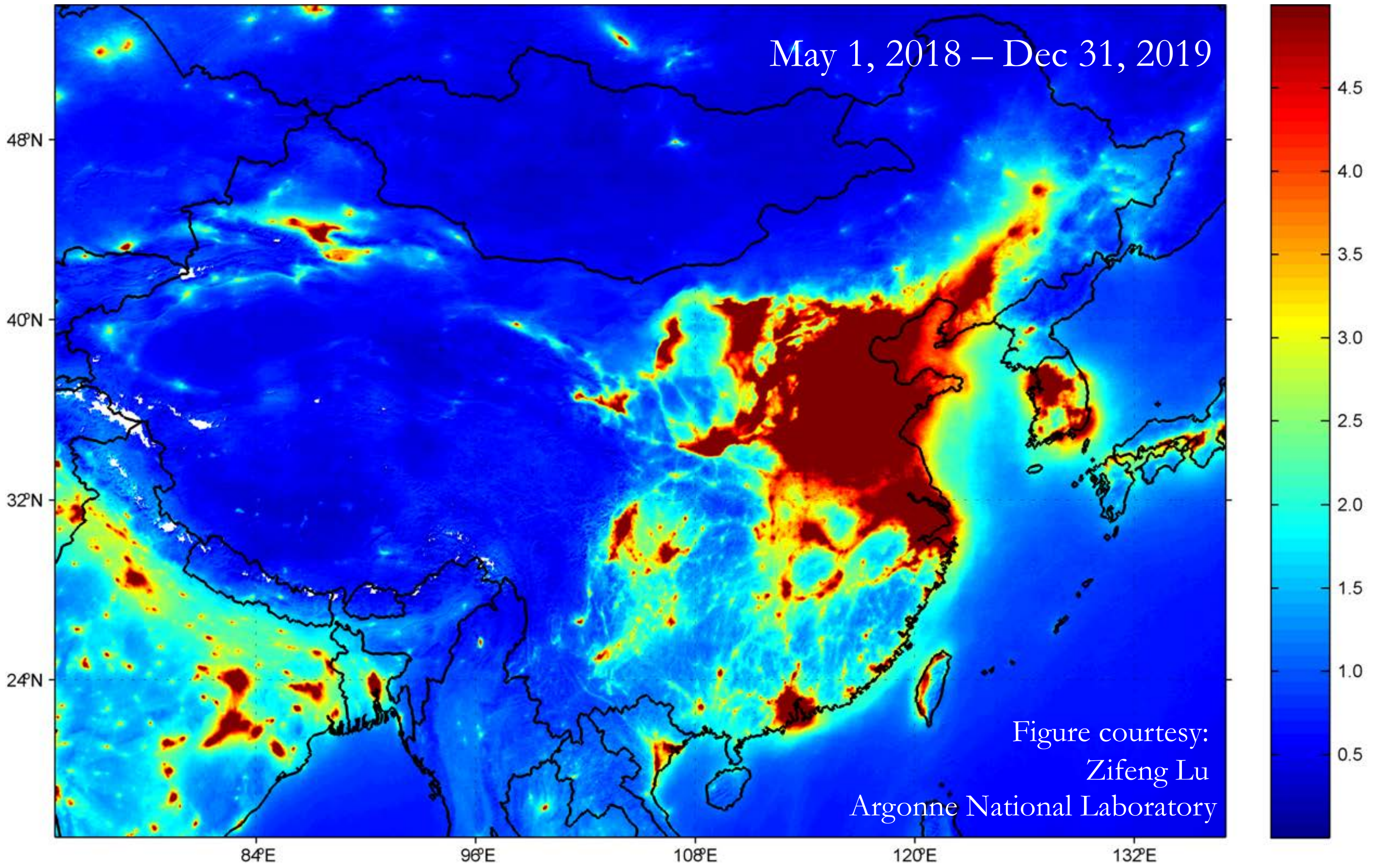


China

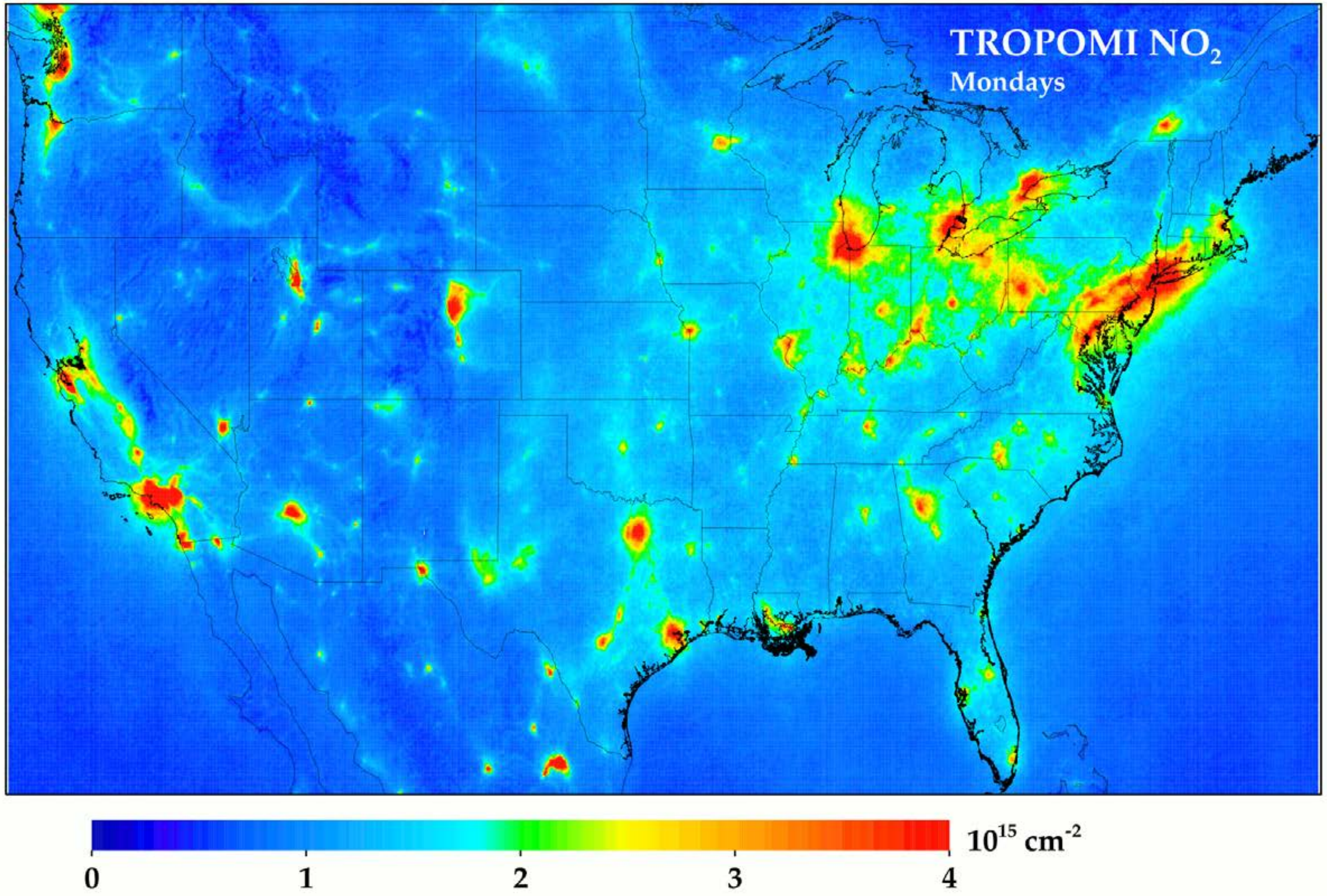
- Trending downward since 2012
- All large power plants have controls
- NO_X originating from other sources (transportation / residential / industrial, etc.)

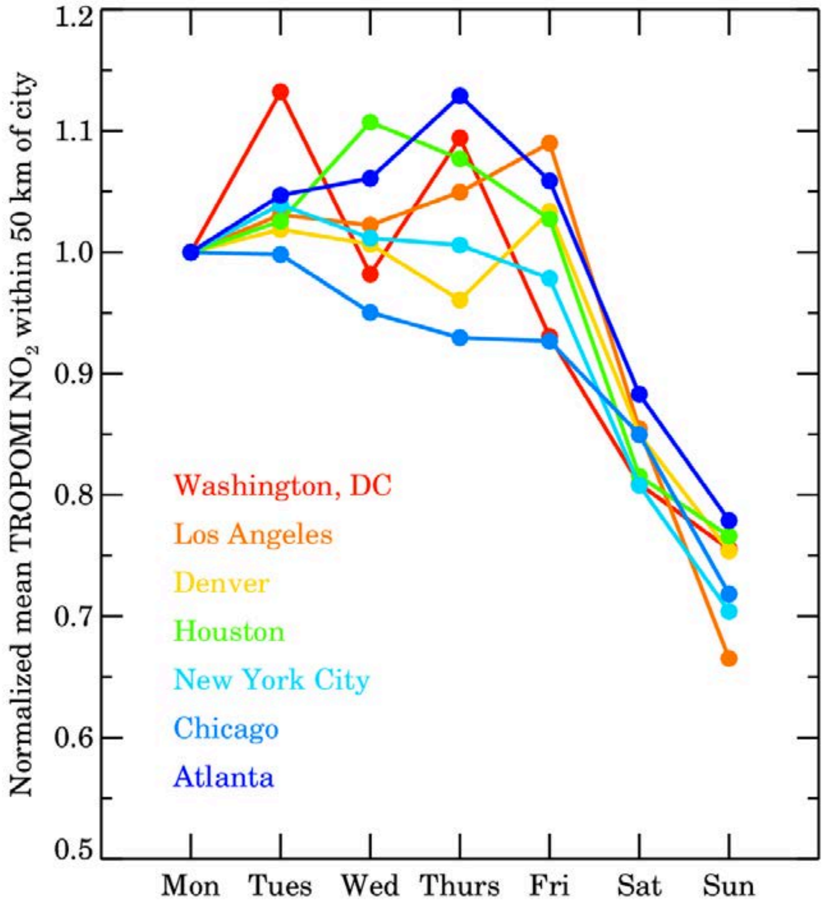
India

- Still trending up in most communities
- Very few power plants have full NOx controls

Check out Fei Liu's work (Bryan Duncan HAQAST PI) if you want information on how precautions due to COVID-19 is affecting air quality in China: https://www.earthobservatory.nasa.gov/images/146362/airborne-nitrogen-dioxide-plummets-over-china

Weekday / Weekend Cycles of Air Pollution





- NO_2 highest on weekdays; lower on Saturdays; lowest on Sundays
- Some interesting unexpected city-specific trends

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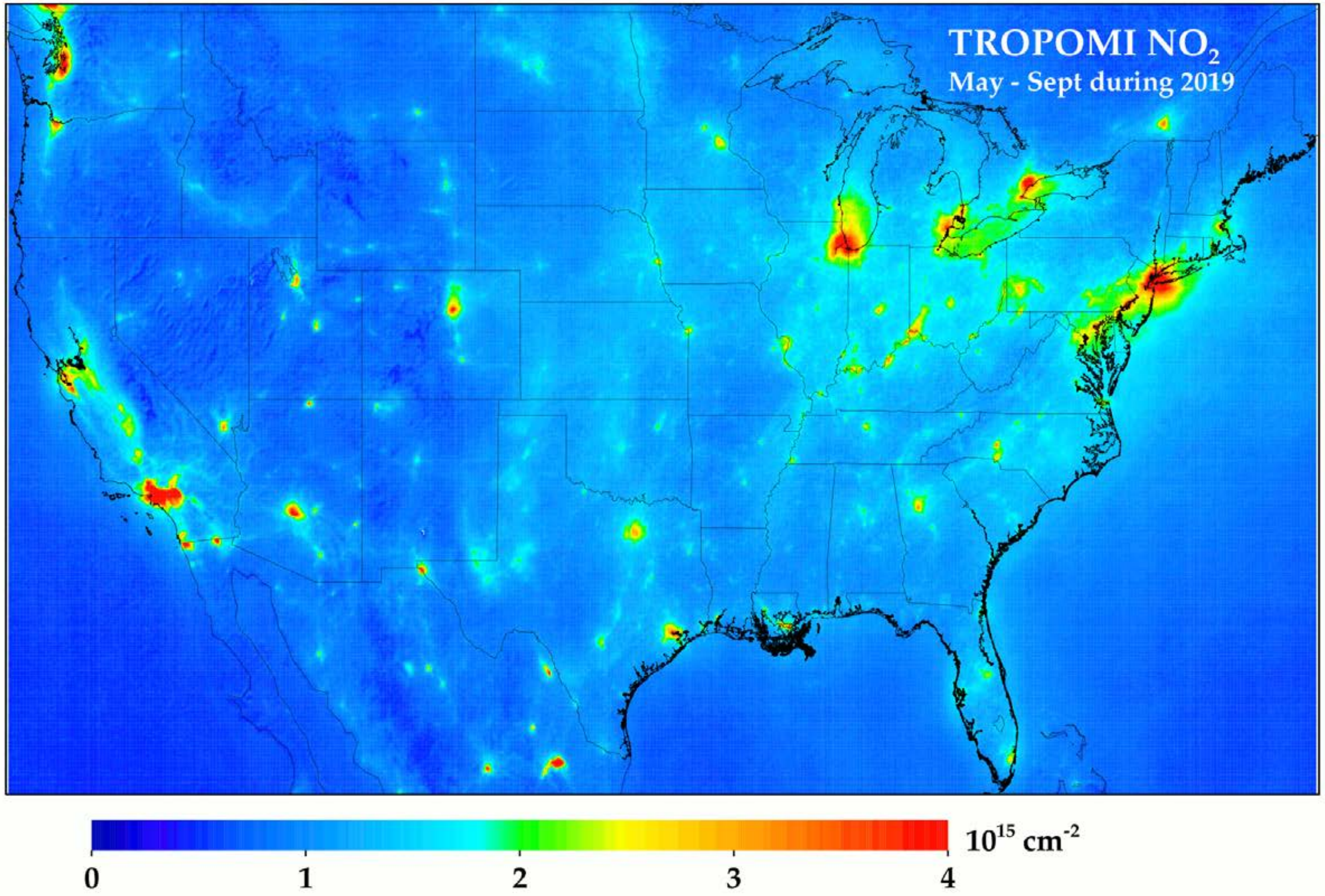
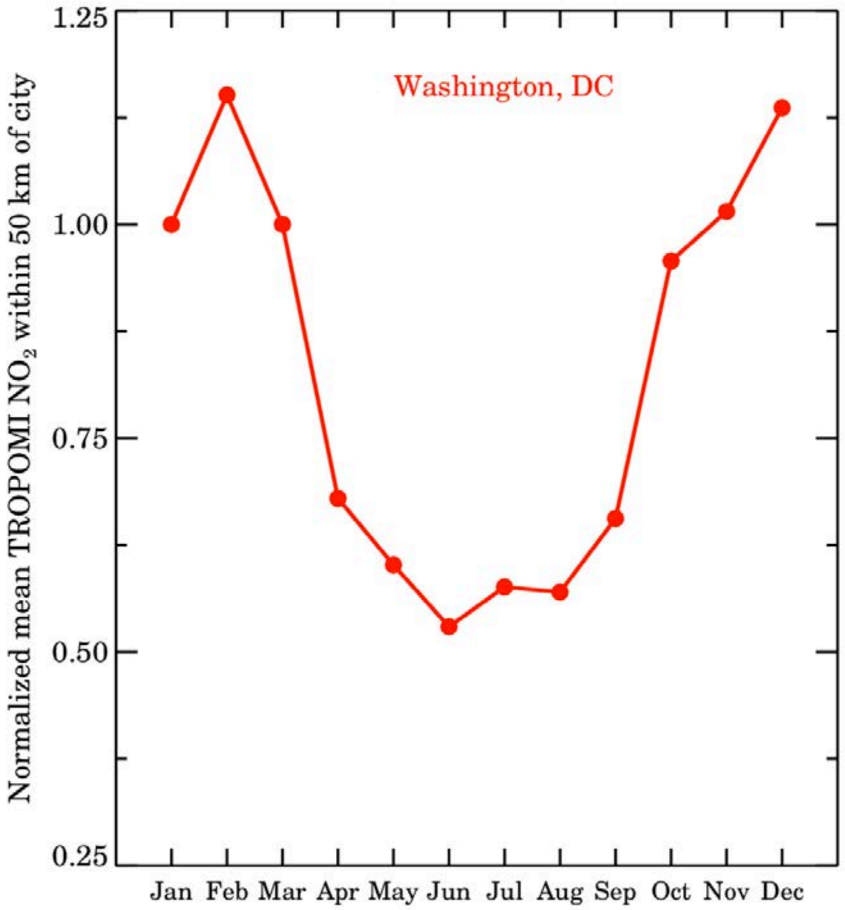
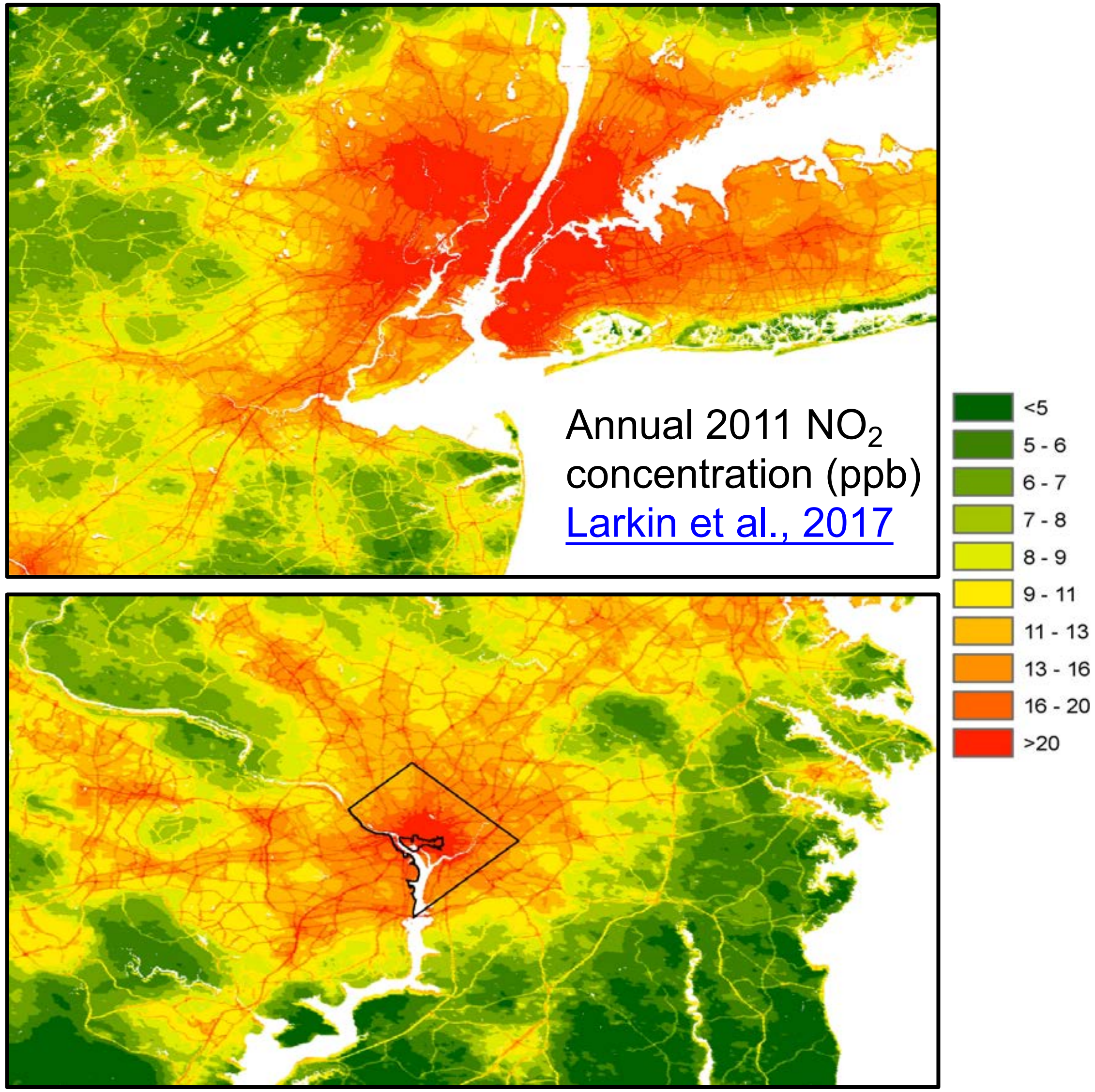
Seasonal Cycles of Air Pollution





- NO_2 is larger during winter (longer NO_2 lifetime) even though emissions are likely larger during summer.
- NO_2 concentrations ≠ NO_x emissions. In many cases, NO_2 concentrations ~ NO_x emissions, but make sure you are comparing similar months or seasons!

Annual Surface NO_2 concentrations



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HEALTH EFFECTS INSTITUTE

The future is now! TEMPO & GEMS

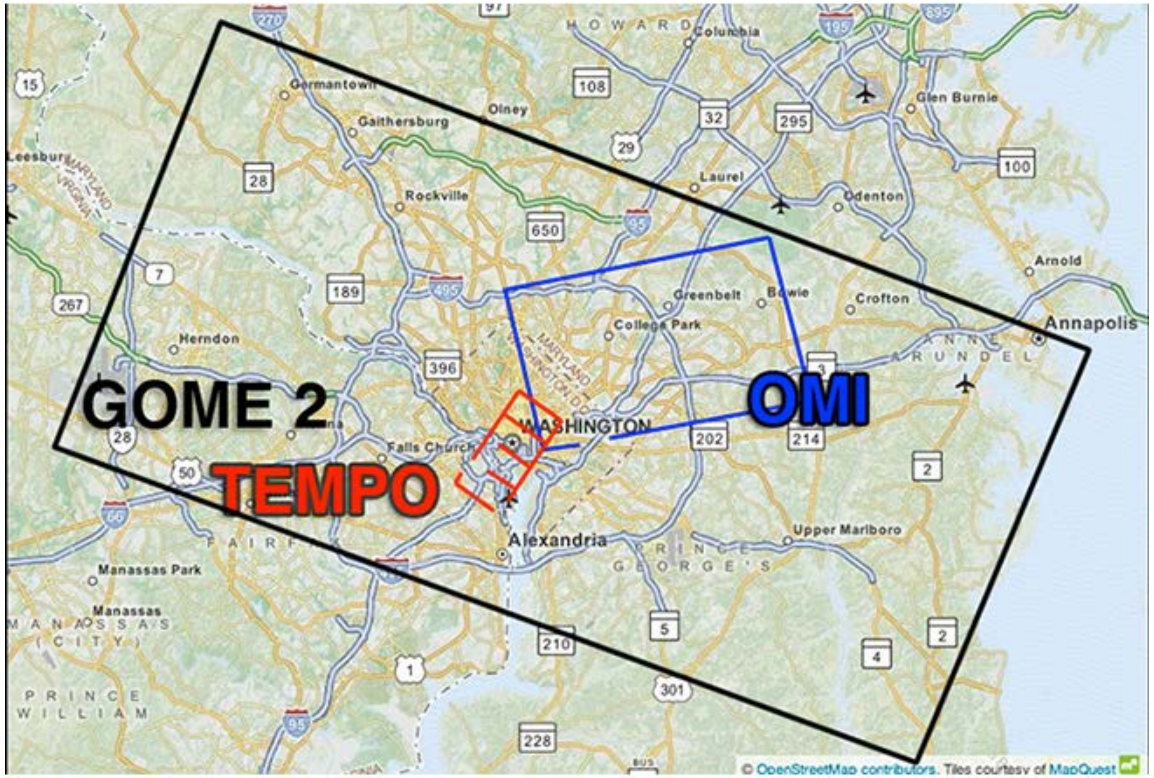


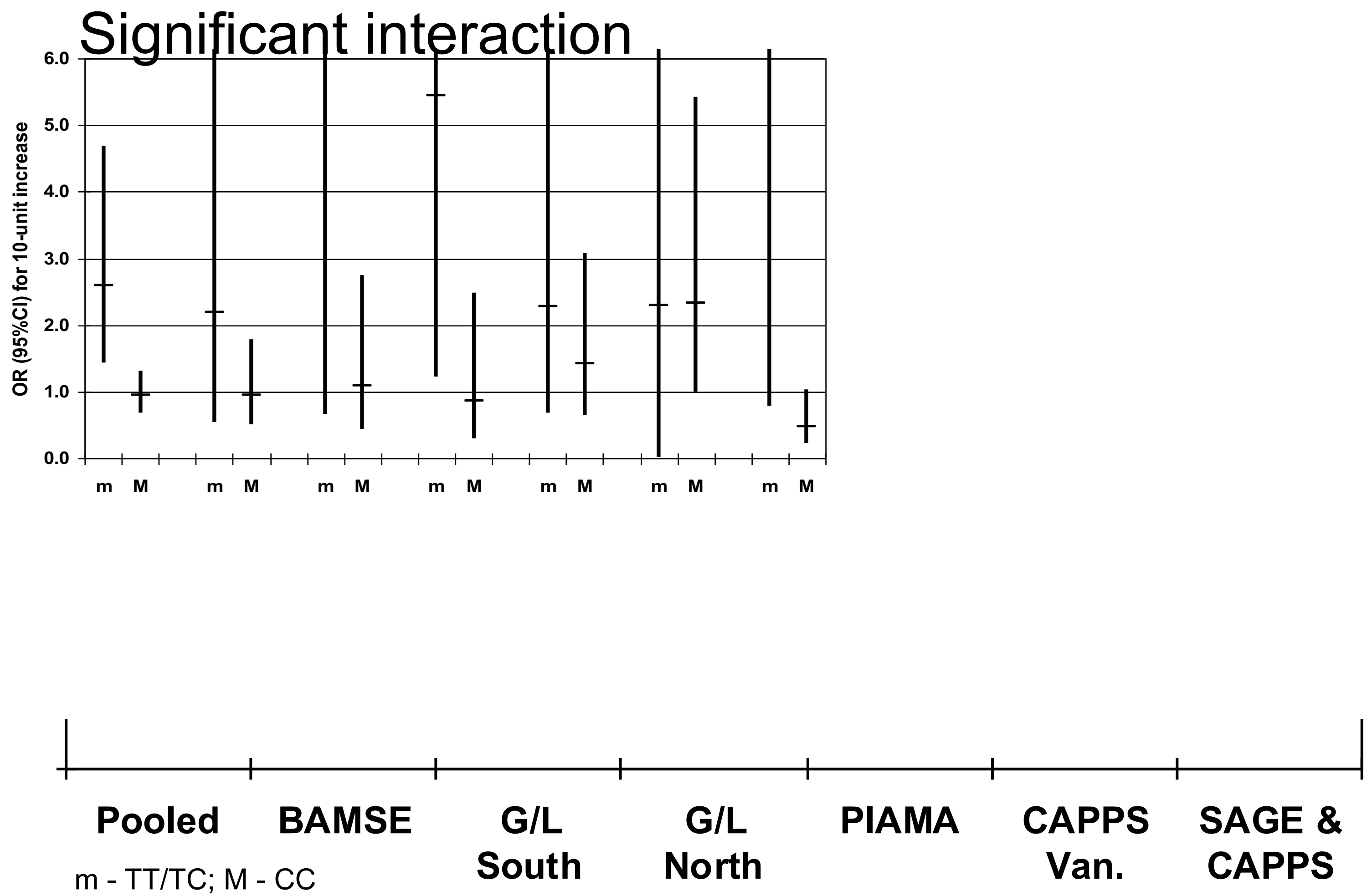
Image: TEMPO Science Team

Characteristics:

- Geostationary orbit
  - TEMPO: North America
  - GEMS: East Asia
- Hourly resolution that can show diurnal variability of emissions!
- Spatial resolution:
  - TEMPO: 2 km x 4.5 km
  - GEMS: 7 km x 8 km

Traffic pollution, Asthma Genetics (TAG)

NO_2 - Asthma, by GSTP1 rs1138272

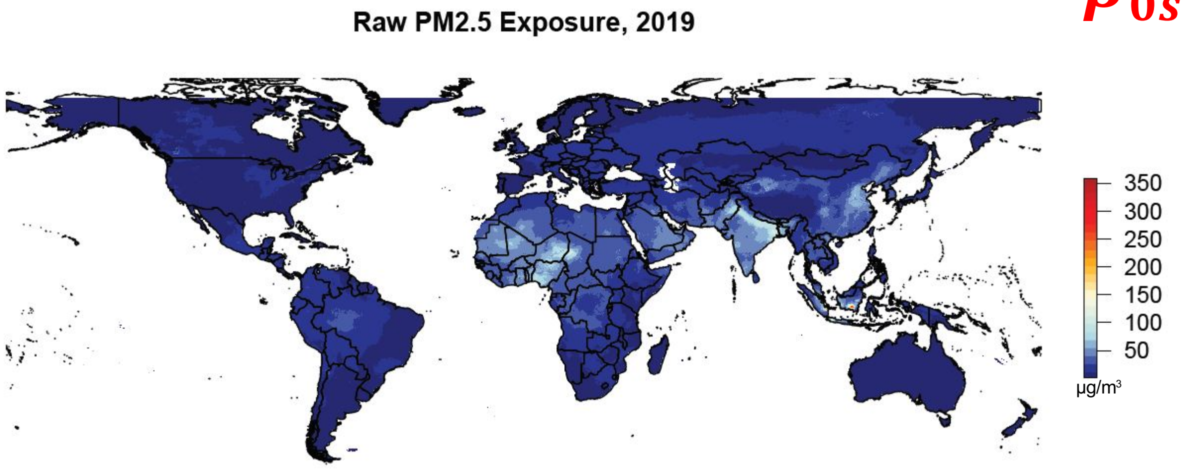


m - TT/TC; M - CC
Adjusted for study, city, intervention, gender, maternal age at birth, maternal smoking during pregnancy, environmental tobacco smoke in the home, birth weight and parental atopy

GSTP1 and TNF Gene variants and associations between air pollution and incident childhood asthma: the traffic, asthma and genetics (TAG) study. MacIntyre EA, Brauer M, Melén E, Bauer CP, Bauer M, Berdel D, Bergström A, Brunekreef B, Chan-Yeung M, Klümper C, Fuertes E, Gehring U, Gref A, Heinrich J, Herbarth O, Kerkhof M, Koppelman GH, Kozyrskyj AL, Pershagen G, Postma DS, Thiering E, Tiesler CM, Carlsten C; TAG Study Group. Environ Health Perspect. 2014 Apr;122(4):418-24. doi: 10.1289/ehp.1307459.

Combining satellite and ground monitoring to estimate exposure

Bayesian Hierarchical Model (DIMAQ2)



$$\log(PM_{2.5st}) = \beta_{0st} + \beta_{1st}\log(SAT_s) + \beta_{3..P}X_{st} + \varepsilon_{st}$$

Spatially varying determinants of AOD-$PM_{2.5}$ relationship (from chemical transport model, other) + hierarchical random effects

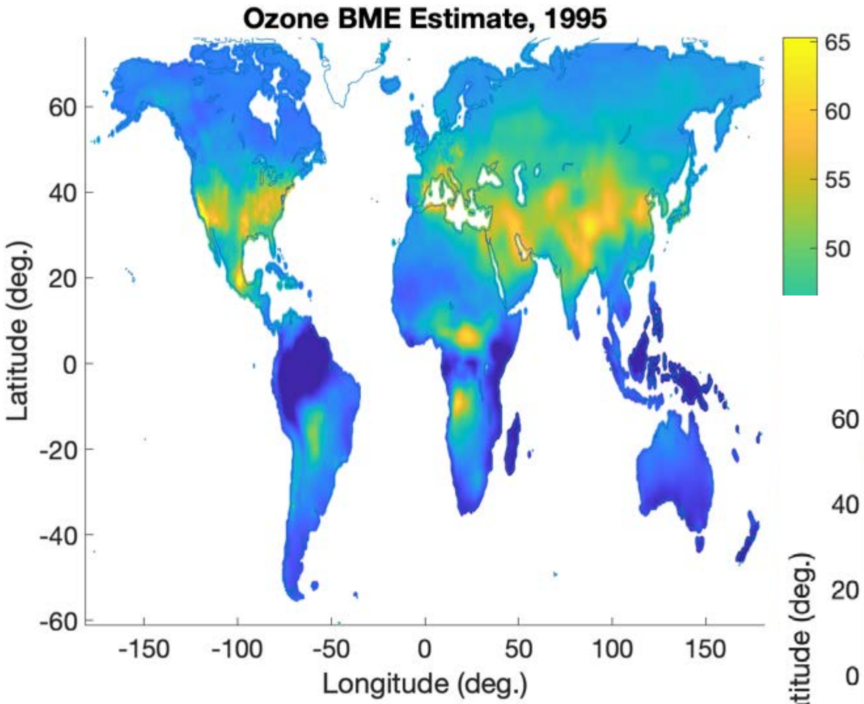
Ground measurements
N = 10,408 unique locations, from 116 countries

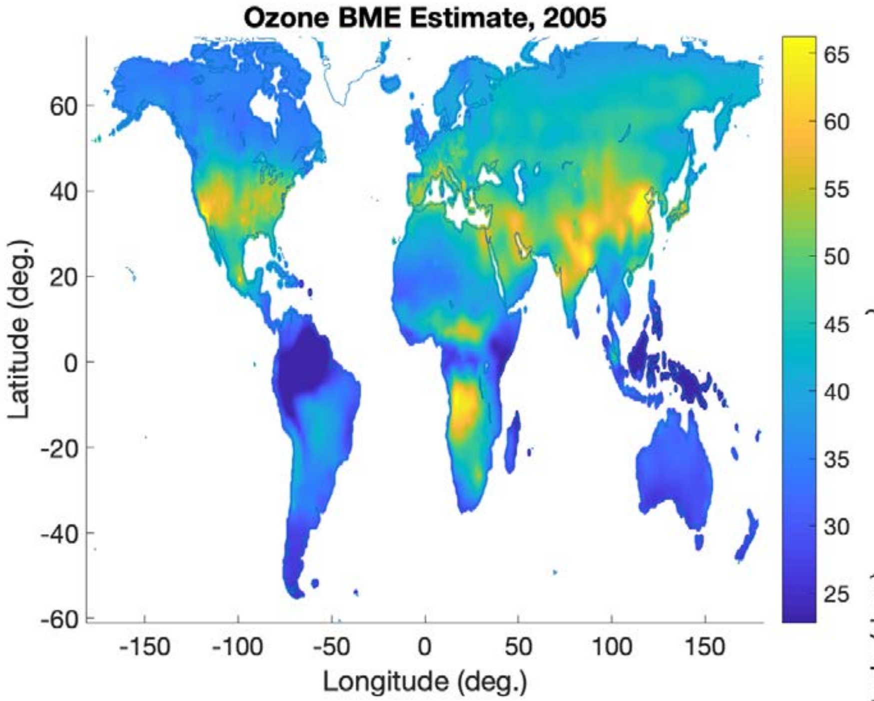
~11 x 11 km resolution, annual average

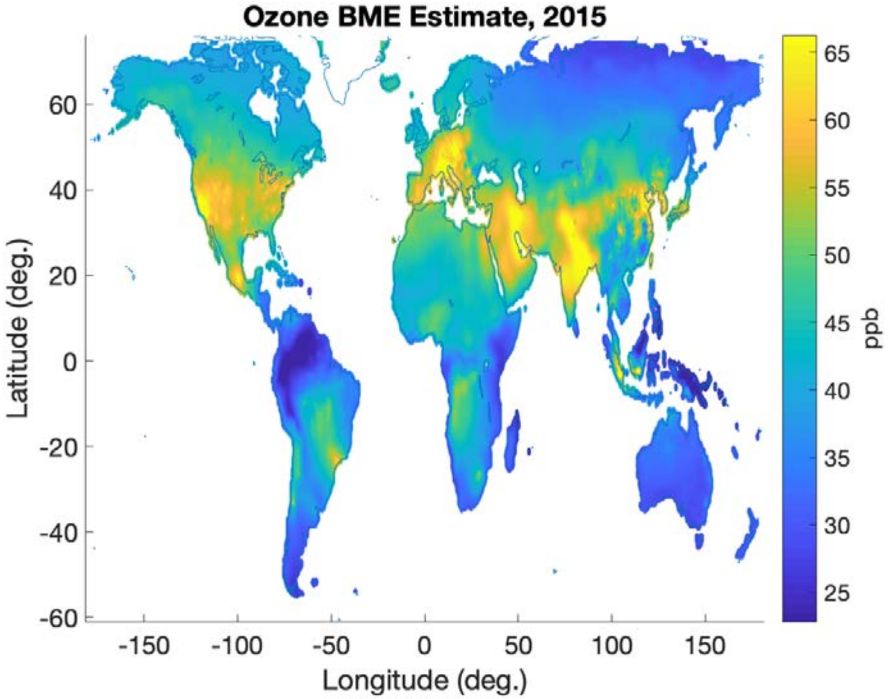
Median R^2 = 0.9
Median Pop-weighted RMSE = 10.1 µg/m^3

- Shaddick et al. 2018. Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. J. R. Stat. Soc. C, 67: 231–253.
- Shaddick et al. 2018. Data Integration for the Assessment of Population Exposure to Ambient Air Pollution for Global Burden of Disease Assessment. Environ Sci Technol. 2018 Aug 21;52(16):9069-9078.

Ozone Trends







Preliminary Results, GBD 2019

Methods: Quantifying the global, national, and urban burdens of pediatric asthma incidence attributable to ambient NO_2

$$Burden = Inc_{c,a} \times \sum_{i,j} Pop_{i,j,a} \times \left(1 - e^{-\beta X_{i,j}}\right)$$

2015 national incidence rates from IHME (for 1-4, 5-9, 10-14, 15-18 year age groups)

2015 gridded population at 250 m x 250 m from the European Commission Joint Research Center GHS-POP + gridded age-group fractions from 2010 NASA CIESIN GPWv4

Relative risk from Khreis et al. (2017)

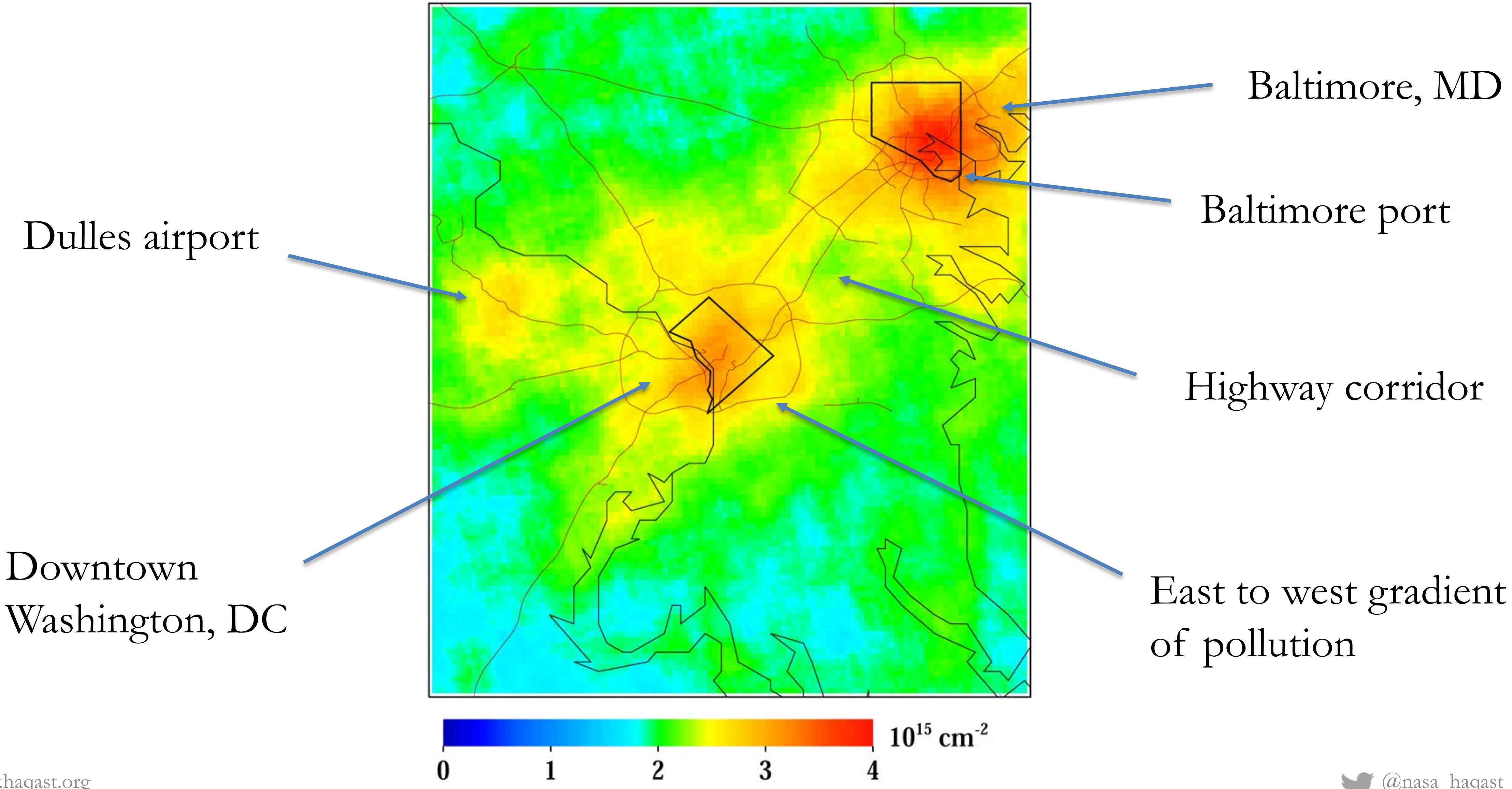
2010-2012 gridded surface NO_2 (100 m x 100 m) from Land Use Regression modeling by Larkin et al. (2017) → aggregated to 250 m x 250 m

We apply the health impact function in each 250 m x 250 m grid cell globally, and sum results over 21 regions, 194 countries, and 125 major cities – assuming counterfactual concentrations of 0, **2**, and 5 ppb.

City extents from the GHS-SMOD (defined as any contiguous cells with ≥50,000 people and a population density of ≥1,500 inhabitants/km^2 or a density of built-up >50%.)

Using TROPOMI NO_2 to quantify urban/rural gradients

Washington, DC & Baltimore, MD (May – Sept 2019)



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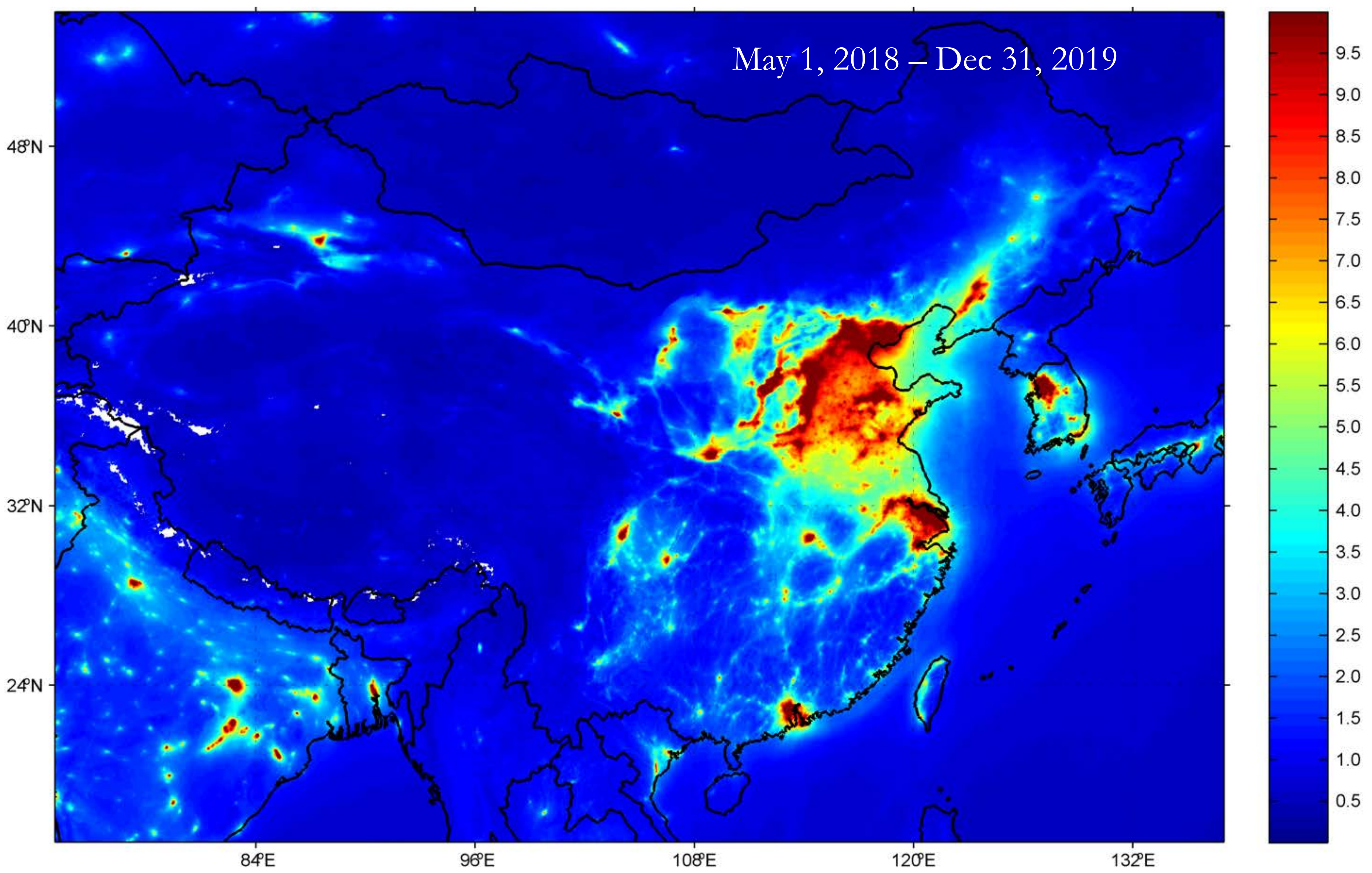

Figure courtesy: Zifeng Lu, Argonne National Laboratory

Using TROPOMI NO_2 to quantify urban/rural gradients

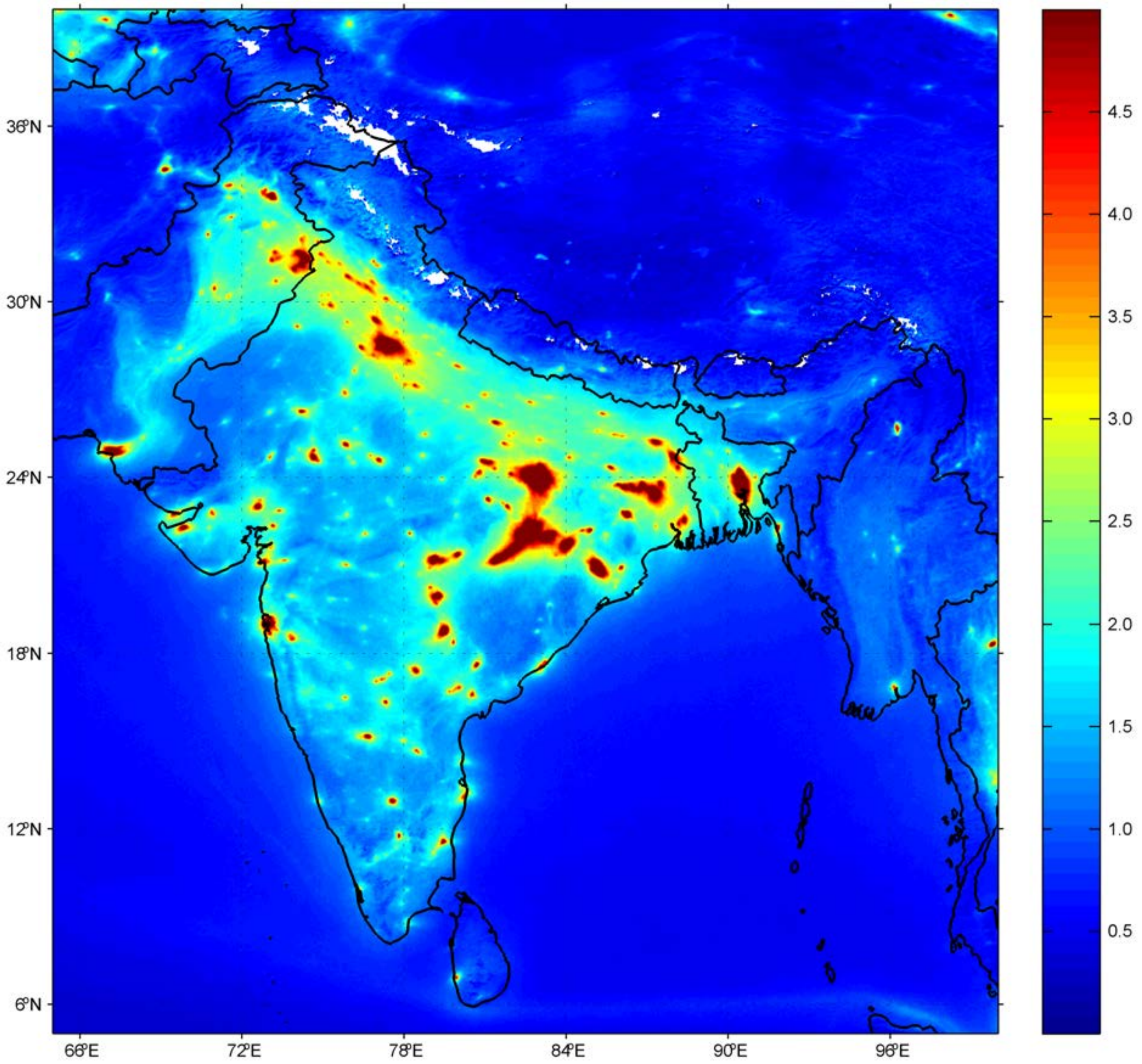

Figure courtesy: Zifeng Lu, Argonne National Laboratory