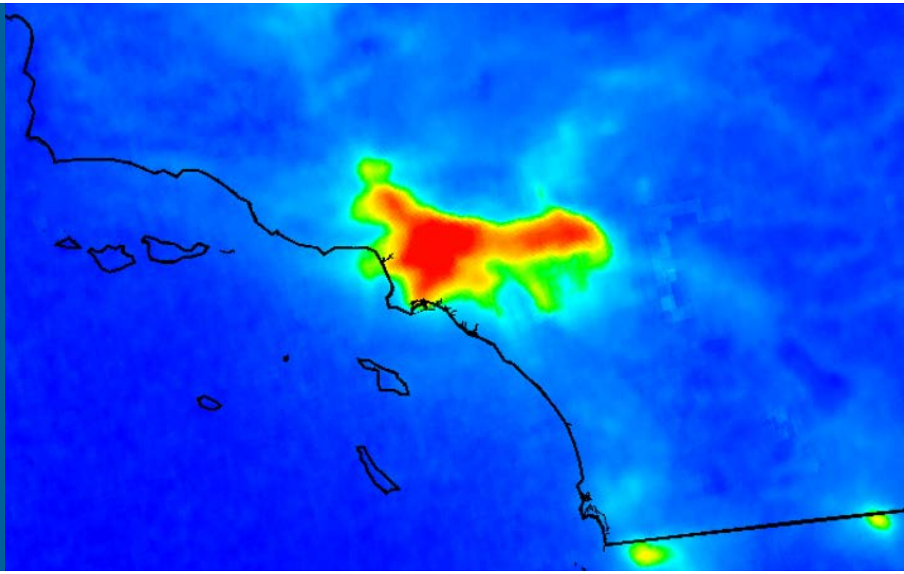
Policy-relevant applications of satellite data:

Estimating air pollution *emissions*, *exposures*, and *public health impacts* in cities worldwide



LA Basin: TROPOMI NO_2: July – Sept 2018

Dan Goldberg, Ph.D.

Argonne National Laboratory
George Washington University
Washington, DC

July 10, 2019
Pasadena, CA
HAQAST6

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George Washington University: Susan Anenberg, Ploy Achakulwisut, Arash Mohegh, Veronica Southerland

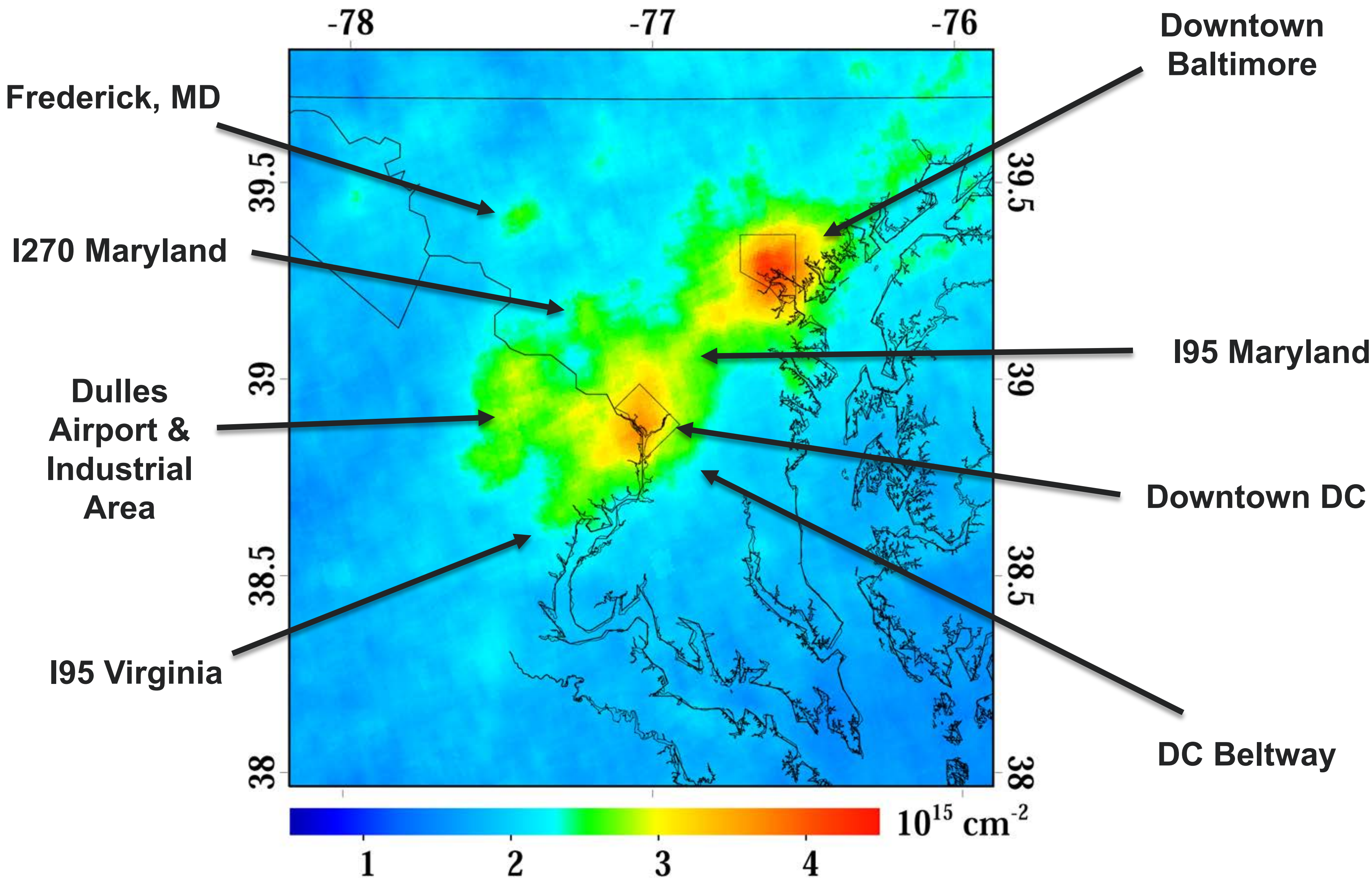
NASA Goddard: Bryan Duncan, Lok Lamsal, Nick Krotkov, Fei Liu

Environment Canada: Debora Griffin, Chris McLinden

Saint Louis University: Benjamin de Foy

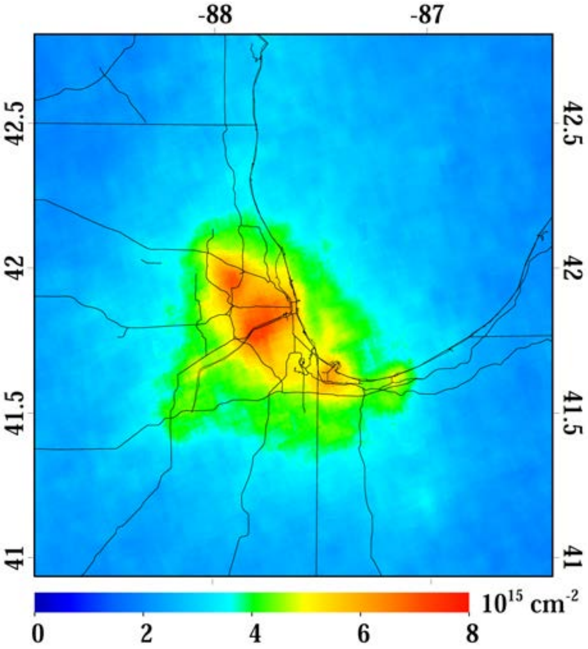
OVERSAMPLED TROPOMI NO_2 FOR BALTIMORE & DC

May – September 2018



HOW TO DERIVE EMISSIONS FROM SATELLITE DATA

<u>Step 1:</u> Isolate data from a single source (showing TROPOMI NO_2 for 2018)



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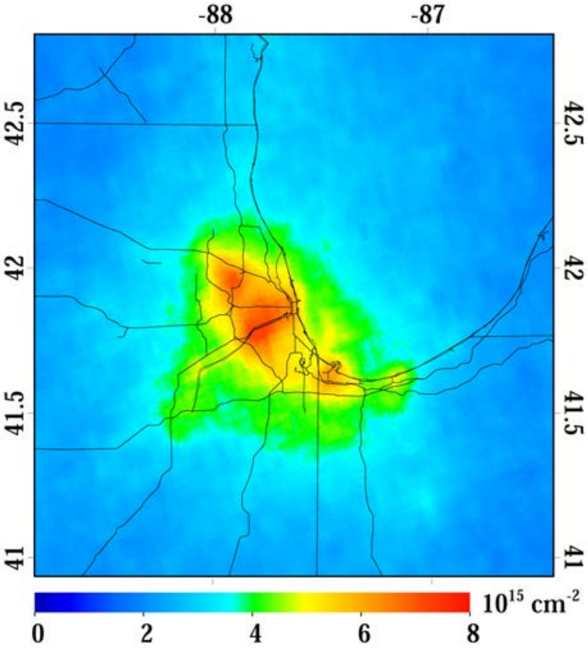
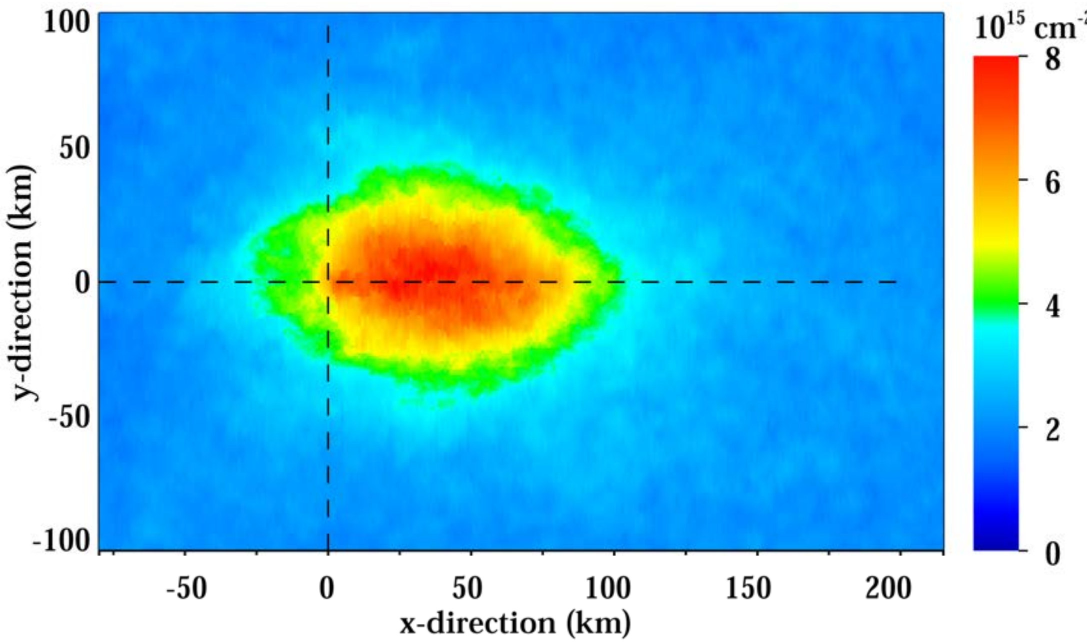


Step 2: Rotate based on each day's winds



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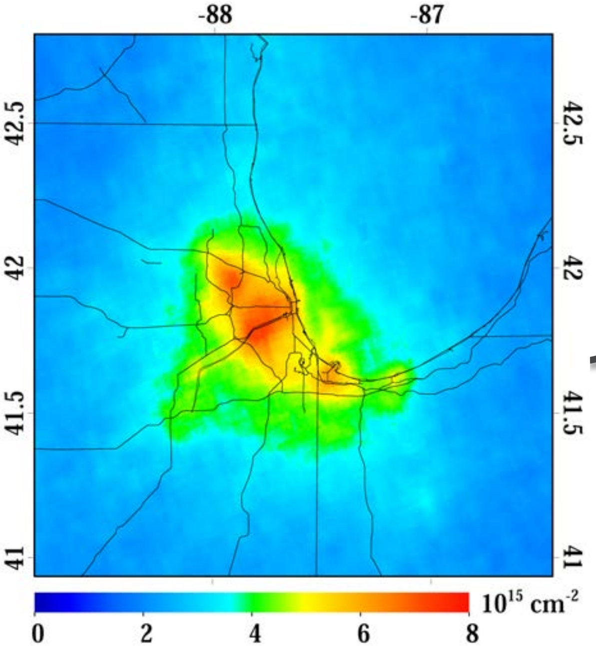

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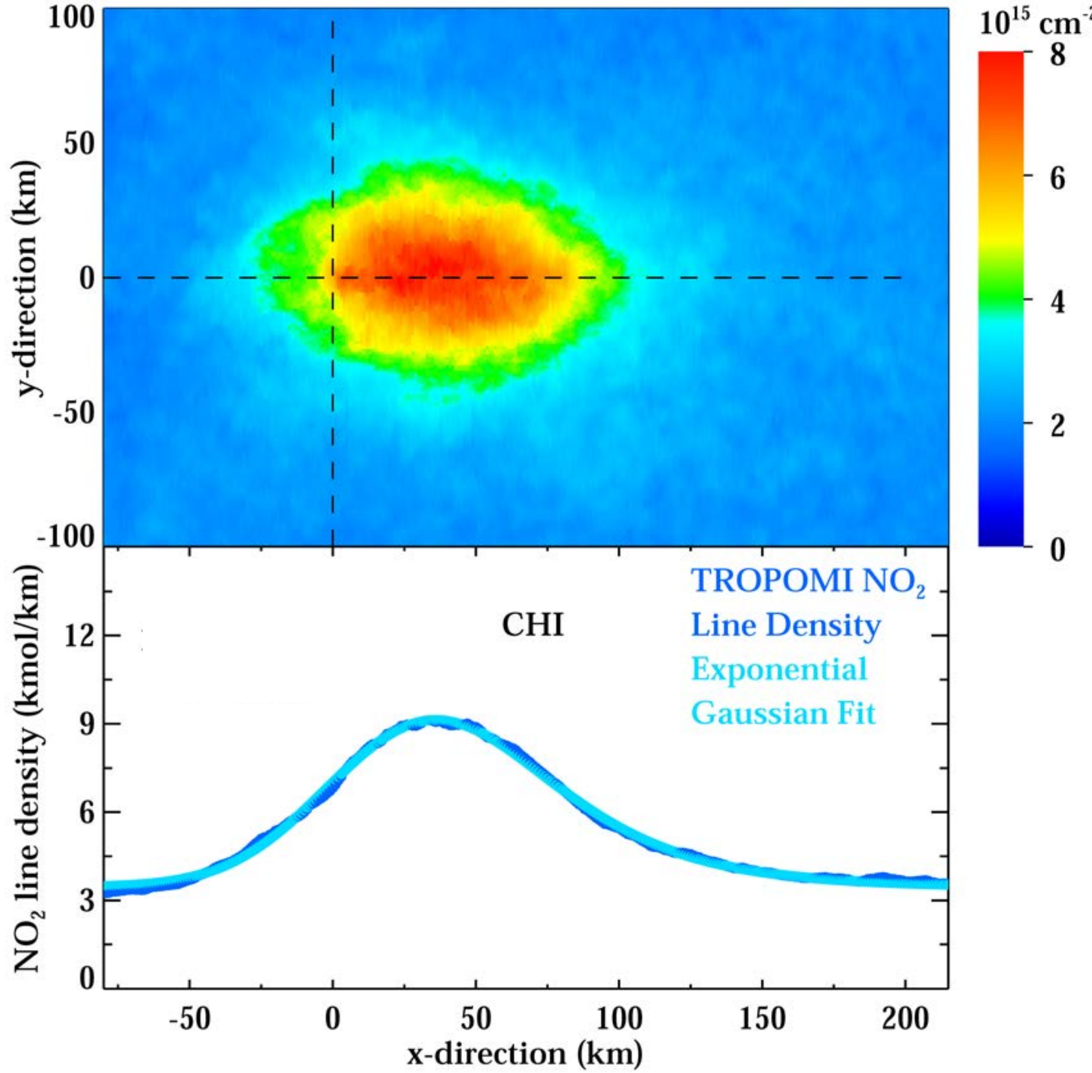

<u>Step 3:</u> Fit the decaying plume to an exponentially modified Gaussian function

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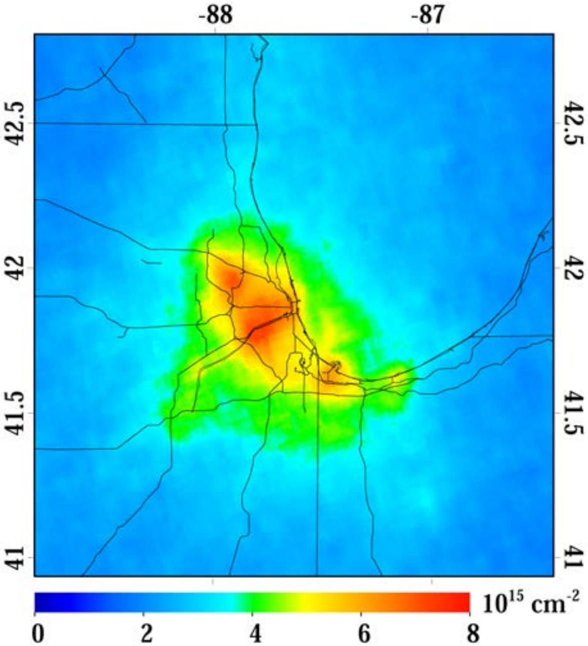

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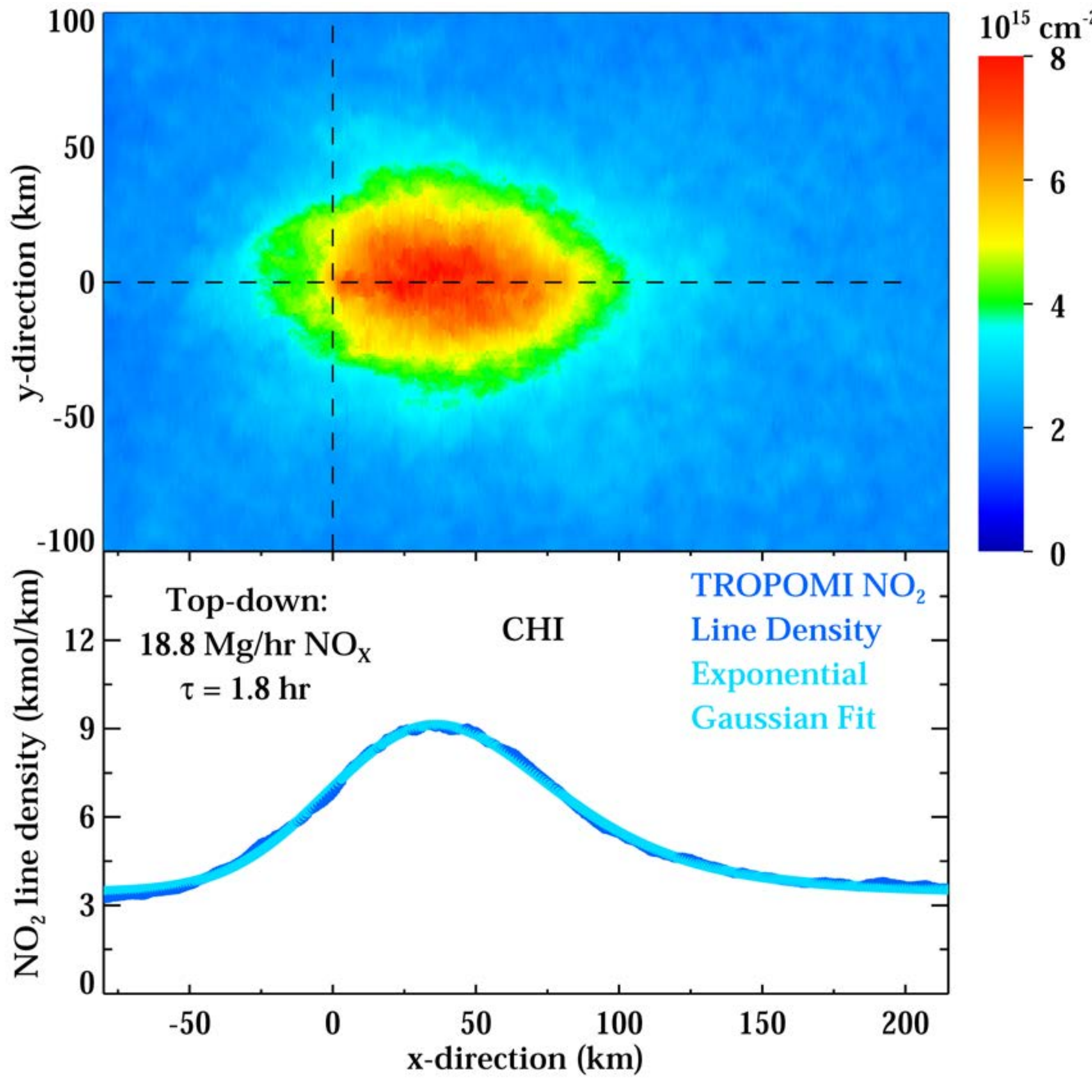


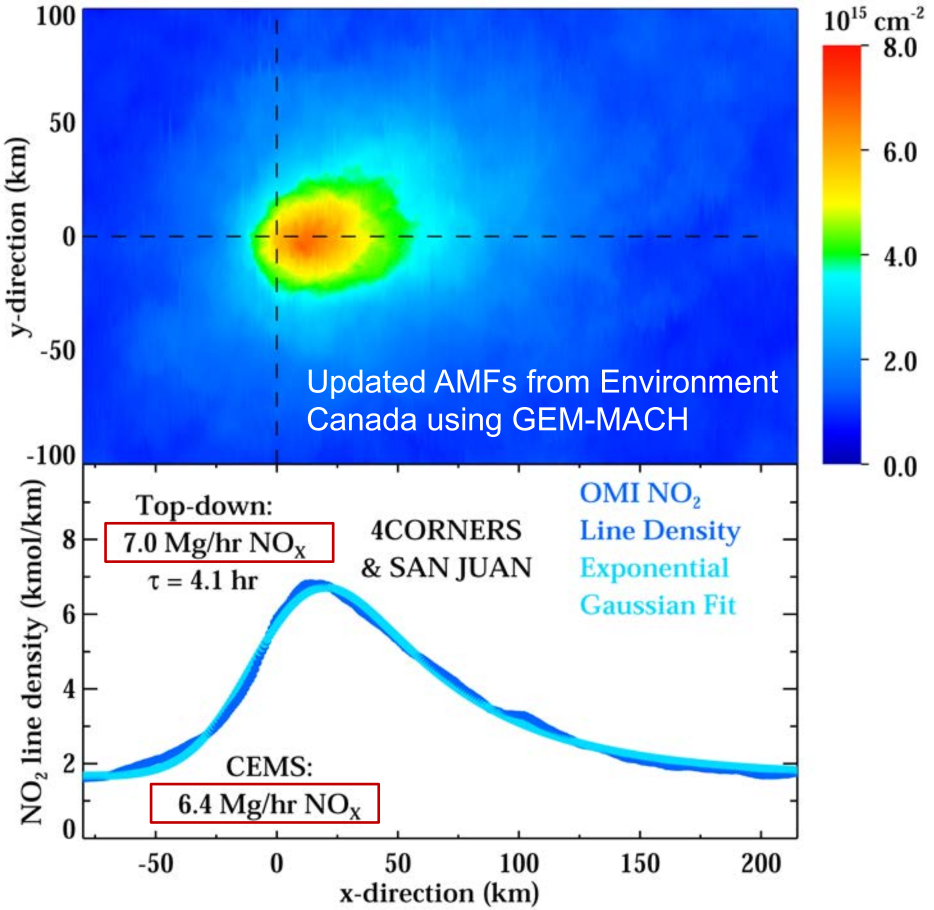
Step 3: Fit the decaying plume to an exponentially modified Gaussian function

Step 4: The fit will give a burden and decay distance, which can be used to calculate the emissions rate and lifetime

HOW DO WE KNOW THIS METHOD WORKS???

We compare to known NO_X emissions sources: US power plants

OMI NO_2 with updated AMFs



- After re-processing satellite data with regional air mass factors, there is very good agreement between the top-down method and the reported emissions (CEMS) to within ± 15%.

For more info on the satellite re-processing methodology see: McLinden et al., 2014; ACP, Goldberg et al., 2017; ACP

For more info on the inverse modeling method see: de Foy et al., 2014, 2015 AE; Goldberg et al., 2019; ACP.

INFERRING CO_2 FROM NO_X: METHODOLOGY

1. Develop a spatially disaggregated bottom-up emissions inventory of CO_2 and NO_X at 1 x 1 km^2 using EPA state-level data
   - Power plant emissions are known, on-road emissions disaggregated based on road density, all other emissions are disaggregated based on population.

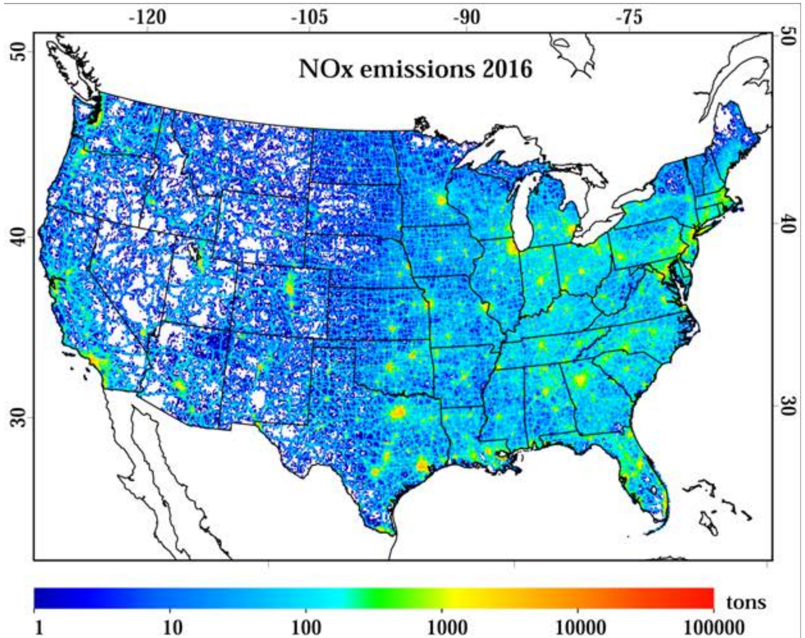
2. Derive top-down NO_X emissions for 8 U.S. megacities using OMI NO_2
   - Use a statistical fit of the oversampled NO_2 plume to derive the NO_2 burden and lifetime.
   - Use NO_2 burden & lifetime to calculate a NO_x emissions rate (Beirle et al., 2011; McLinden et al., 2014; Lu et al., 2015; Liu et al., 2107; Goldberg et al., 2019)

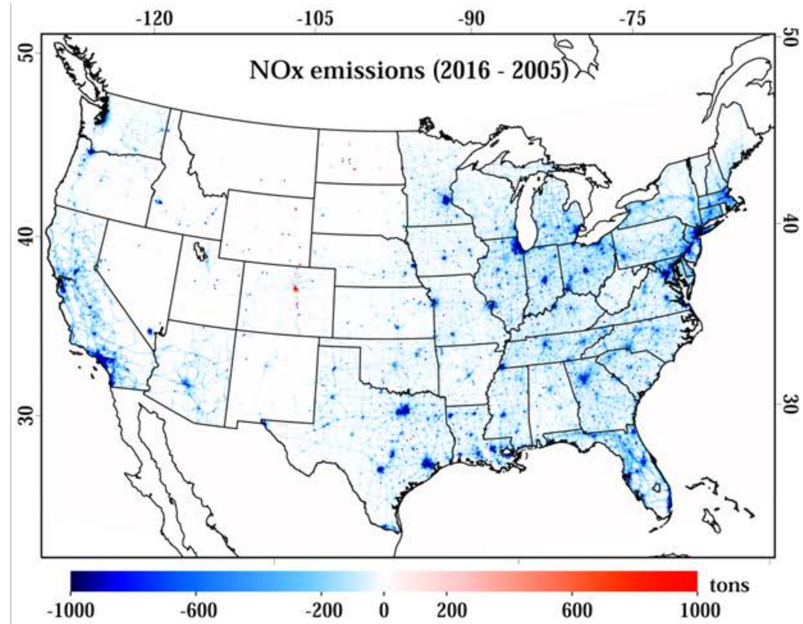
3. Combine top-down NO_X emissions with NO_x-to-CO_2 ratios developed from the bottom-up emissions inventory to calculate top-down “OMI” CO_2

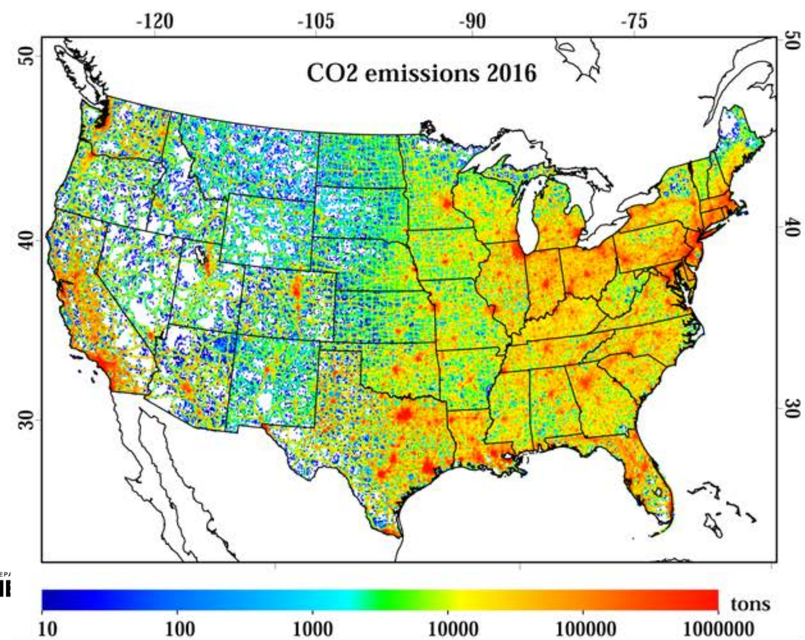
Main assumption of this work: Emission factors are roughly correct, but that activity data (i.e., when/where fuel is burned) is the unknown.

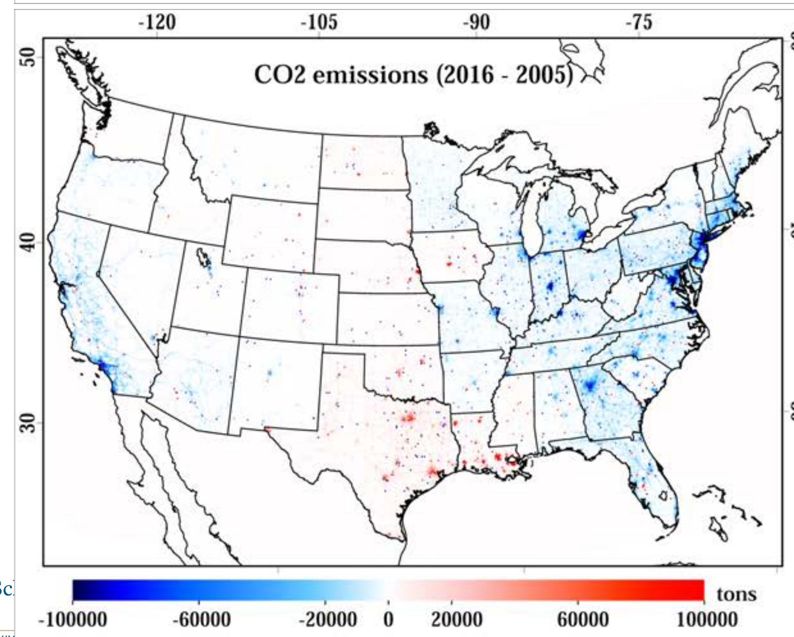
Main advantage of this work: Isolate fossil-fuel emissions, minimal influence from biosphere!

REPORTED ANNUAL BOTTOM-UP EMISSIONS





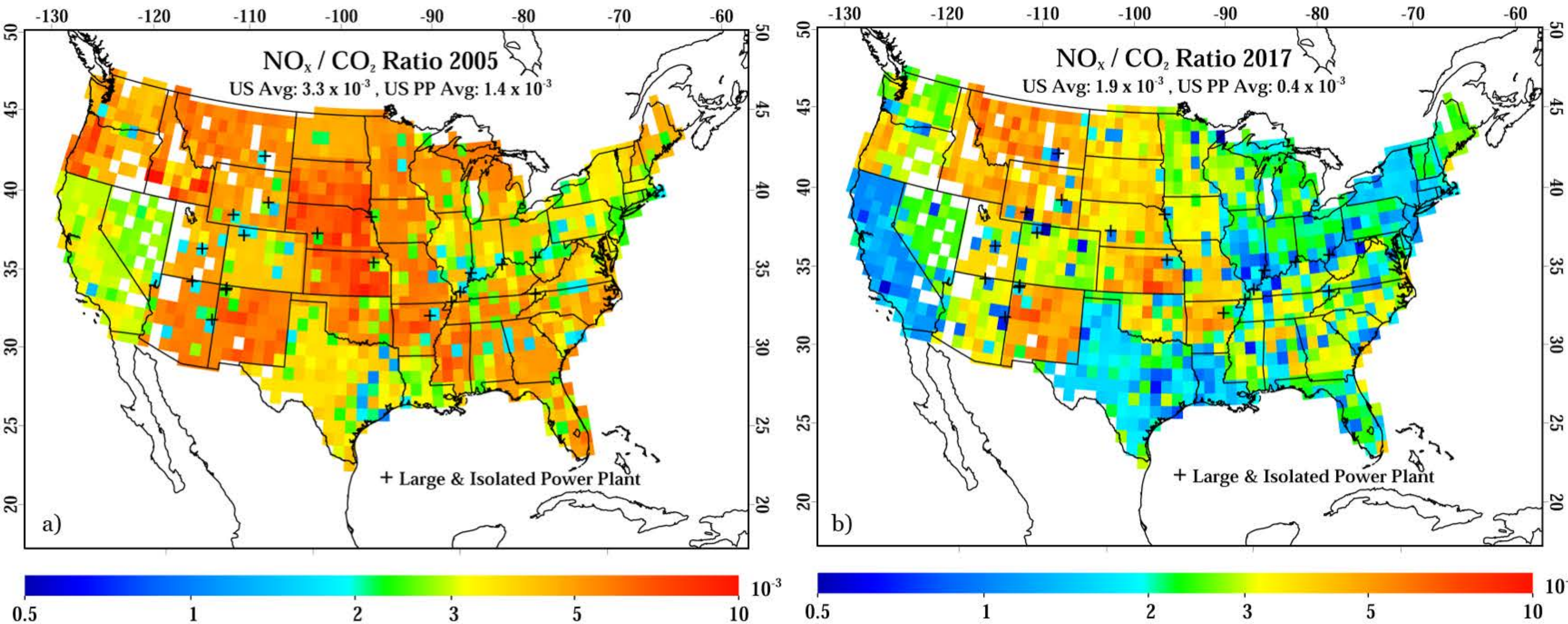




NO_X-TO-CO_2 RATIOS FROM THE INVENTORY

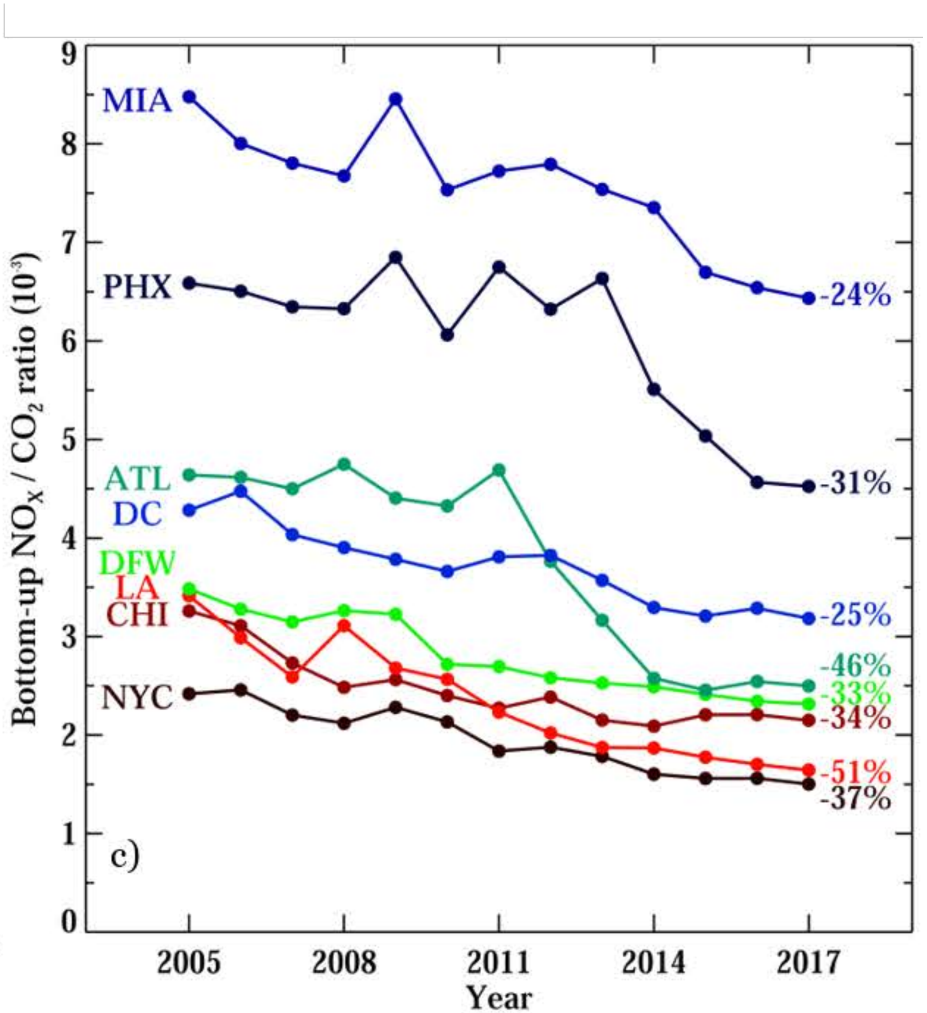
NO_x-to-CO_2 ratios computed to 100 × 100 km^2 grid boxes

2005 **2017**



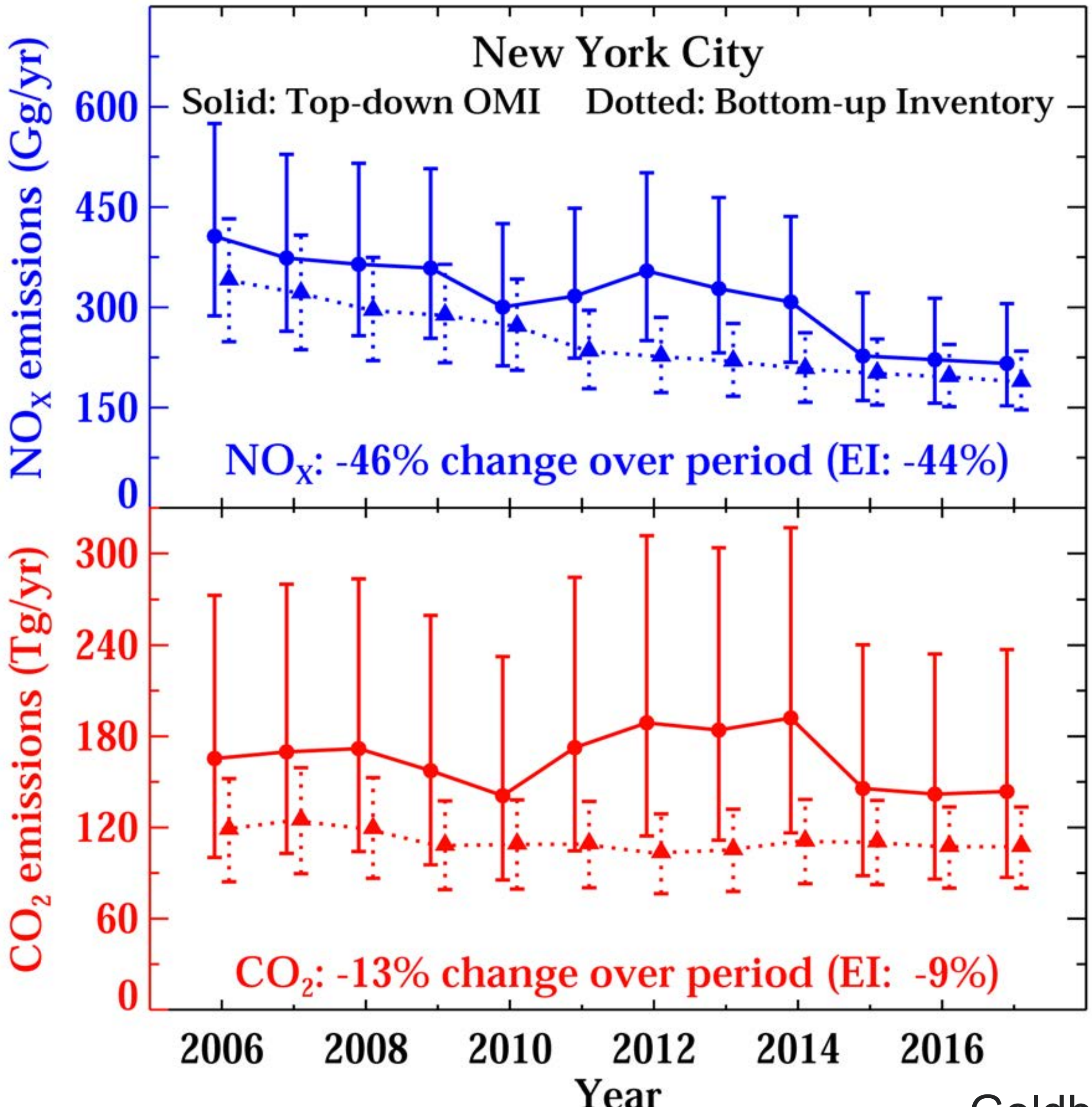
- NO_x has been controlled more effectively than CO_2 (due to AQ regulations).
- Spatial heterogeneities across US → Larger ratios in central US, in compliance with $PM_{2.5}$ and O_3 standards, and no vehicle emissions monitoring.
- Discontinuities at state borders are an artifact of the state-by-state inventories.

REGIONAL DIFFERENCES IN THE NO_X-TO-CO_2 RATIO



- Larger cities with a legacy of O_3 and $PM_{2.5}$ problems, have stricter regulations for NO_X for all sources.
- NO_X-to-CO_2 ratios can differ by a factor of 3 regionally!
- While the ratio has inherent uncertainties, the regional differences are likely valid due to varying regulations, economic activity, and lifestyles.

DERIVING "TOP-DOWN" OMI EMISSIONS: NO_X & CO_2 NEW YORK CITY

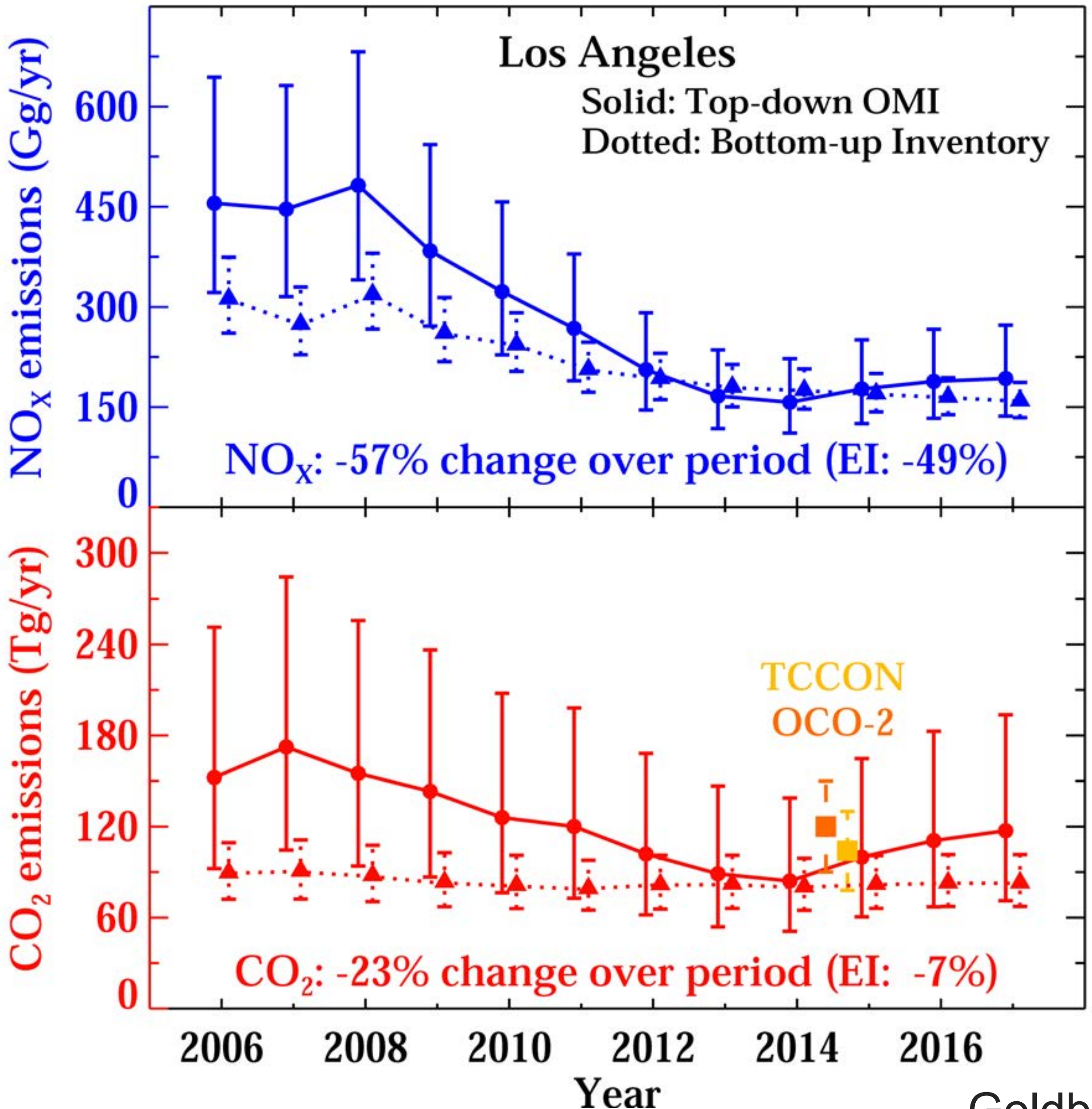


Top-down NO_X computed using oversampled OMI data over a 3-year warm season (e.g., 2006 = Apr thru Sept 2005 thru 2007)

Top-down CO_2 computed by dividing the top-down NO_X emissions rate by the local (within 75 km radius) NO_X-to-CO_2 ratio.

Goldberg et al., in review

DERIVING "TOP-DOWN" OMI EMISSIONS: NO_X & CO_2 LOS ANGELES



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Goldberg et al., in review

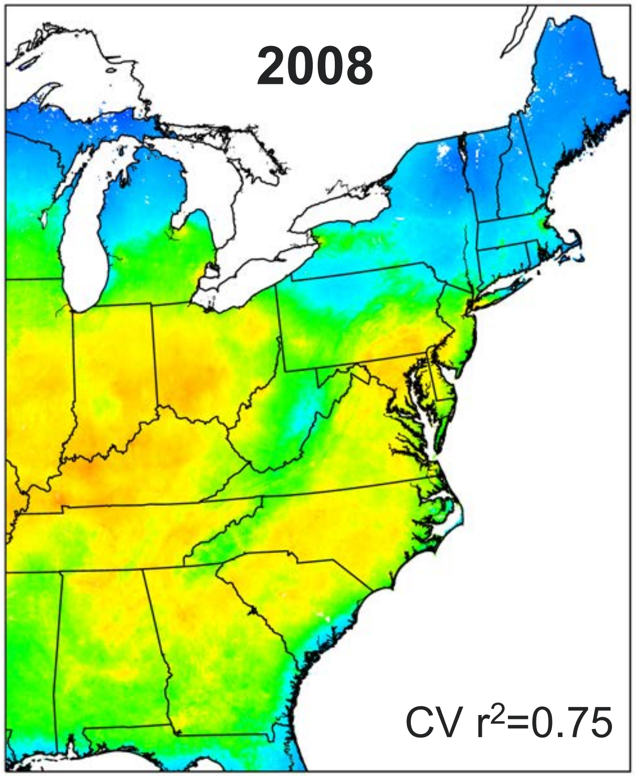
TOP-DOWN NO_X AND CO_2 EMISSIONS BY CITY

City	Inventory	NOx (Gg/yr)			CO2 (Tg/yr)		
		2006	2017	% change	2006	2017	% change
New York City	Top-down	407	216	-46.9%	165	144	-13.1%
	Bottom-up	340	188	-44.6%	119	107	-9.5%
Chicago	Top-down	197	126	-35.8%	60	55	-9.0%
	Bottom-up	287	165	-42.5%	75	61	-18.2%
Los Angeles	Top-down	445	193	-56.7%	147	113	-23.0%
	Bottom-up	261	134	-48.6%	72	67	-6.6%
Dallas	Top-down	64	48	-25.2%	20	21	6.5%
	Bottom-up	128	96	-24.9%	33	35	6.9%
Atlanta	Top-down	61	35	-42.9%	13	13	0.0%
	Bottom-up	77	47	-39.3%	14	15	6.3%
DC	Top-down	82	43	-47.3%	18	13	-26.3%
	Bottom-up	94	54	-42.7%	18	15	-19.2%
Miami	Top-down	56	46	-16.9%	7	7	4.0%
	Bottom-up	54	41	-24.5%	6	6	-5.5%
Phoenix	Top-down	78	39	-49.6%	14	10	-31.1%
	Bottom-up	53	37	-29.2%	8	8	-3.1%

$PM_{2.5}$ EXPOSURES AT 1 KM FOR THE EASTERN US USING MAIAC SATELLITE DATA AS AN INPUT

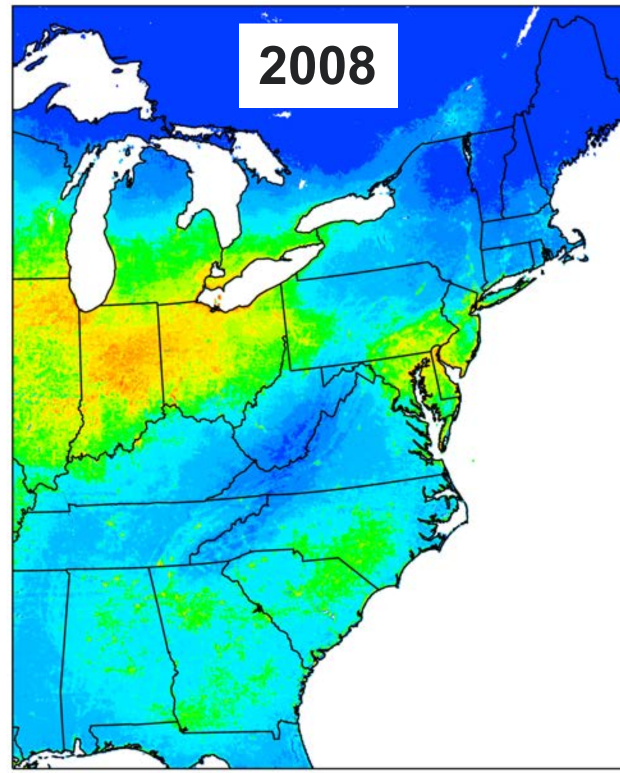
Argonne Annual* $PM_{2.5}$ data

(https://doi.org/10.1016/j.atmosenv.2018.11.049)



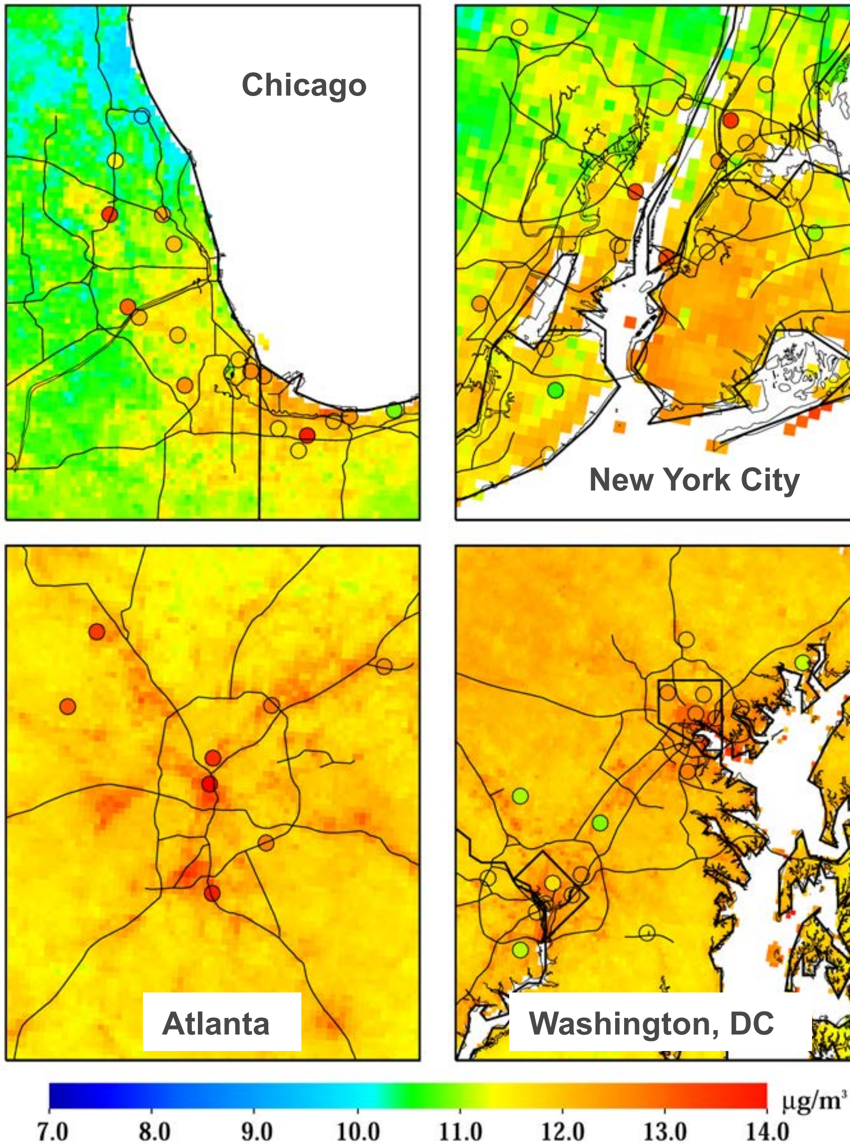
Dalhousie Annual $PM_{2.5}$ data

(https://doi.org/10.1021/acs.est.5b05833)



*Daily data is also available

EXAMPLE OF ANNUAL AVERAGED SURFACE $PM_{2.5}$ FROM OUR REGRESSION MODEL

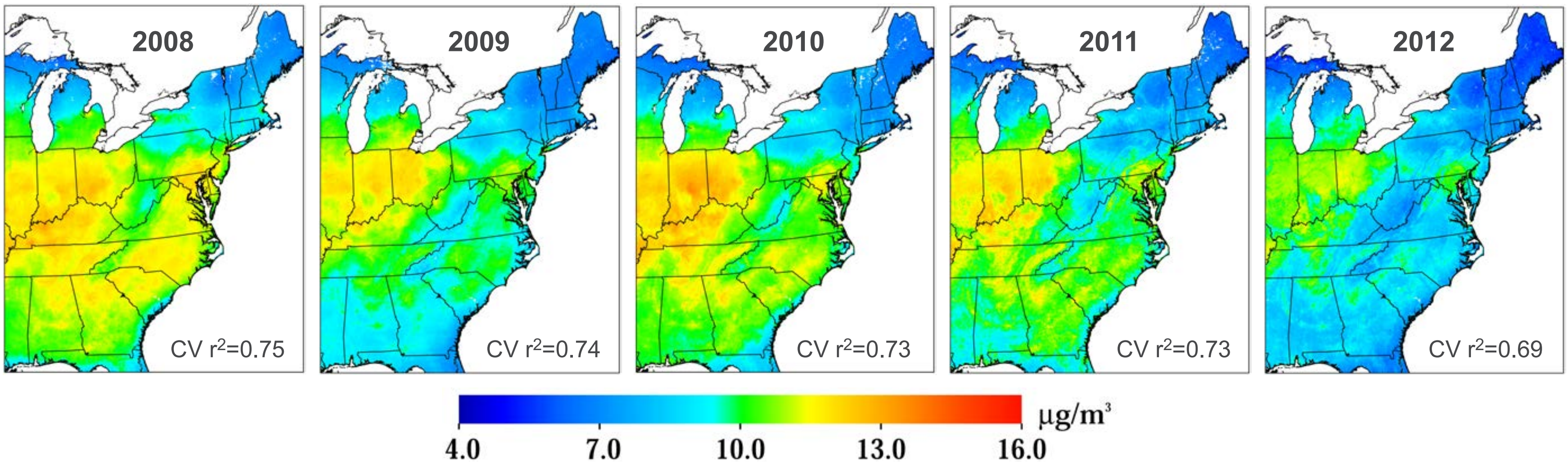


Argonne Annual $PM_{2.5}$ data
(https://doi.org/10.1016/j.atmosenv.2018.11.049)

Observations are overlaid. (Note: not an exact comparison because many $PM_{2.5}$ monitors only measure once every 3 days!)

DAILY $PM_{2.5}$ EXPOSURES AT 1 KM FOR THE EASTERN US USING MAIAC SATELLITE DATA AS AN INPUT

Argonne Annual $PM_{2.5}$ data (https://doi.org/10.1016/j.atmosenv.2018.11.049)



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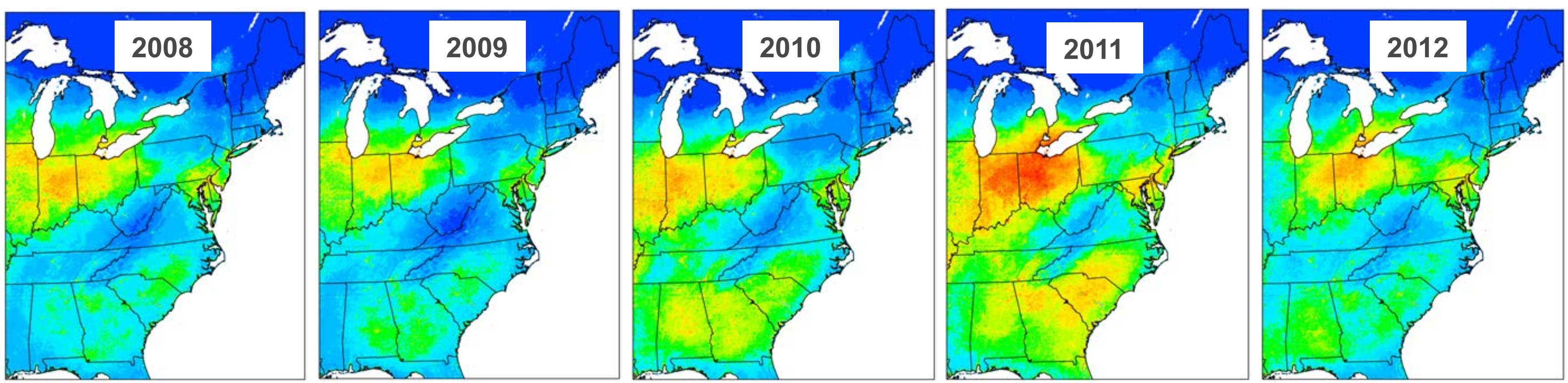
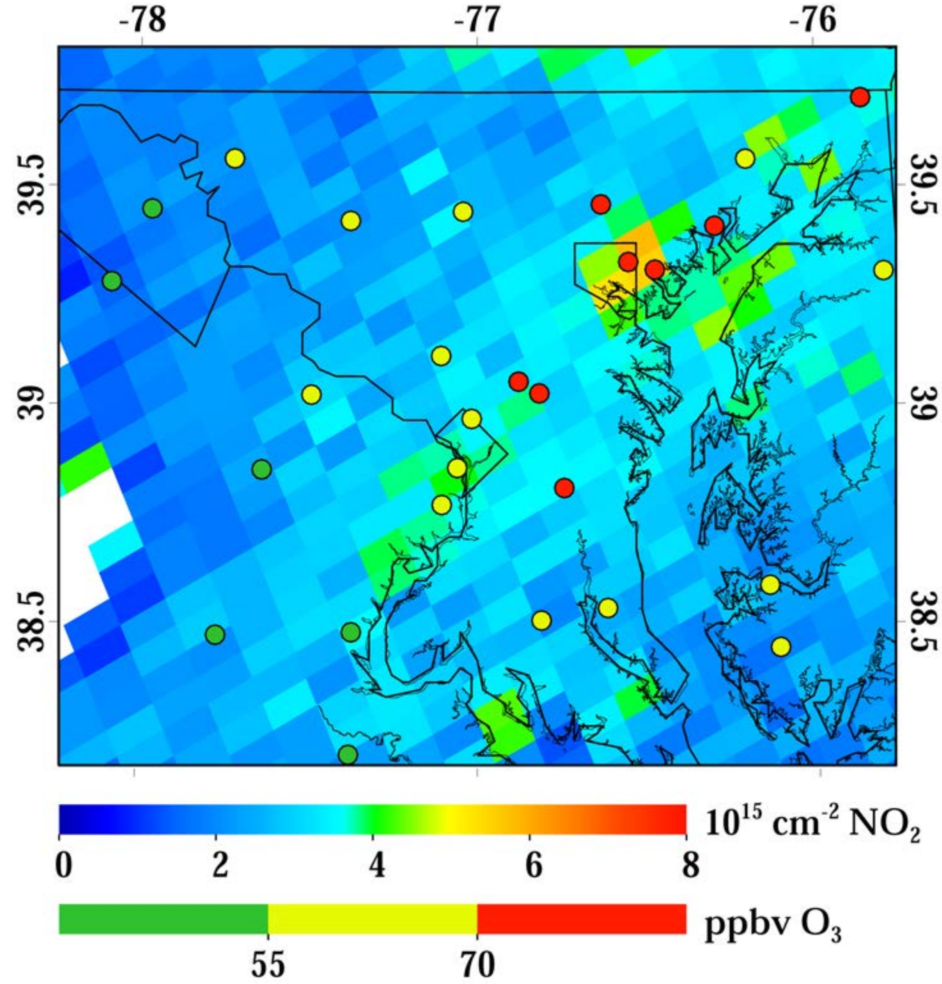


USING SPATIAL PATTERNS OF TROPOMI NO_2 TO INFER SURFACE O_3 CONCENTRATIONS

Baltimore, MD / Washington, DC



June 28, 2019

TROPOMI NO_2 can provide context for observed O_3 patterns.

Generally, largest O_3 values occur immediately downwind of largest NO_2 (in the DC area)

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

Susan C. Anenberg,[1] Daven K. Henze,[2] Veronica Tinney,[1] Patrick L. Kinney,[3] William Raich,[4] Neal Fann,[5] Chris S. Malley,[6] Henry Roman,[4] Lok Lamsal,[7] Bryan Duncan,[7] Randall V. Martin,[8,9] Aaron van Donkelaar,[8] Michael Brauer,[10,11] Ruth Doherty,[12] Jan Eiof Jonson,[13] Yanko Davila,[2] Kengo Sudo,[14,15] and Johan C.I. Kuylenstierna[6]

https://doi.org/10.1289/EHP3766

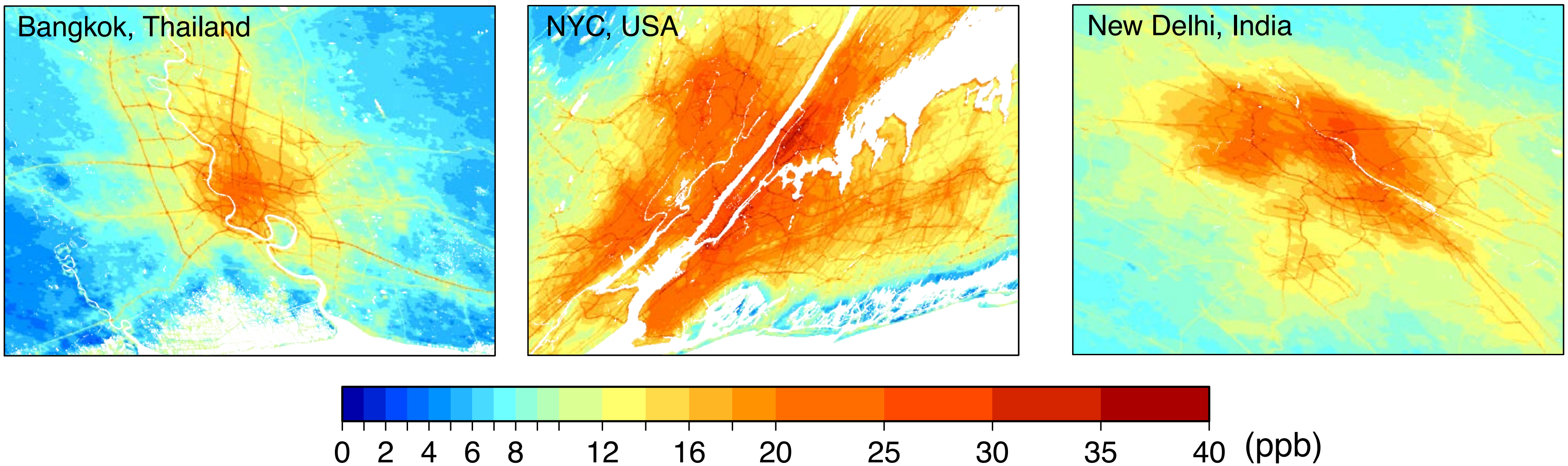
In 2015:

- Ozone: 9 – 23 million annual asthma emergency room visits globally
- $PM_{2.5}$: 5 – 10 million annual asthma emergency room visits globally
- Anthropogenic emissions were responsible for 37% of the ozone impacts and 73% of the $PM_{2.5}$ impacts

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)

https://doi.org/10.1021/acs.est.7b01148



- NO_2 is a major component and commonly used surrogate for the traffic-related pollution (TRAP) mixture
- Traffic-related NO_2 generally declines to urban background levels at a distance beyond 300-500 m from roadways (HEI, 2010).

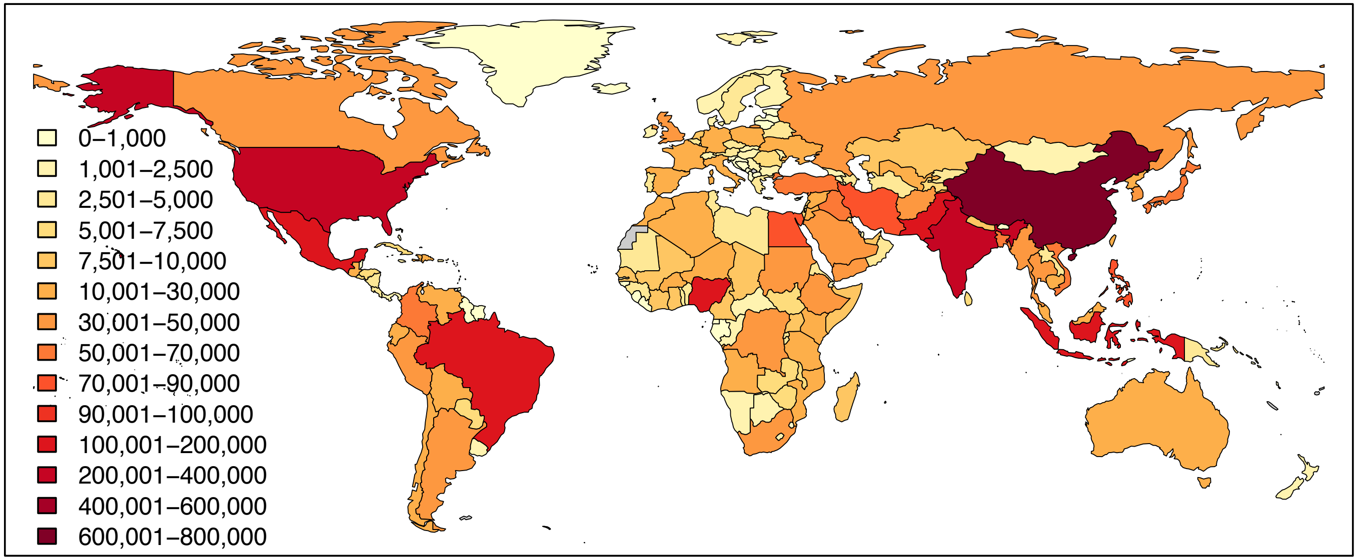
Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: estimates from global datasets

https://doi.org/10.1016/S2542-5196(19)30046-4

Pattanun Achakulwisut, Michael Brauer, Perry Hystad, Susan C Anenberg

In 2010-2015, 4 million (95% UI 1.8-5.2) children developed asthma due to NO_2 pollution each year

(a) Number of new asthma cases due to NO_2 exposure

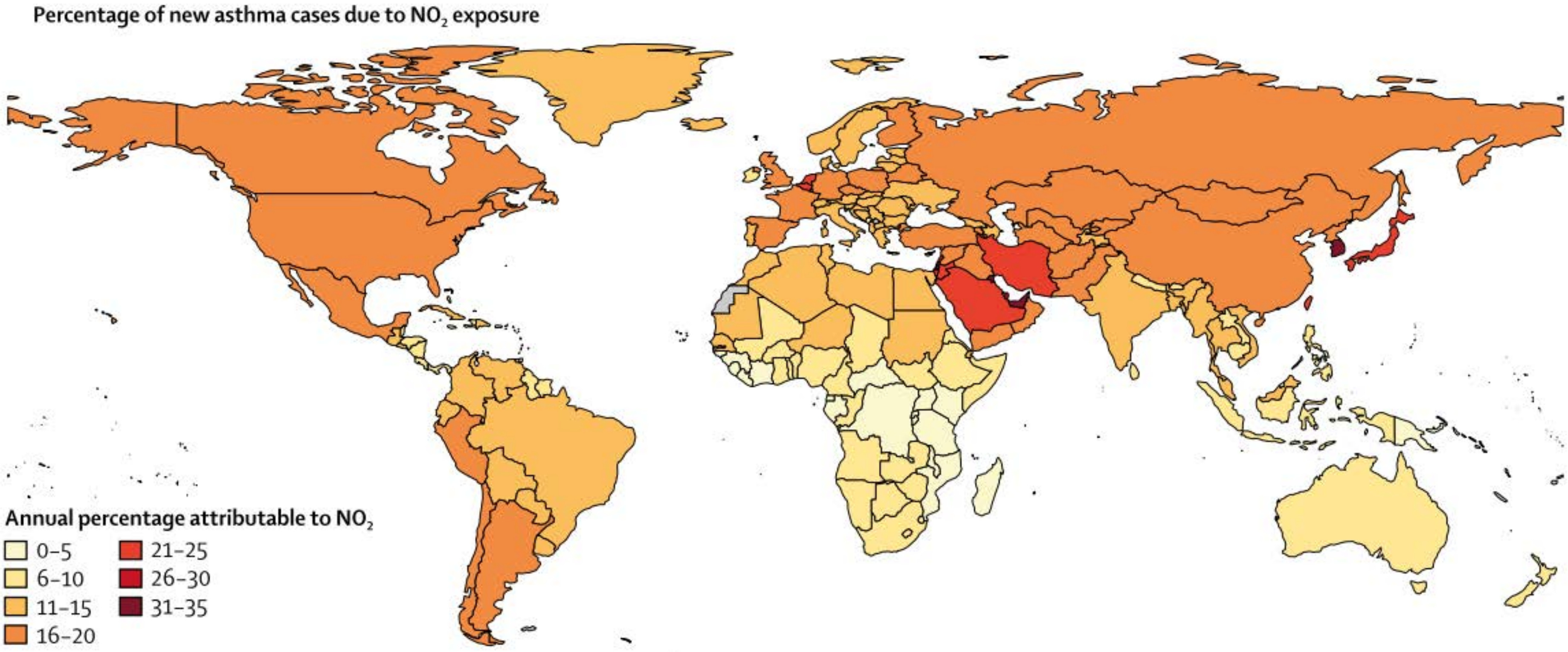


- Top 3 national burdens (cases/year): China (760,000), India (350,000), USA (240,000).
- Top 3 national rates (case/year per 100,000): Kuwait (550), United Arab Emirates (460), Canada (450).

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

https://doi.org/10.1016/S2542-5196(19)30046-4

Pattanun Achakulwisut, Michael Brauer, Perry Hystad, Susan C Anenberg



- Approximately 10 – 25% of pediatric asthma cases can be attributed to NO_2 or co-emitted pollutants

HAQAST TIGER TEAM: Using Satellite Remote Sensing to Derive Global Climate and Air Indicators

Stakeholders:

LANCET COUNTDOWN: TRACKING PROGRESS ON HEALTH AND CLIMATE CHANGE

Nick Watts

Now: Global Pollution Observatory

Phil Landrigan, Richard Fuller

HEI

Institute for Health Metrics and Evaluation

STATE OF GLOBAL AIR /2018

Katy Walker

C40 CITIES CLIMATE LEADERSHIP GROUP

Iyad Kheirbek

EDF ENVIRONMENTAL DEFENSE FUND® Finding the ways that work

Ananya Roy

Clean Air Institute

Juan Castillo

CCAC CLIMATE AND CLEAN AIR COALITION TO REDUCE SHORT-LIVED CLIMATE POLLUTANTS

Sandra Cavalieri

MAY 9, 2019: SCIENCE TO ACTION ROUNDTABLE

FACILITATING INFORMATION EXCHANGE BETWEEN SCIENTISTS AND STAKEHOLDERS

- The following topics were discussed:
  - Examples of integrated air quality/climate planning and action in cities
  - Data and tools that are still needed
  - Communicating air quality and city burden of disease estimates
  - Advancing a message of joint action on air quality and climate change

HAQAST TIGER TEAM: Using Satellite Remote Sensing to Derive Global Climate and Air Indicators

Which indicators for which stakeholders?

- NO_2 concentrations (Duncan)
- Ozone concentrations (West, Fiore, Henze)
- $PM_{2.5}$ disease burdens in cities worldwide (Anenberg, Henze, Kinney)
- Pollen concentrations, season length, and season start date (Hess)
- Wildfires (Liu)
- Dust storms (Tong)

- Global Pollution Observatory
- HEI State of Global Air
- Clean Air Institute
- C40
- Climate and Clean Air Coalition
- Environmental Defense Fund
- Lancet Countdown

HAQAST TIGER TEAM: Using Satellite Remote Sensing to Derive Global Climate and Air Indicators

PROGRESS TO DATE

- August 2018: Tiger team launched
- October 1, 2018: Launched webpage (www.haqastindicators.org)
- October 16, 2018: First full team telecon
- November 20, 2018: Investigator telecon
- December 12, 2018: Investigator meeting at AGU
- January 3-4, 2019: HAQAST5
- January 15, 2019: Investigator telecon
- February 2019: Second full team telecon
- May 2019: Stakeholder meeting in DC
- June 2019: Investigator telecon
- November 2019: Third (and final?) full team telecon

Added stakeholders: Clean Air Institute, C40, Climate and Clean Air Coalition, EDF

Spin off with GPO and NASA on global air pollution visualizations

Spin off with Anenberg, Duncan on NO_2 and global asthma impacts

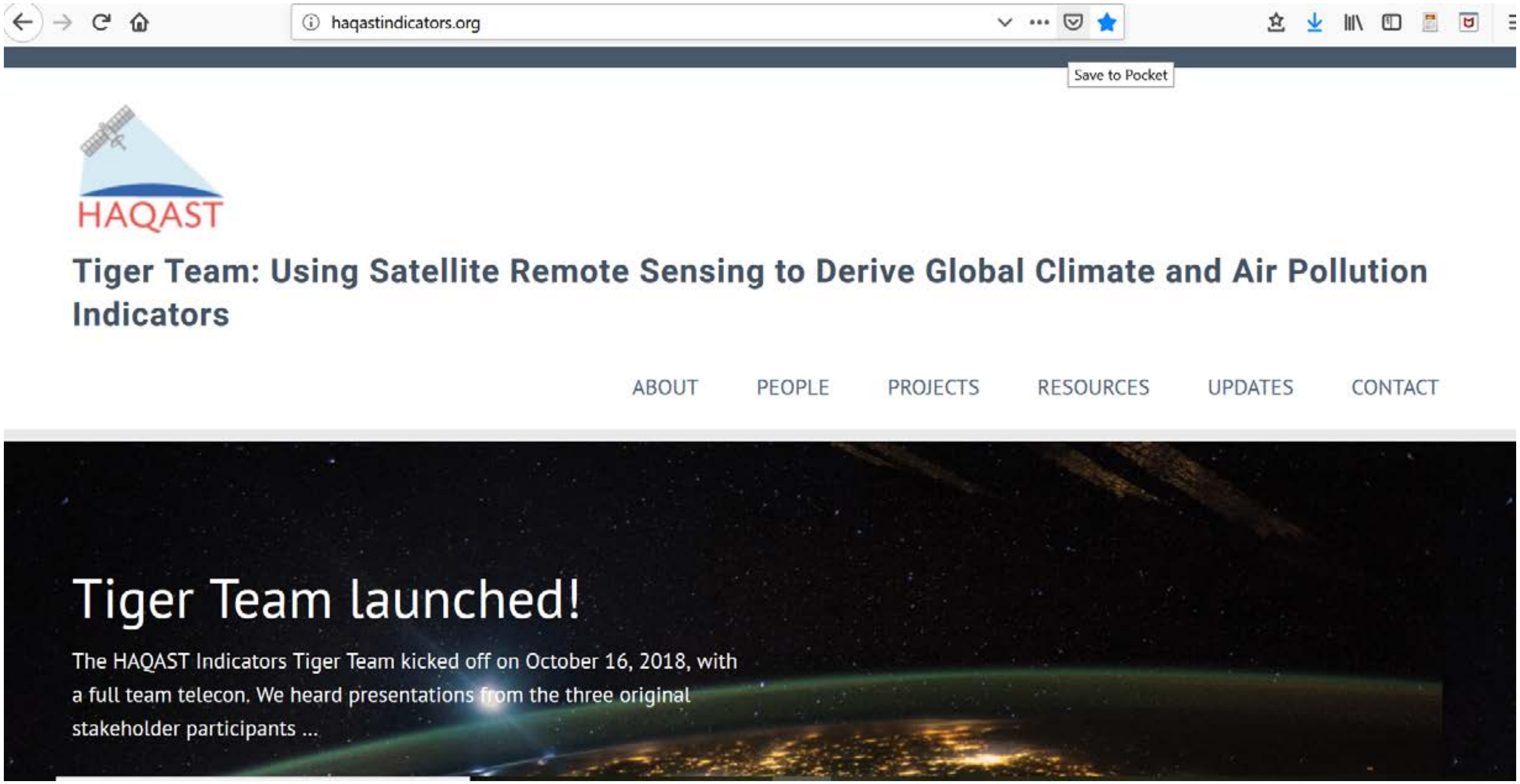
Spin off with Anenberg, Kinney, Henze, and C40 on city burden of disease

Spin off with Duncan, Anenberg, and NASA on public communications

Spin off with Hess, Liu, Tong, and Lancet Countdown on wildfires and dust

Spin offs with West, Duncan, and HEI, EDF on ozone and NO_2

WWW.HAQASTINDICATORS.ORG



Tiger team: Susan Anenberg, Ploy Achakulwisut, Bryan Duncan, Arlene Fiore, Daven Henze, Jeremy Hess, Xiaomeng Jin, Casey Kalman, Pat Kinney, Lok Lamsal, Yang Liu, Daniel Tong, & Jason West

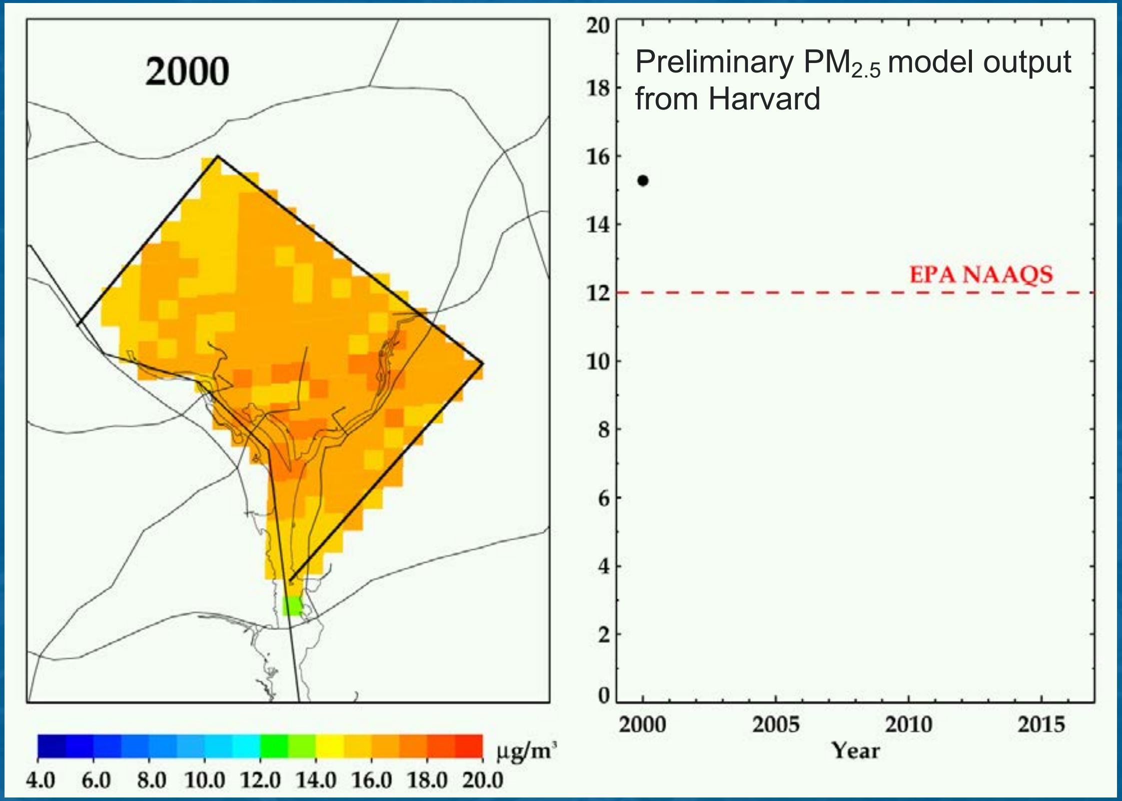
CONCLUSIONS

- Emissions: OMI and TROPOMI NO_2 have been used to estimate top-down NO_X emissions
  - Advantages: Timely & independent of bottom-up methods
  - Disadvantages: Spatially aggregated (little info on sectors)

- Exposure: MAIAC AOD and TROPOMI NO_2 can be extremely useful inputs when trying to estimate surface $PM_{2.5}$ and O_3 concentrations

- Public health impacts: Recent papers by the Anenberg group quantified O_3, $PM_{2.5}$, and NO_2 global burdens on asthma. Upcoming paper on $PM_{2.5}$ mortality in cities.

PM$_{2.5}$ in DC: A SUCCESS STORY!



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