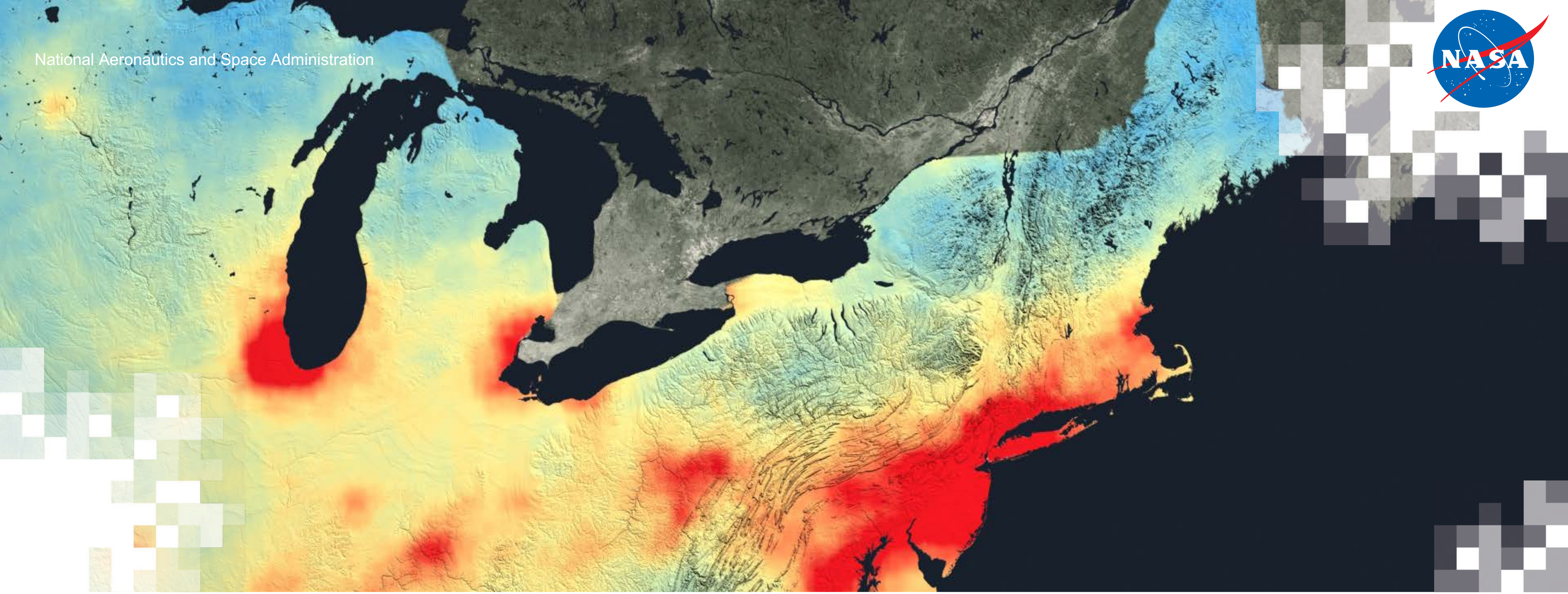


Satellite-Based $PM_{2.5}$ Datasets

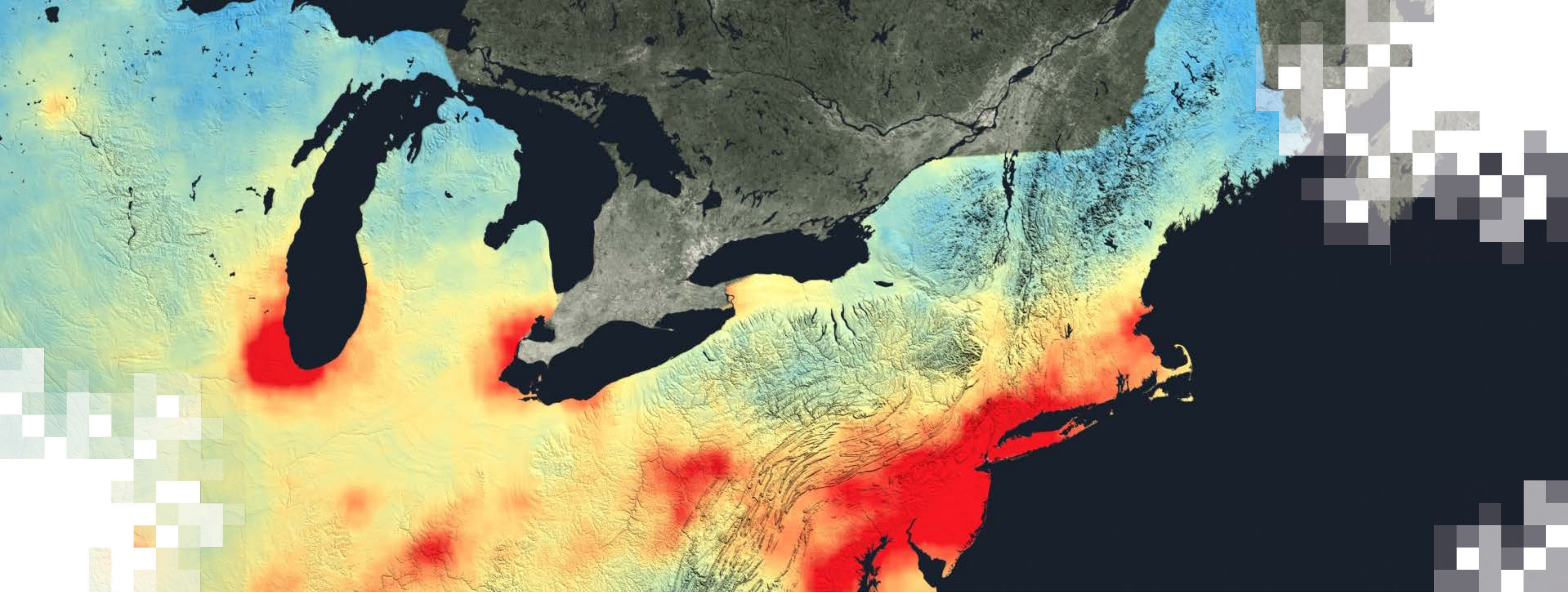
Melanie Follette-Cook, Pawan Gupta, Carl Malings, Sarah Strode

NASA Air Quality Remote Sensing Training for EPA, March 21-23, 2023

Learning Objectives

By the end of this presentation, you will be able to:

- Give examples of applications for surface $PM_{2.5}$ estimates
- List several ways satellite observations can be used to estimate surface PM2.5
- Locate relevant PM2.5 estimates

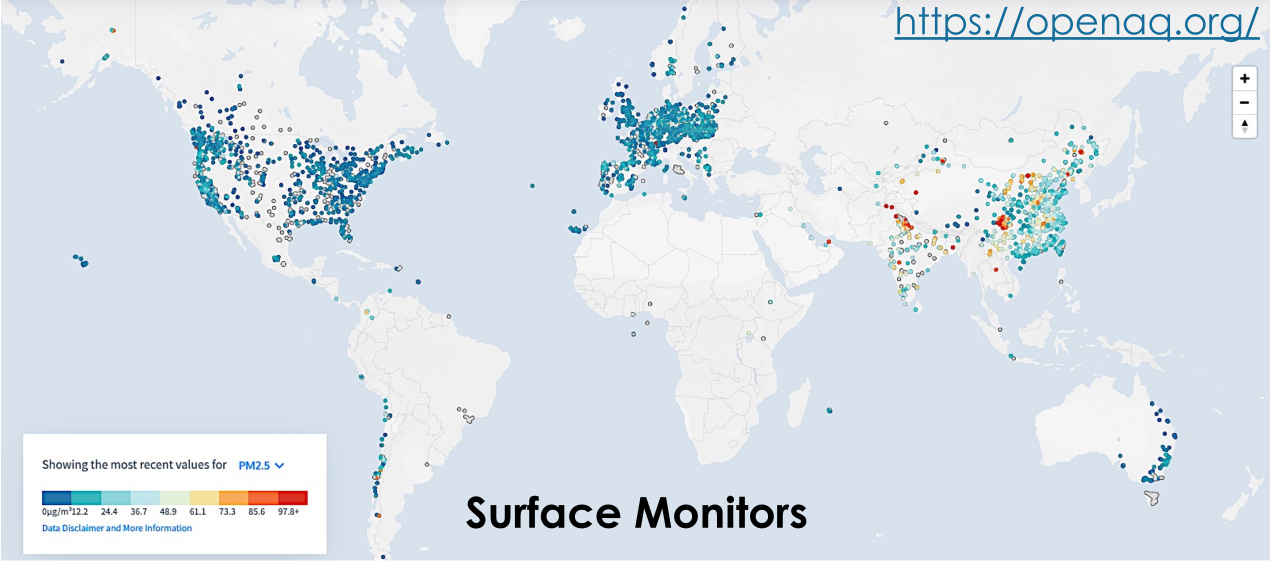


Examples of Applications Using Surface $PM_{2.5}$ Estimates

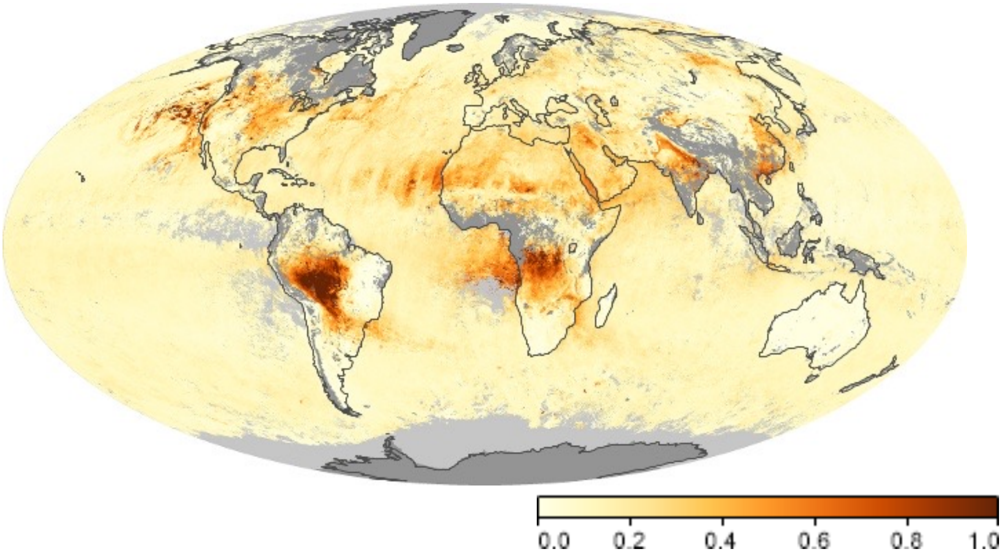
Satellites Provide a "God's Eye" View of the Earth

Spatial coverage is the primary advantage of satellite data.

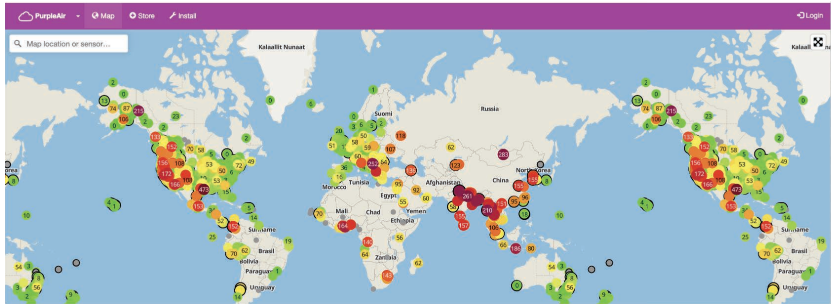
https://openaq.org/



MODIS Terra AOD Sep 2020

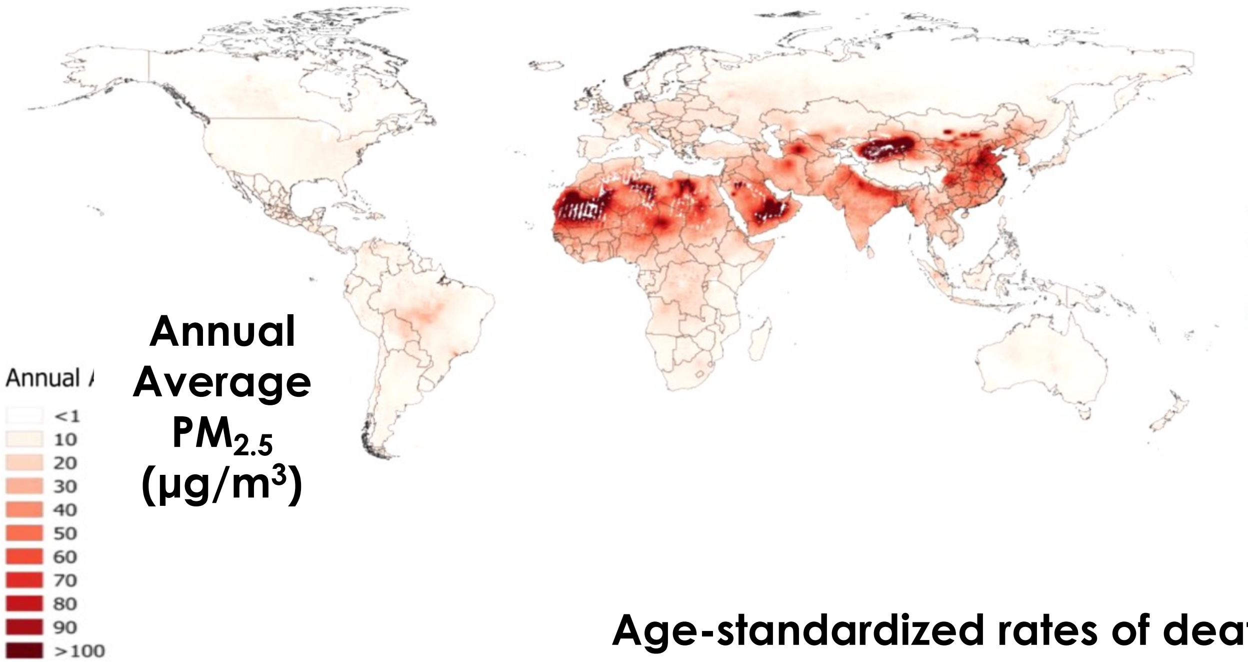


https://earthobservatory.nasa.gov/global-maps/MODAL2_M_AER_OD



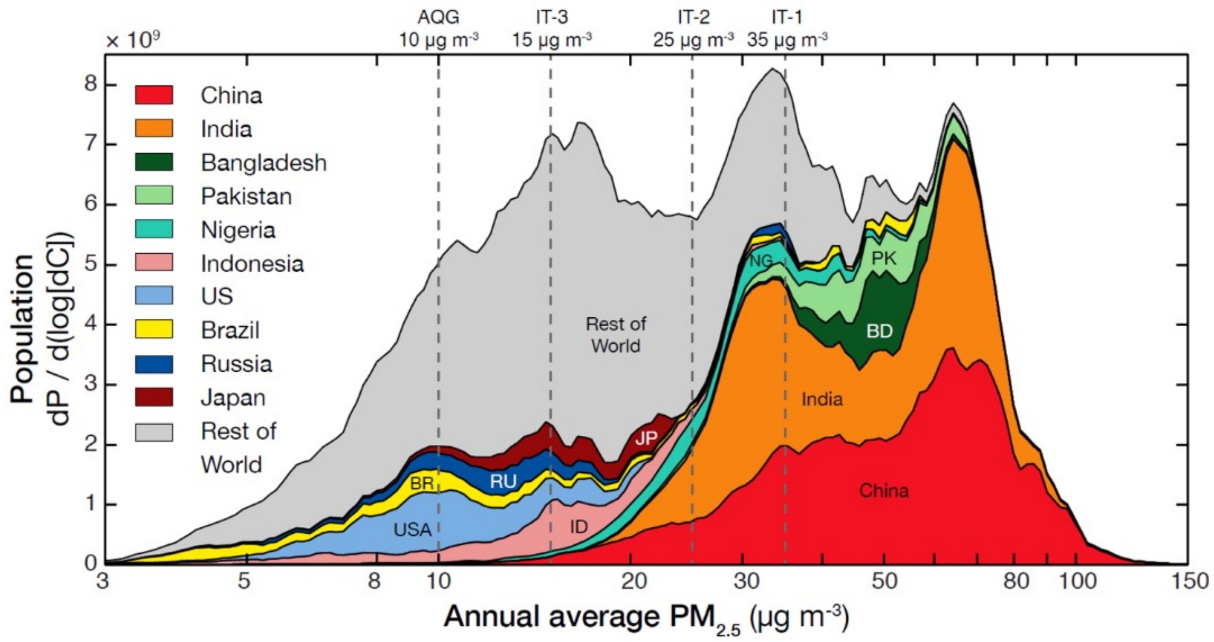
https://www.purpleair.com/

Health Studies of Exposure

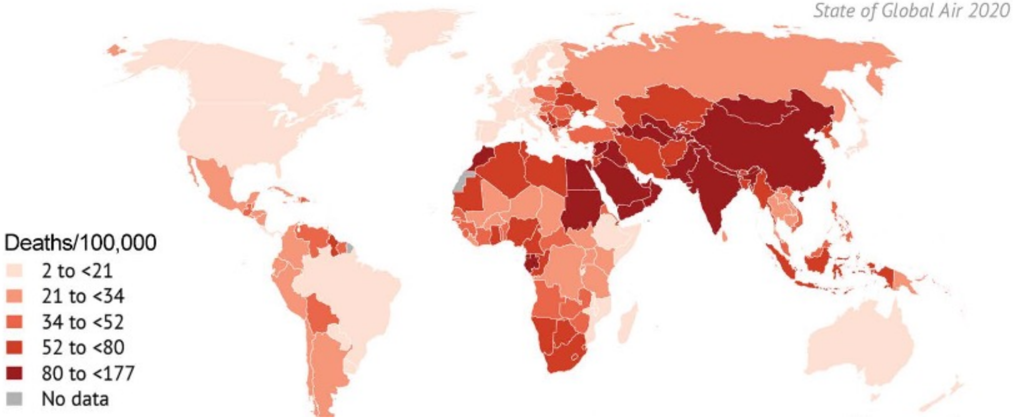


Annual Average $PM_{2.5}$ ($\mu g/m^3$)

WHO Interim Targets



Age-standardized rates of death attributable to PM2.5 in 2019



https://www.stateofglobalair.org/

UN Sustainable Development Goals (SDGs)

Transforming Our World: The 2030 Agenda for Sustainable Development

Goal 3 – Good Health and Well Being

- Target 3.9; Indicator 3.9.1
- Mortality rate attributed to household and ambient air pollution (annual mean levels of air pollution [$PM_{2.5}$])

Goal 11 – Sustainable Cities and Communities

- Target 11.6; Indicator 11.6.2
- Annual mean levels of fine particulate matter (e.g., $PM_{2.5}$ and PM_{10}) in cities (population weighted)

Text adapted from "Transforming our world: the 2030 Agenda for Sustainable Development"

$PM_{2.5}$ Estimation: Popular Methods

Difficulty Level

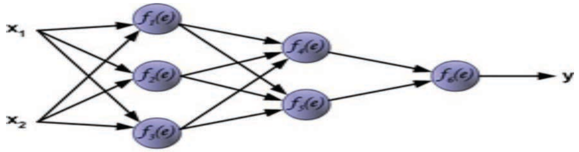
Two-Variable Method

$Y=mX + c$

Multivariable Method

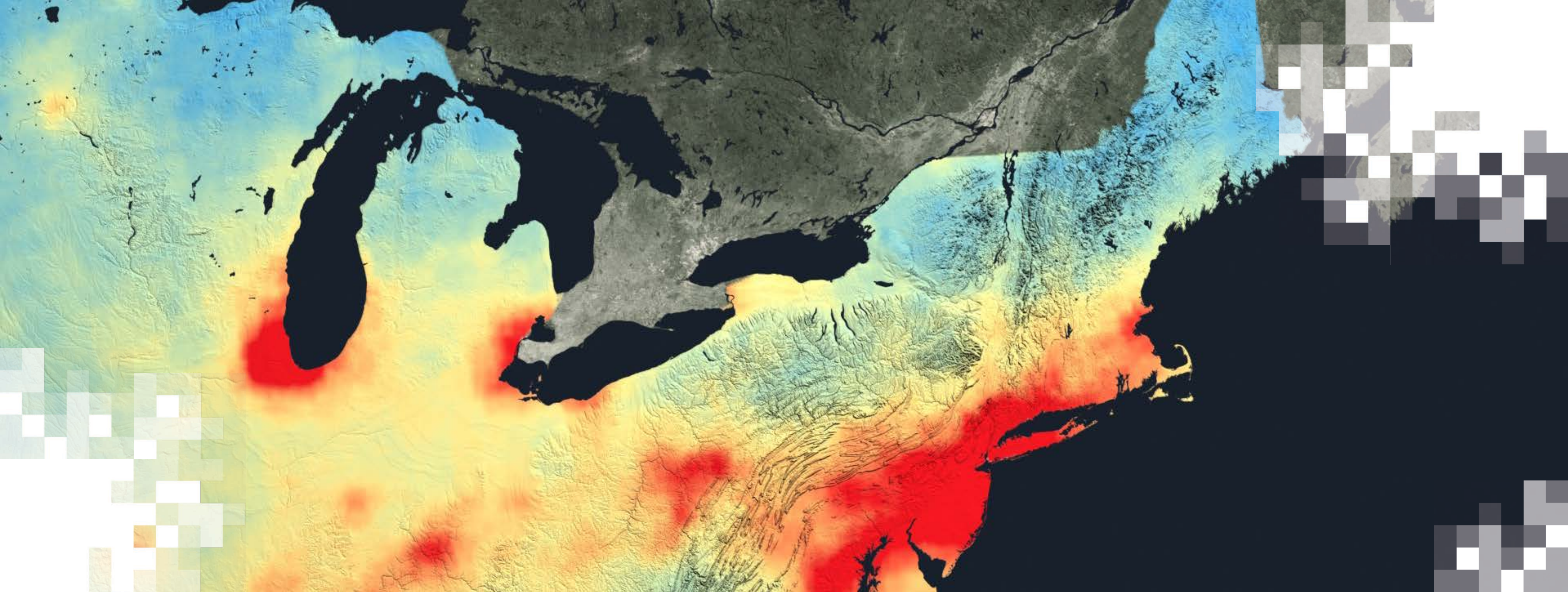
$$PM_{2.5} = \beta_0 + \alpha \times \tau + \sum_{n=1}^{m} (\beta_n \times M_n)$$

Artificial Intelligence



MSC

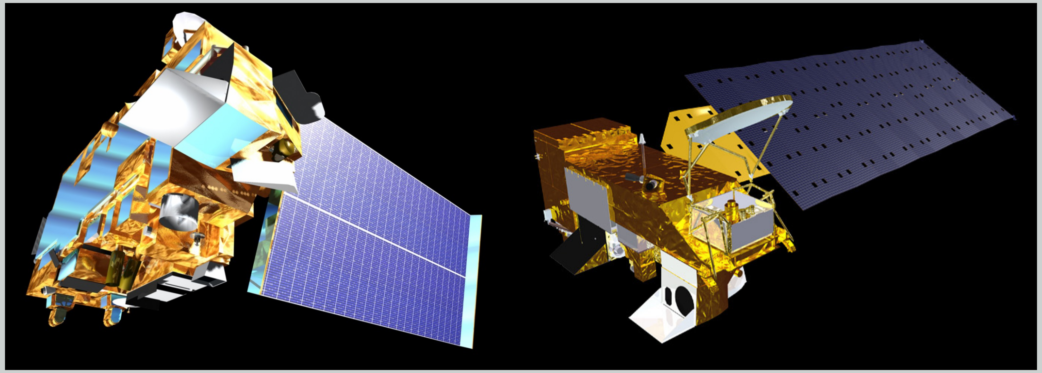
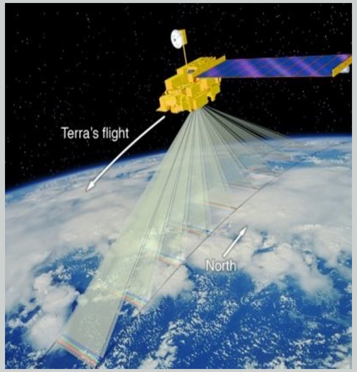
$$\text{Estimated } PM_{2.5} = \frac{\text{Model Surface Area Concentration}}{\text{Model AOD}} \text{ x Satellite AOD}$$



Satellite-Based Estimates of Surface $PM_{2.5}$ and Chemical Composition - Van Donkelaar et al. (2021)

Van Donkelaar et al. (2021)

Eight retrievals of AOD from four different instruments

Instrument	MODIS: Terra/Aqua			MISR	SeaWiFS
					
Retrieval Algorithm	Deep Blue	Dark Target	MAIAC	MISR	Deep Blue
Horizontal Resolution	10 km	10 km	1 km	17.6 km	13.5 km

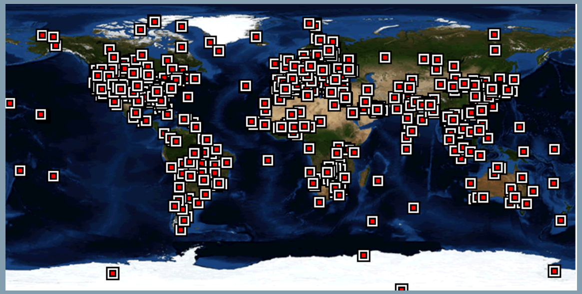
Van Donkelaar et al., 2021, https://pubs.acs.org/doi/pdf/10.1021/acs.est.1c05309

Van Donkelaar et al. (2021)

AOD ⇨ $PM_{2.5}$

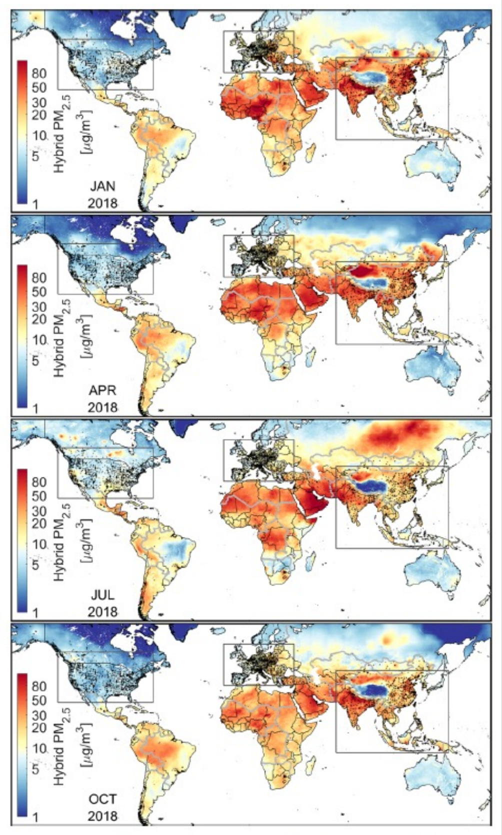
AOD (8 retrievals) & AOD from Model Simulations

Calibrate all using surface observations of AOD from the AERONET network



Calculate $PM_{2.5}$ from AOD using model AOD-to-$PM_{2.5}$ relationship

Calculate Monthly Mean



Van Donkelaar et al. (2021)

Geographic Weighted Regression (GWR)

GWR corrects the satellite estimate using the relationship between $PM_{2.5}$ from ground monitors and variables such as model aerosol composition, elevation data, and land use indicators.

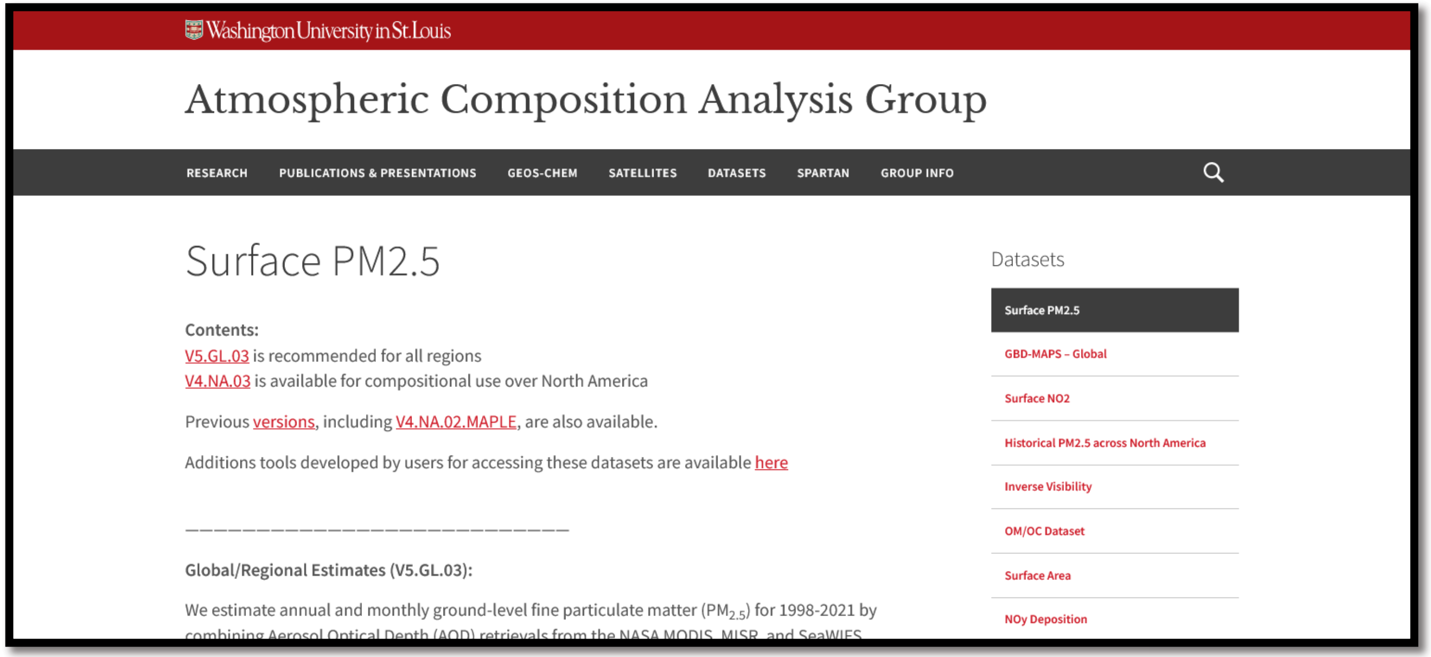
PM2.5 Uncertainty Estimates

Uncertainty is estimated by using 1) the range of AOD values going into the best estimate and simulated PM2.5/AOD relationships, and 2) the predictor coefficients of the GWR.

Washington Univ of St. Louis - Atmospheric Composition Analysis Group

https://sites.wustl.edu/acag/datasets/surface-pm2-5/

- **Global and Regional PM2.5 (V5.GL.03) (1998-2021)**
  - Annual and Monthly Means at 0.01° x 0.01°
  - Annual and Monthly Means at 0.1° x 0.1°
  - Annual and Monthly Mean Uncertainty at 0.01° x 0.01°
- **North American Regional Estimates (with composition) (V4.NA.03)(2000-2016)**
  - Annual and Monthly Means at 0.01° x 0.01°



North American Regional Estimates (V4.NA.03)

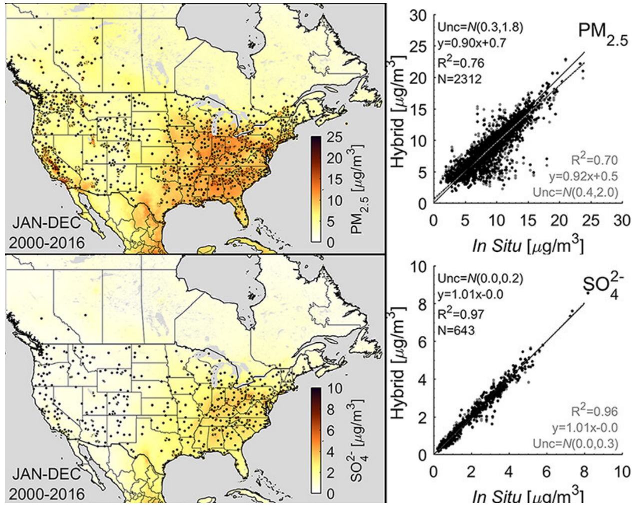
https://pubs.acs.org/doi/pdf/10.1021/acs.est.8b06392

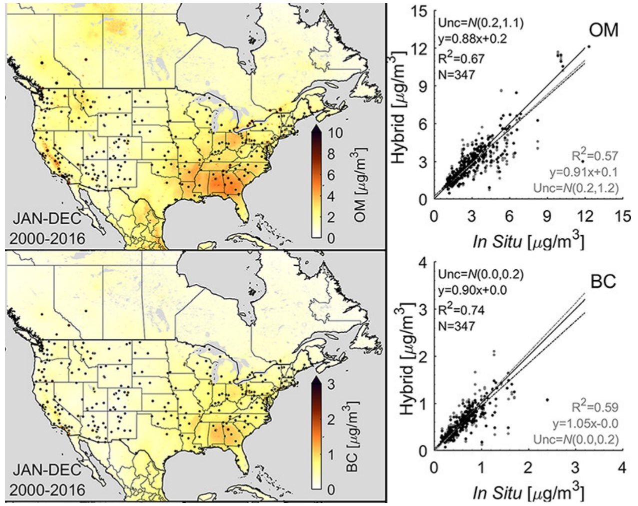
"We estimate ground-level fine particulate matter ($PM_{2.5}$) total and compositional mass concentrations over North America by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrated to regional ground-based observations of both total and compositional mass using Geographically Weighted Regression (GWR) as detailed in the below reference."

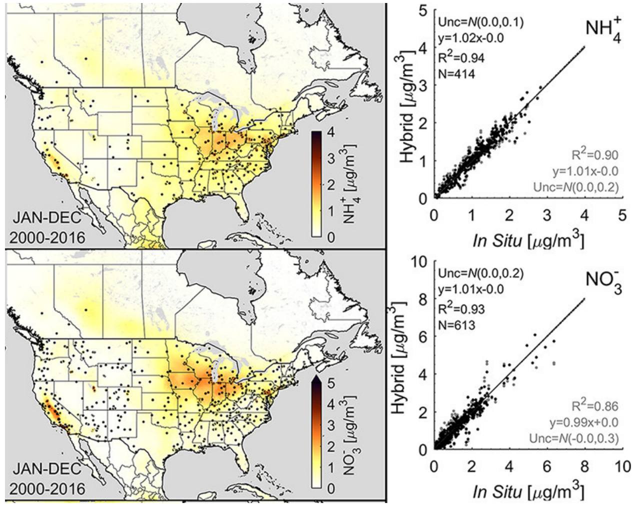
- https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V4.NA.03
- 2000-2017, 0.01° × 0.01°

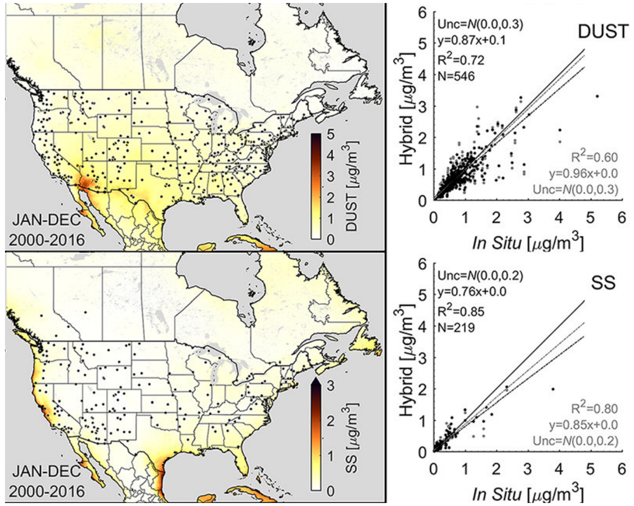
North American Regional Estimates (V4.NA.03)

https://pubs.acs.org/doi/pdf/10.1021/acs.est.8b06392

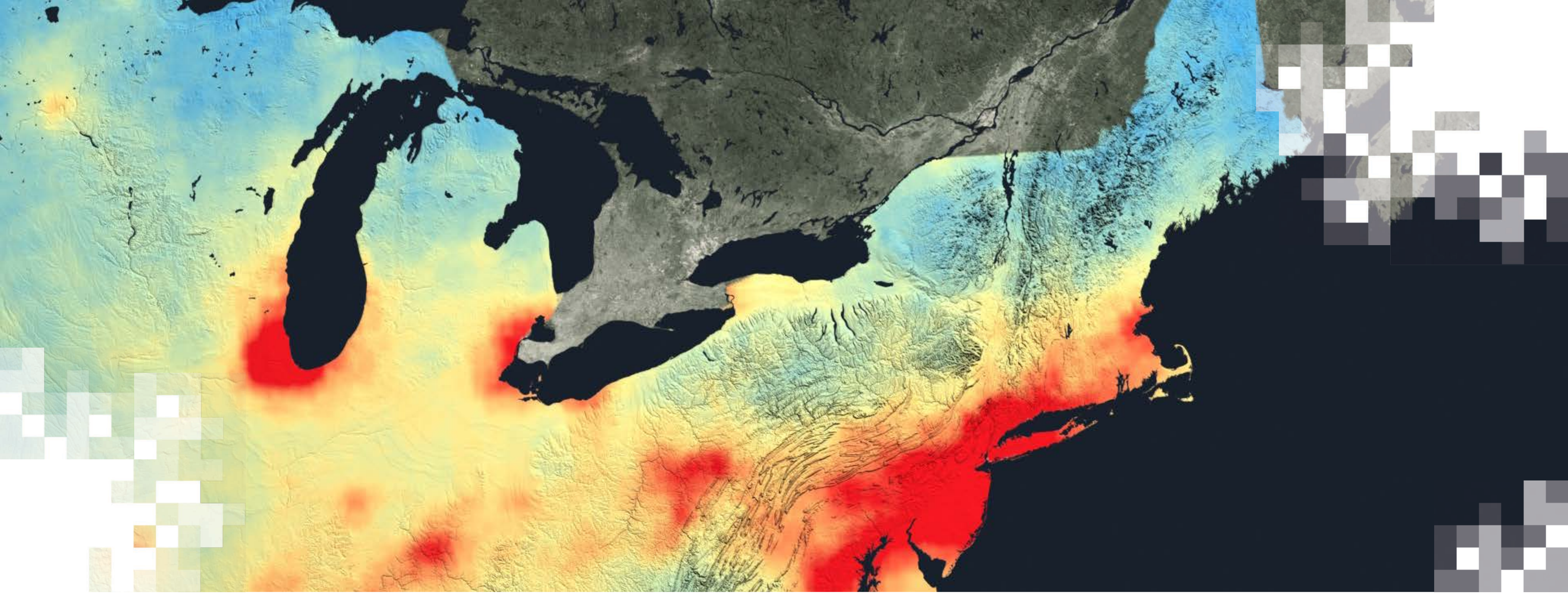








Donkelaar et al., 2019

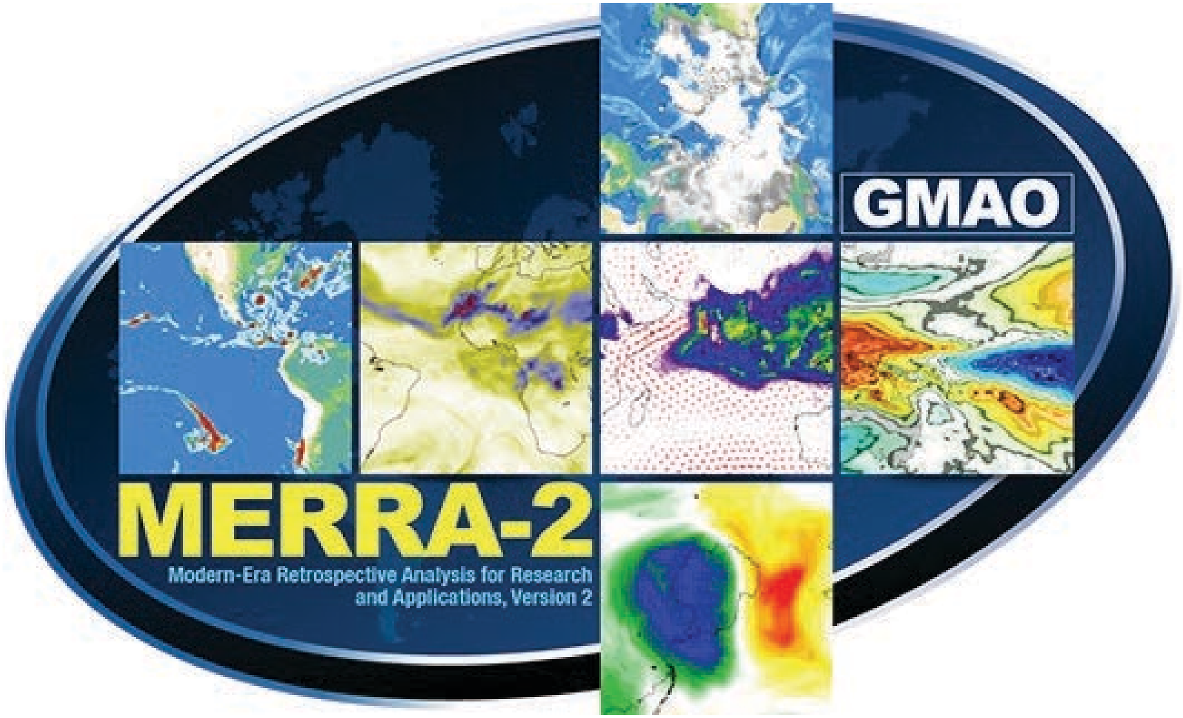


Reanalysis-Based Estimates of Surface $PM_{2.5}$ and Chemical Composition – MERRA-2

Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2)

https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/

- NASA's Global Model and Assimilation Office (GMAO) produces estimates of surface $PM_{2.5}$ over the period of 1980 to the present day.
- The model system assimilates meteorological data as well as some atmospheric constituents (e.g., ozone, AOD).
- Spatial Resolution: 0.5x0.625 deg.



MERRA-2 Aerosol Observations

- Aerosol assimilation is described in detail in Randles et al. 2017 and https://gmao.gsfc.nasa.gov/pubs/docs/Randles887.pdf.
- In MERRA-2, AOD at 550 nm is assimilated.
- Some Notes:
  - No information on vertical structure or composition
  - Daylight observations only
  - Subject to meteorological conditions (e.g., clouds) and viewing geometry (e.g., sun glint)
  - When there are no observations, MERRA-2 draws towards the GEOS/GOCART simulation.

Sensor	Temporal coverage	Description
AVHRR NNR	1980–August 2002	PATMOS-x radiances over ocean only (PM orbit)
AERONET	Station dependent (1999–October 2014)	AOD from land station network
MISR	February 2000–June 2014	AOD over bright land surfaces only (albedo > 0.15)
MODIS *Terra* NNR	March 2000 onward (NRT)	Collection 5 "Dark Target" land and ocean radiances (AM orbit)
MODIS *Aqua* NNR	August 2002 onward (NRT)	Collection 5 "Dark Target" land and ocean radiances (PM orbit)

Table 2 from Randles et al. 2017

MERRA-2 Aerosol Observations

- When using MERRA-2 products, one must take care to consider the changing observing system over time.

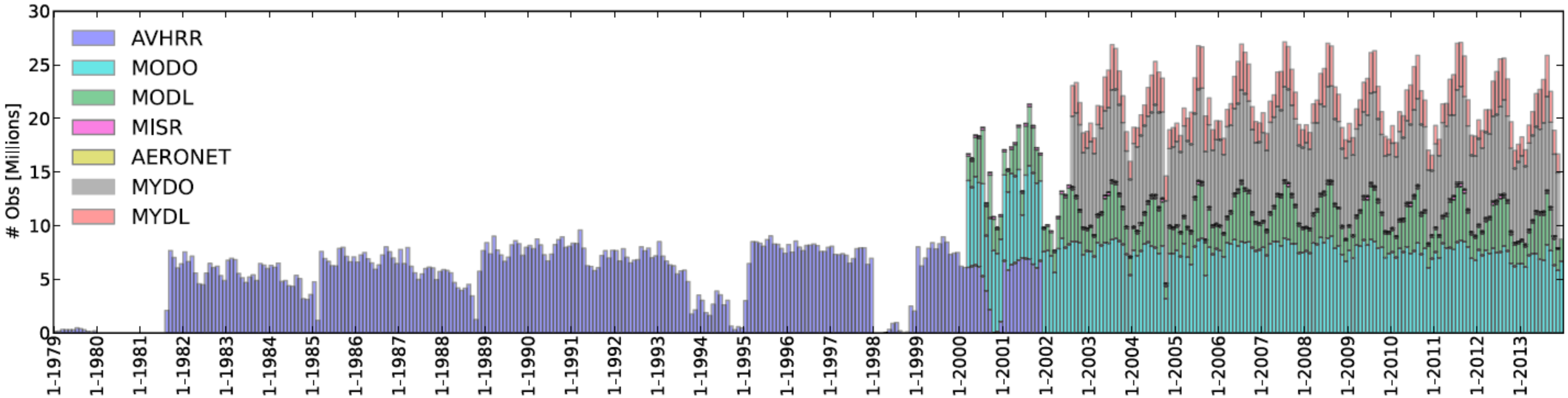
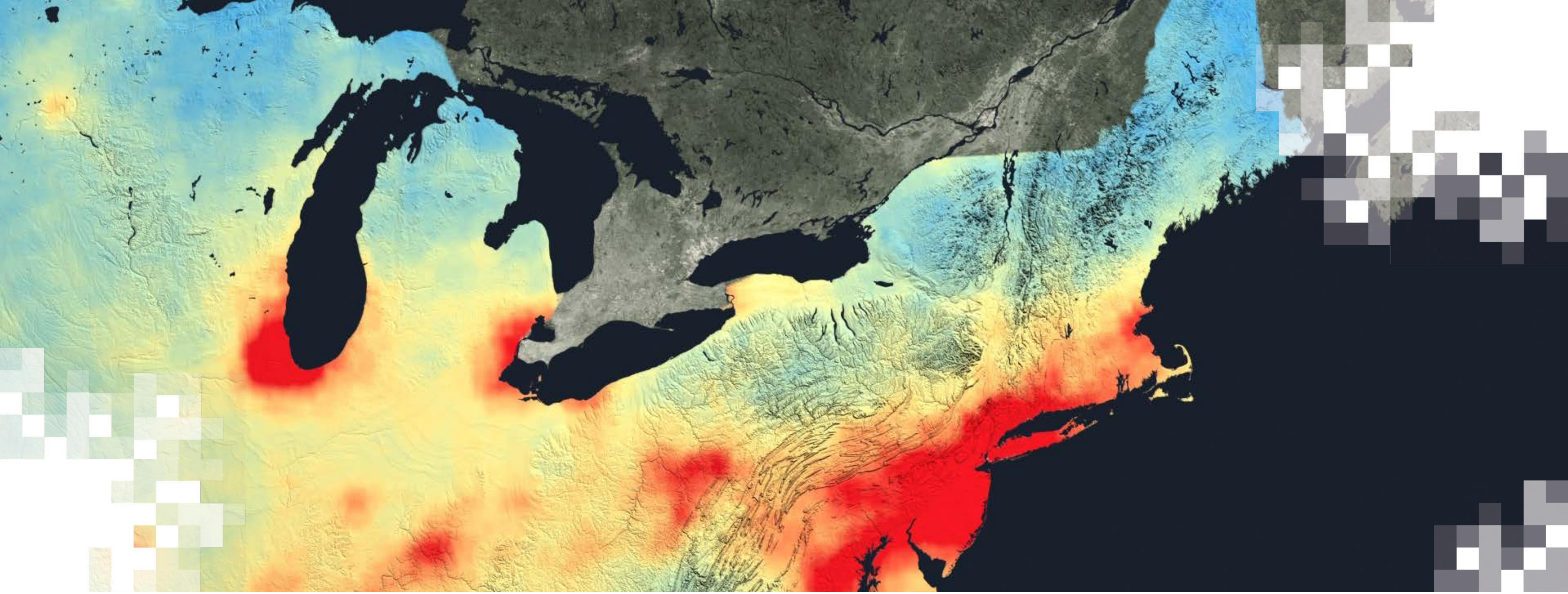


Figure 3 from Randles et al. 2017



Machine Learning-Based Estimates of Surface $PM_{2.5}$

Machine Learning Ensemble-based PM2.5 over CONUS (2000-2016)

https://sedac.ciesin.columbia.edu/data/set/aqdh-pm2-5-concentrations-contiguous-us-1-km-2000-2016

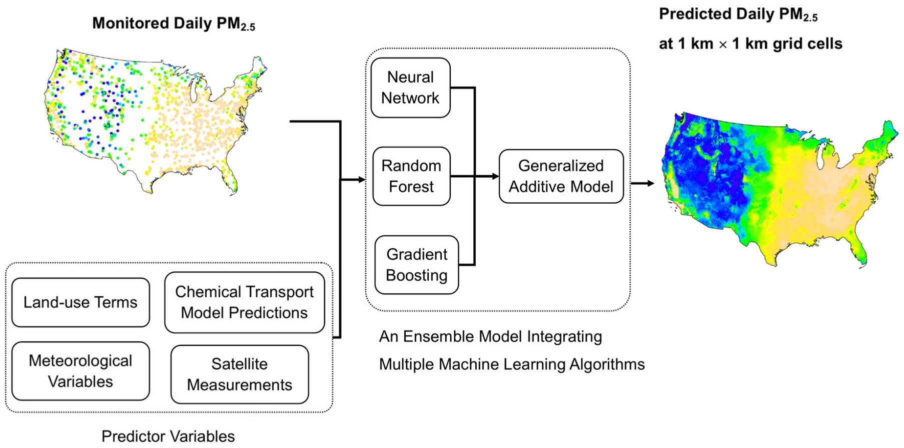
- Daily and Annual, 1 km^2
- Available in RDS and GeoTIFF
- Also Available at Zip Code Level
  - https://sedac.ciesin.columbia.edu/data/set/aqdh-pm2-5-o3-no2-concentrations-zipcode-contiguous-us-2000-2016

Machine Learning Ensemble-Based PM2.5 over CONUS (2000-2016)

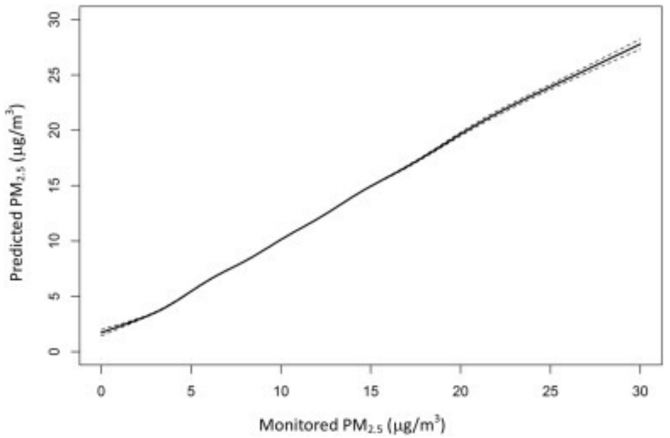
Di et al., 2019, Environmental International

https://www.sciencedirect.com/science/article/pii/S0160412019300650

- Meteorology:
  - NARR (North American Regional Reanalysis)
- Satellite Observations:
  - MODIS MAIAC
  - MERRA-2 Speciation
- CTM:
  - GEOS-Chem, CMAQ
- Land-Use Terms:
  - Coverage Type, Road Density, Restaurant Density, Elevation, NDVI



Relationship Between Monitored and Predicted $PM_{2.5}$ at Annual Level



- Additional downscaling to 100 m
- Includes uncertainty estimates

Global Deep Ensemble Machine Learning (2000-2019)

Yu et al., 2023, Lancet, https://www.thelancet.com/action/showPdf?pii=S2542-5196%2823%2900008-6

- Deep Ensemble Machine Learning (DEML)
- Inputs:
  - Station PM2.5 (Daily Mean)
  - GEOS-Chem
  - ERA5 Reanalysis
  - MODIS Land Cover
  - Population Data
- Daily, Global, PM2.5 Estimates
- 0.1° x 0.1°
- Data not available yet

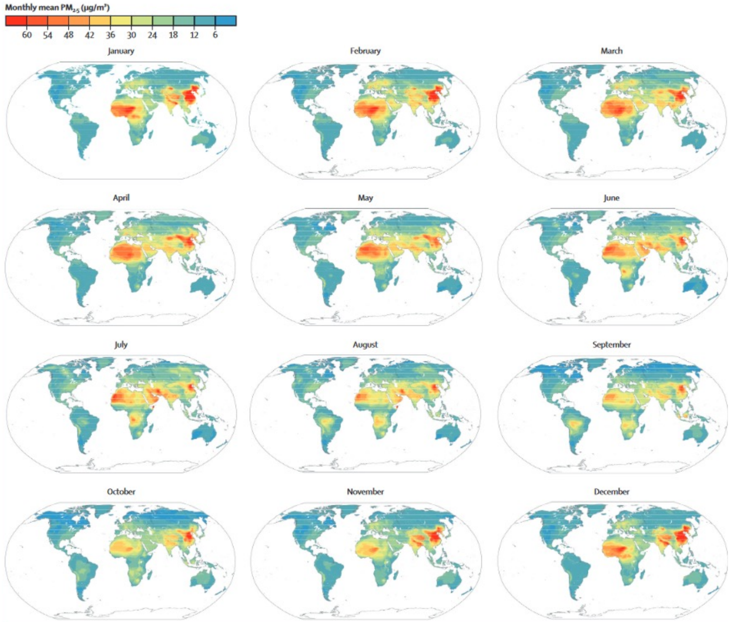
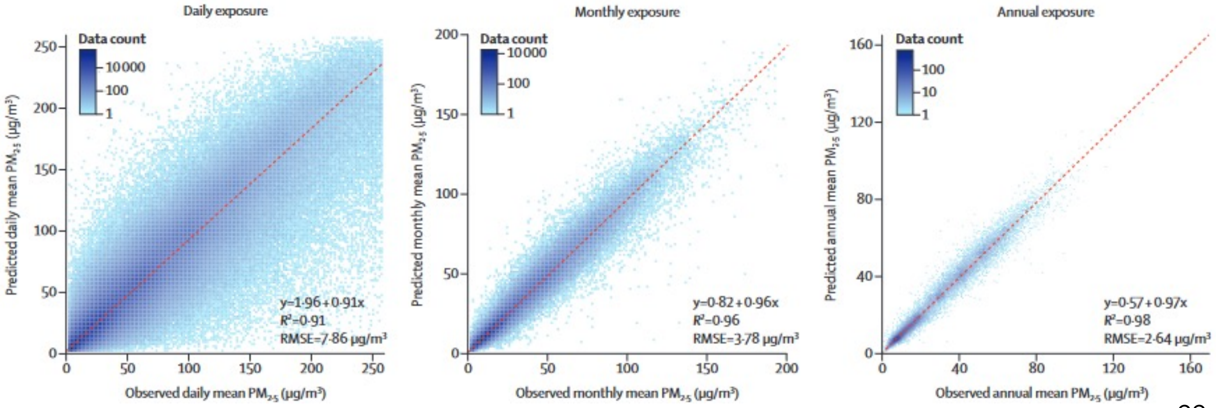
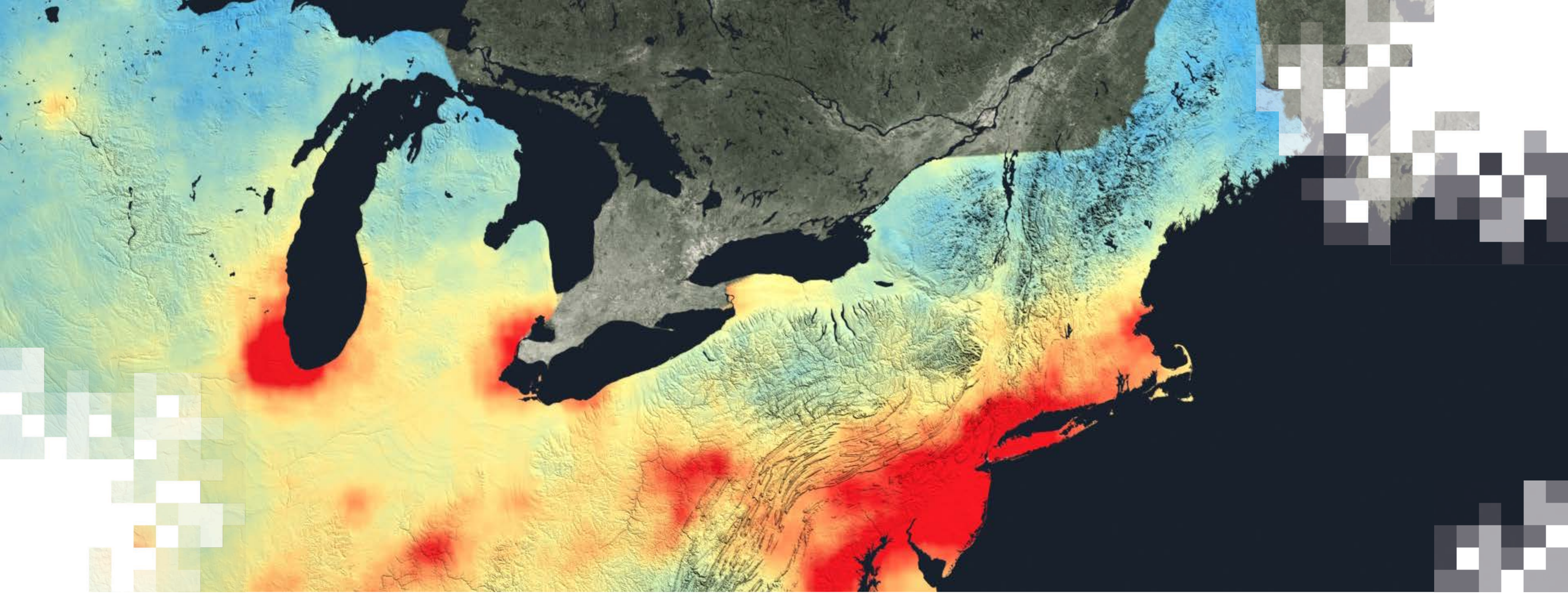


Figure 6, Yu et al., 2023

Figure 2, Yu et al., 2023





Questions?