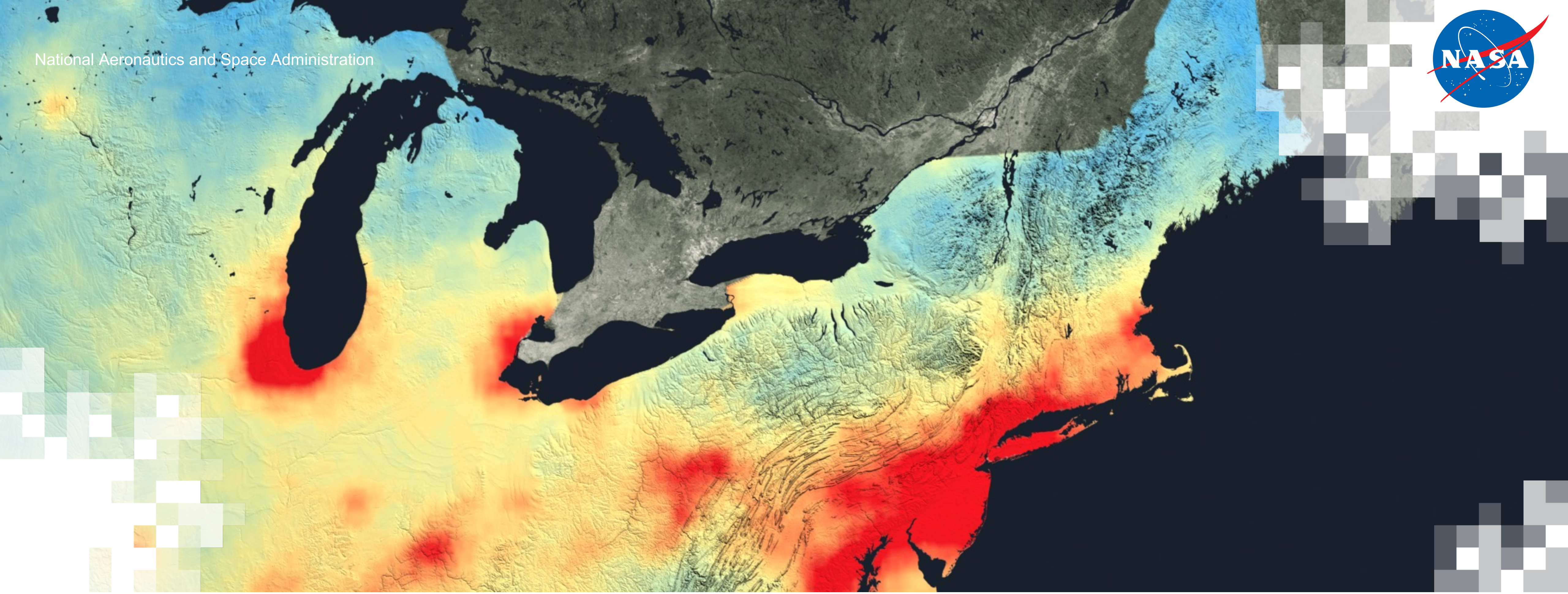


Theoretical Basis for Converting Satellite Observations to Ground-Level $PM_{2.5}$ Concentrations

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

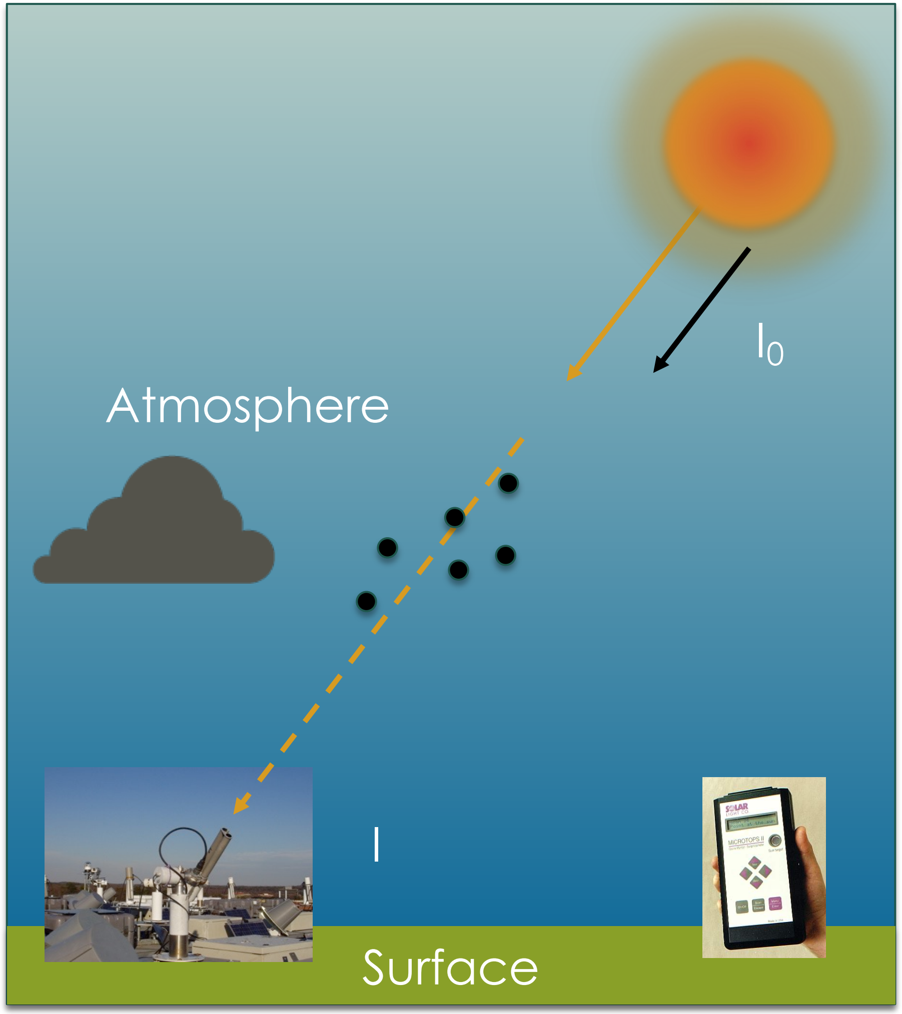
NASA Air Quality Remote Sensing Training, US EPA, Raleigh, NC, March 20-23, 2023

Objectives

By the end of this presentation, you will have an understanding of:

- Methods to estimate $PM_{2.5}$ mass concentration at surface level (μg m^{-3}) while using satellite derived Aerosol Optical Depth (AOD) at visible wavelengths

Optical Depth



The optical depth expresses the quantity of light removed from a beam by **scattering** and/or **absorption** during its path through a medium.

Optical Depth τ as:

$$I = I_o e^{-m\tau}$$

$$m = \sec\theta_0$$

$$\tau = \tau_{Rayl} + \tau_{aer} + \tau_{gas}$$

$PM_{2.5}$

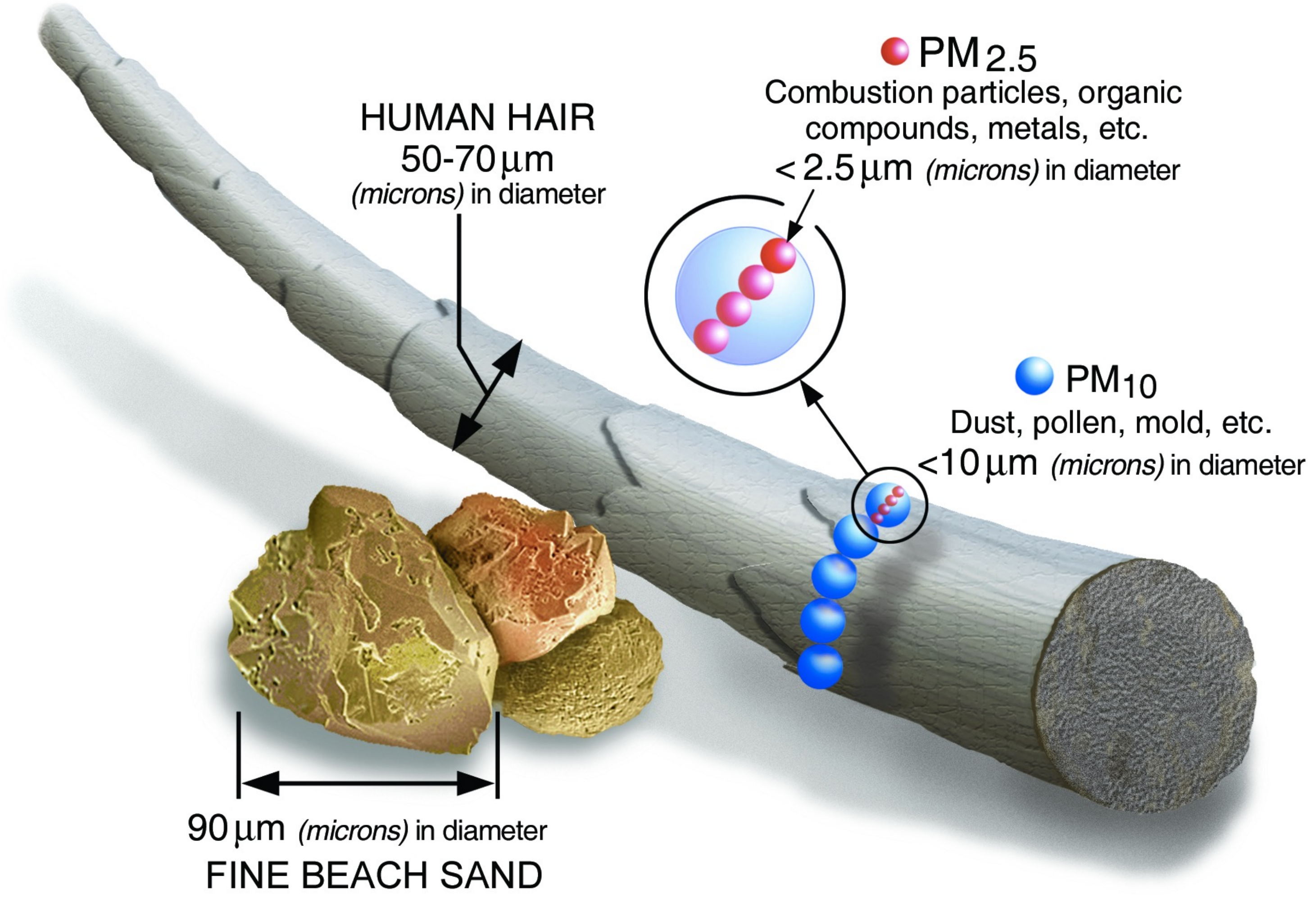


Image Credit: [U.S. EPA]

Surface vs. Satellite Measurements

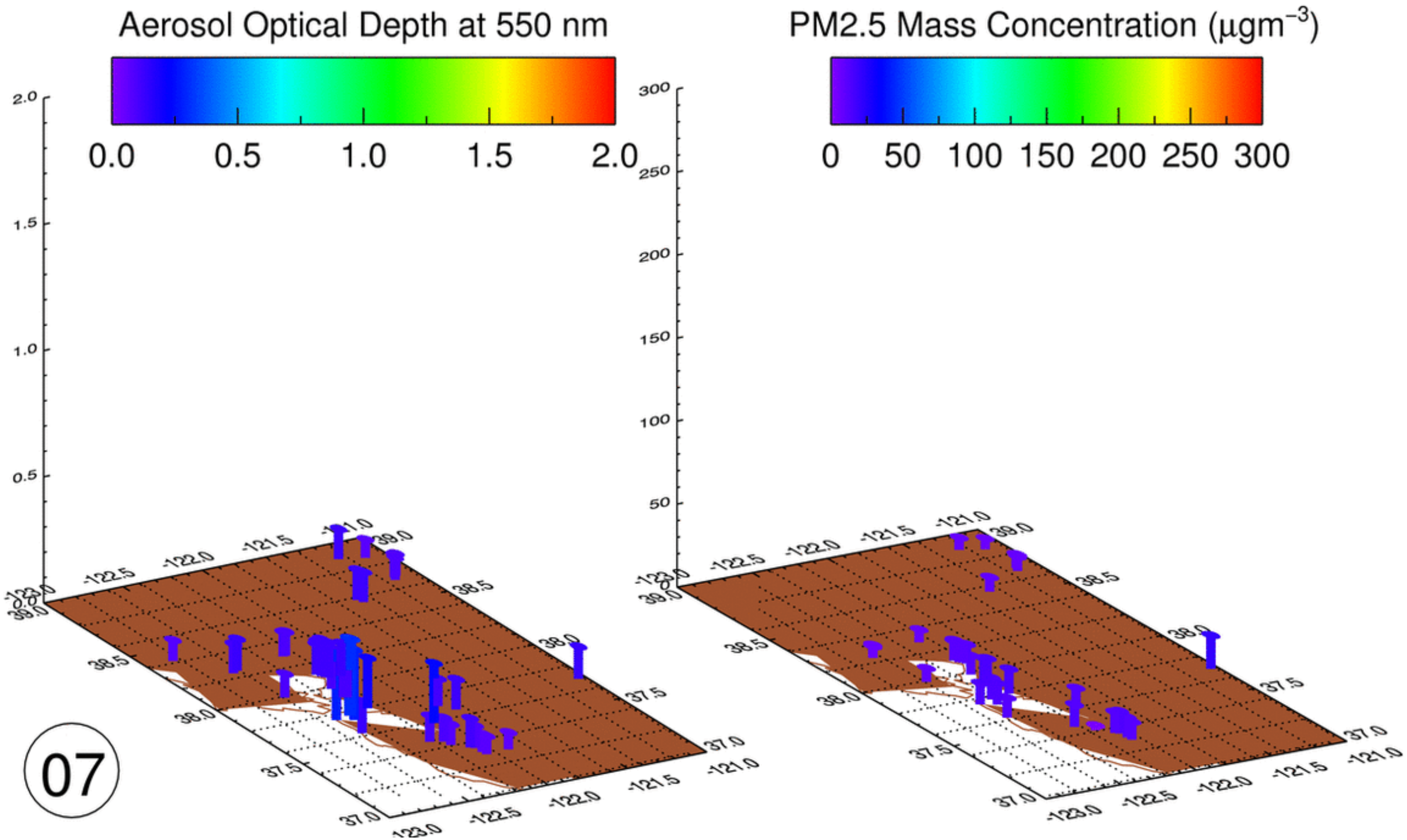
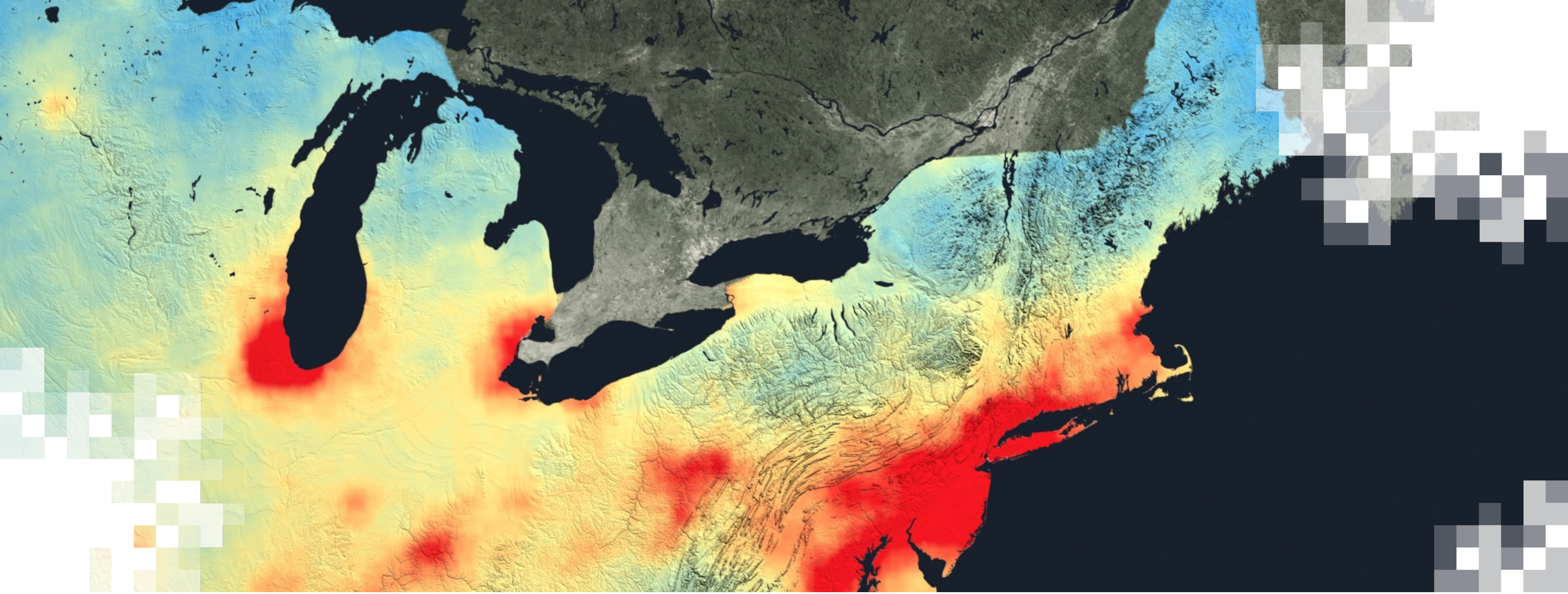
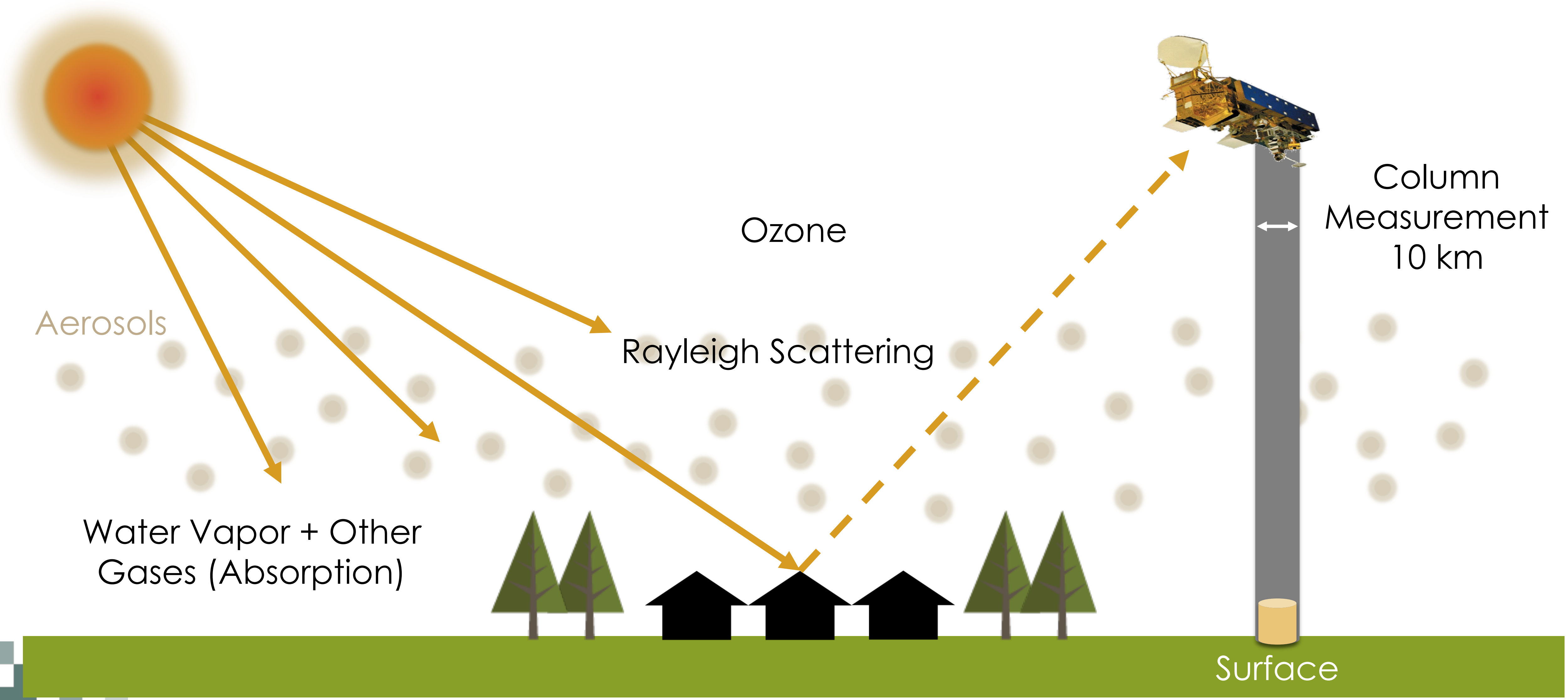


Image Credit: Gupta et al., 2018

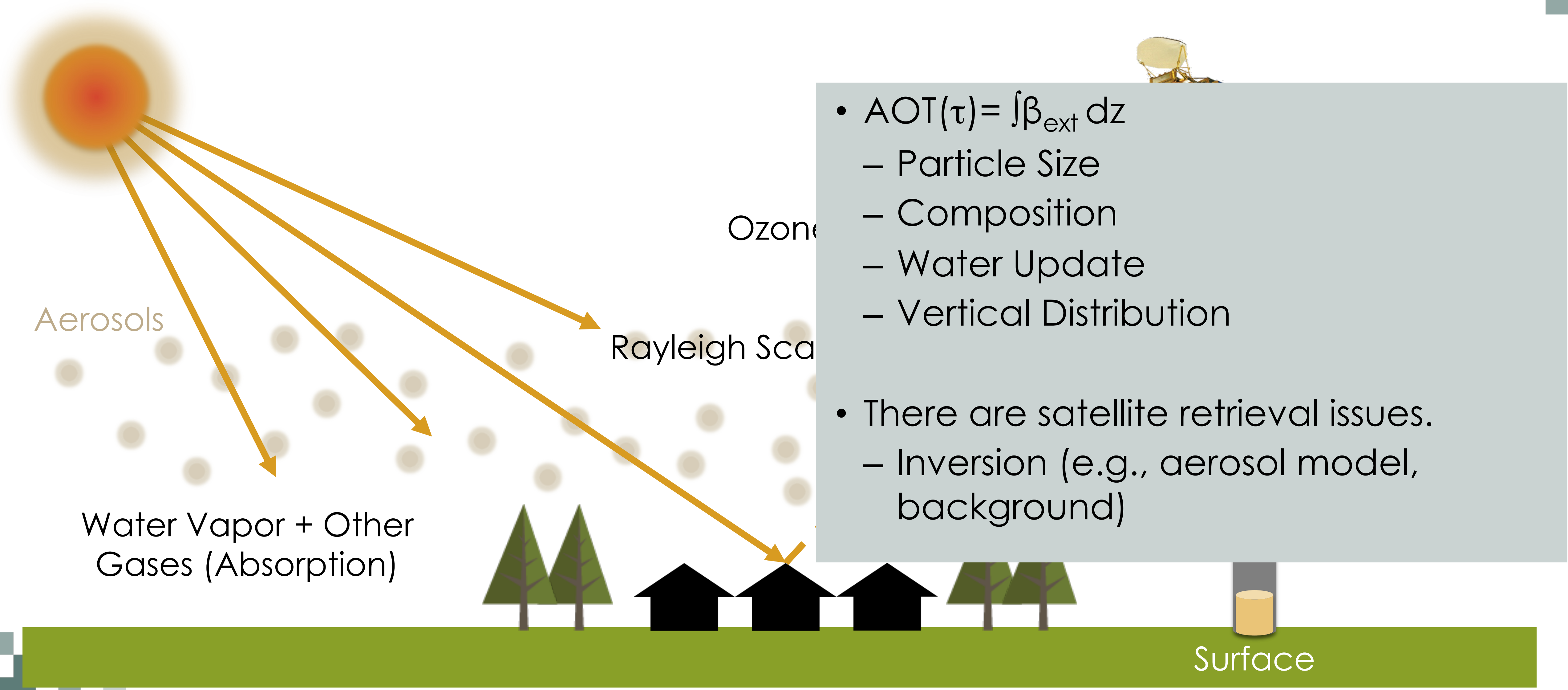


AOD (or AOT) to PM

Aerosol Optical Depth from Satellites



Aerosol Optical Depth from Satellites

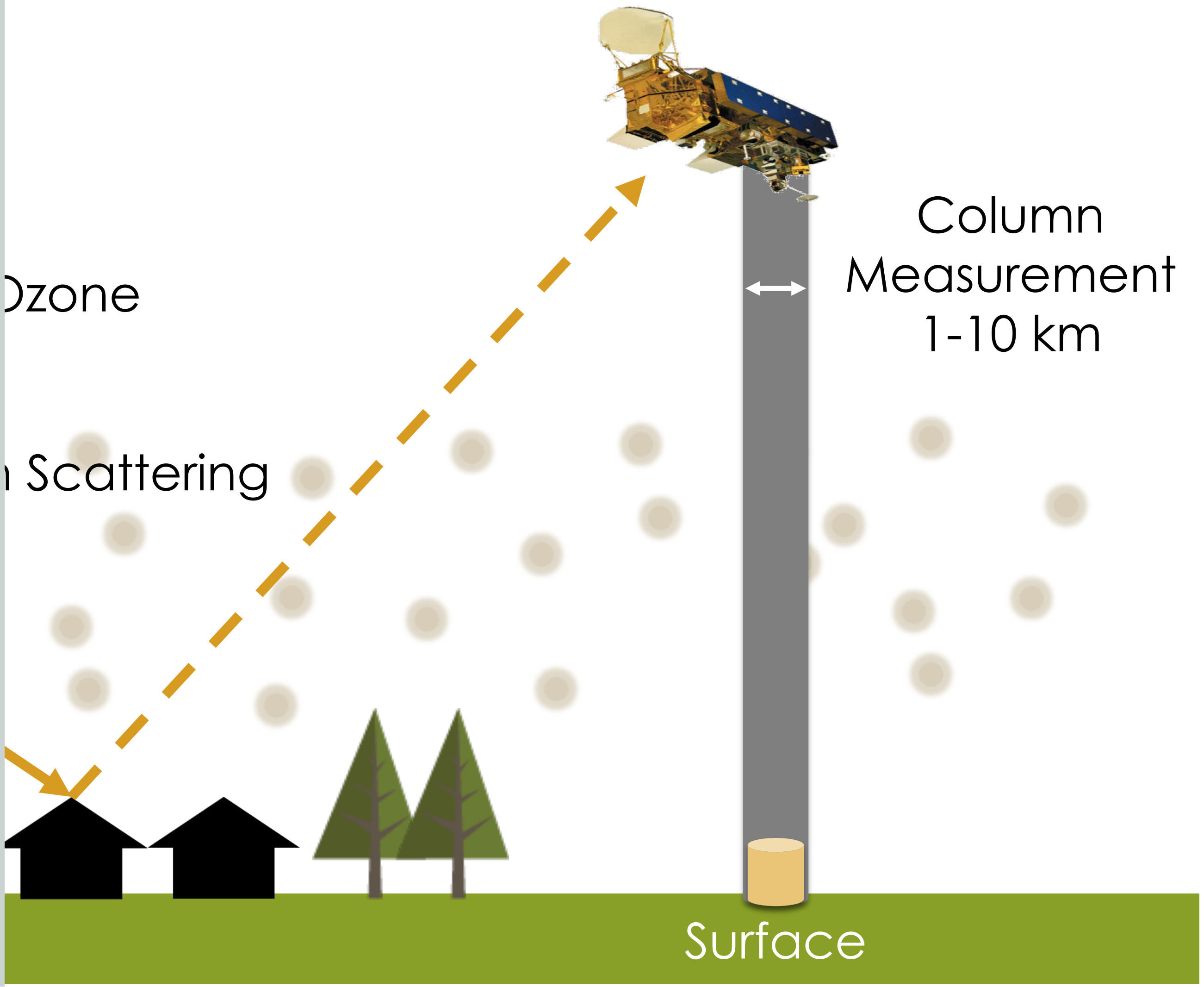


- AOT(τ)= $\int \beta_{ext}\, dz$
  - Particle Size
  - Composition
  - Water Update
  - Vertical Distribution

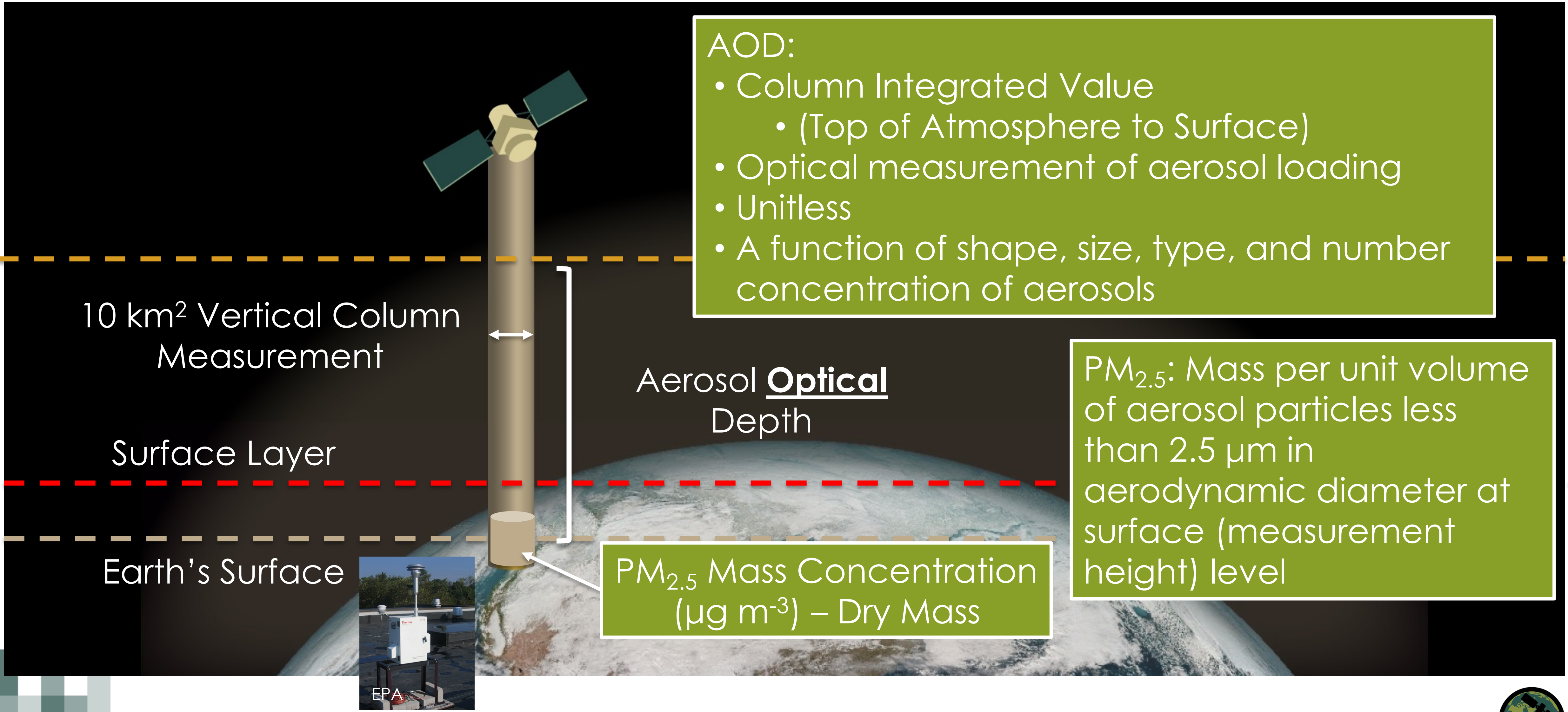
- There are satellite retrieval issues.
  - Inversion (e.g., aerosol model, background)

Aerosol Optical Depth from Satellites

- Seven MODIS bands are utilized to derive aerosol properties.
  - **0.47 µm**
  - 0.55 µm
  - **0.65 µm**
  - 0.86 µm
  - 1.24 µm
  - 1.64 µm
  - **2.13 µm**
- 10x10 km^2 resolution
- 6x6 km^2 resolution
- 3x3 km^2 resolution
- 1x1 km^2 resolution
- 0.75x0.75 km^2 resolution

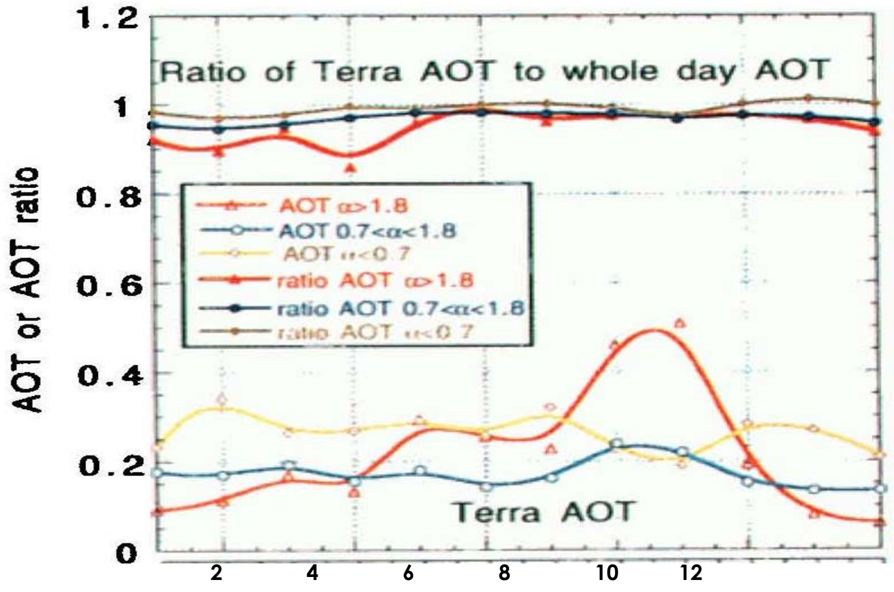


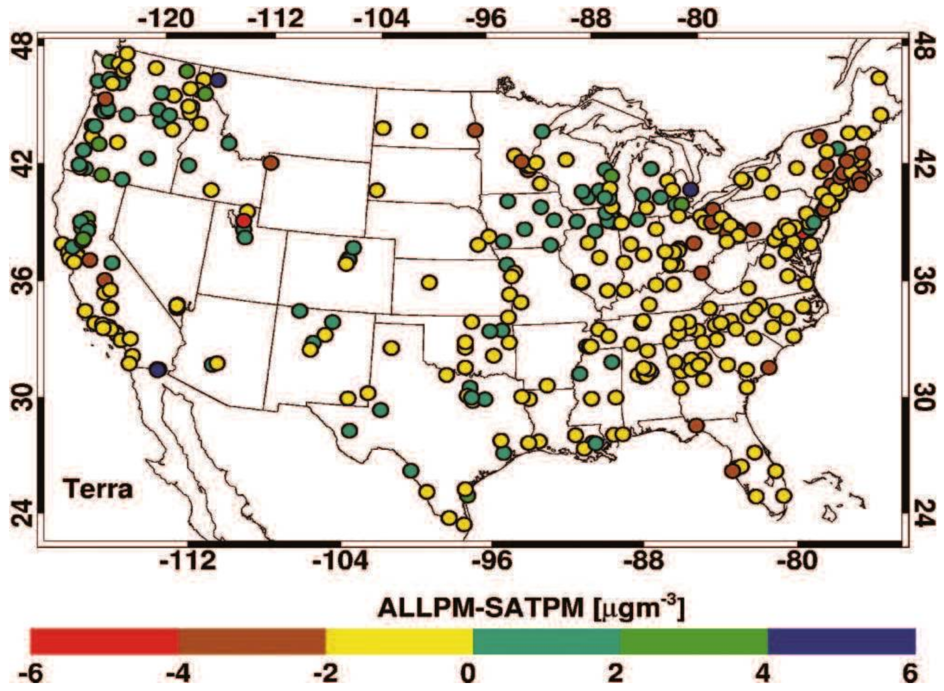
Satellite vs. Ground Observation



Support for AOD-$PM_{2.5}$ Linkage

- Satellite AOD is sensitive to $PM_{2.5}$.
  - Kahn et al. 1998
- Polar-orbing satellites can represent at least daytime average aerosol loadings.
  - Kaufman et al. 2000
- Missing data due to cloud cover appear random in general.
  - Gupta and Christopher, 2008
  - Christopher and Gupta, 2010





AOD-PM Relationship

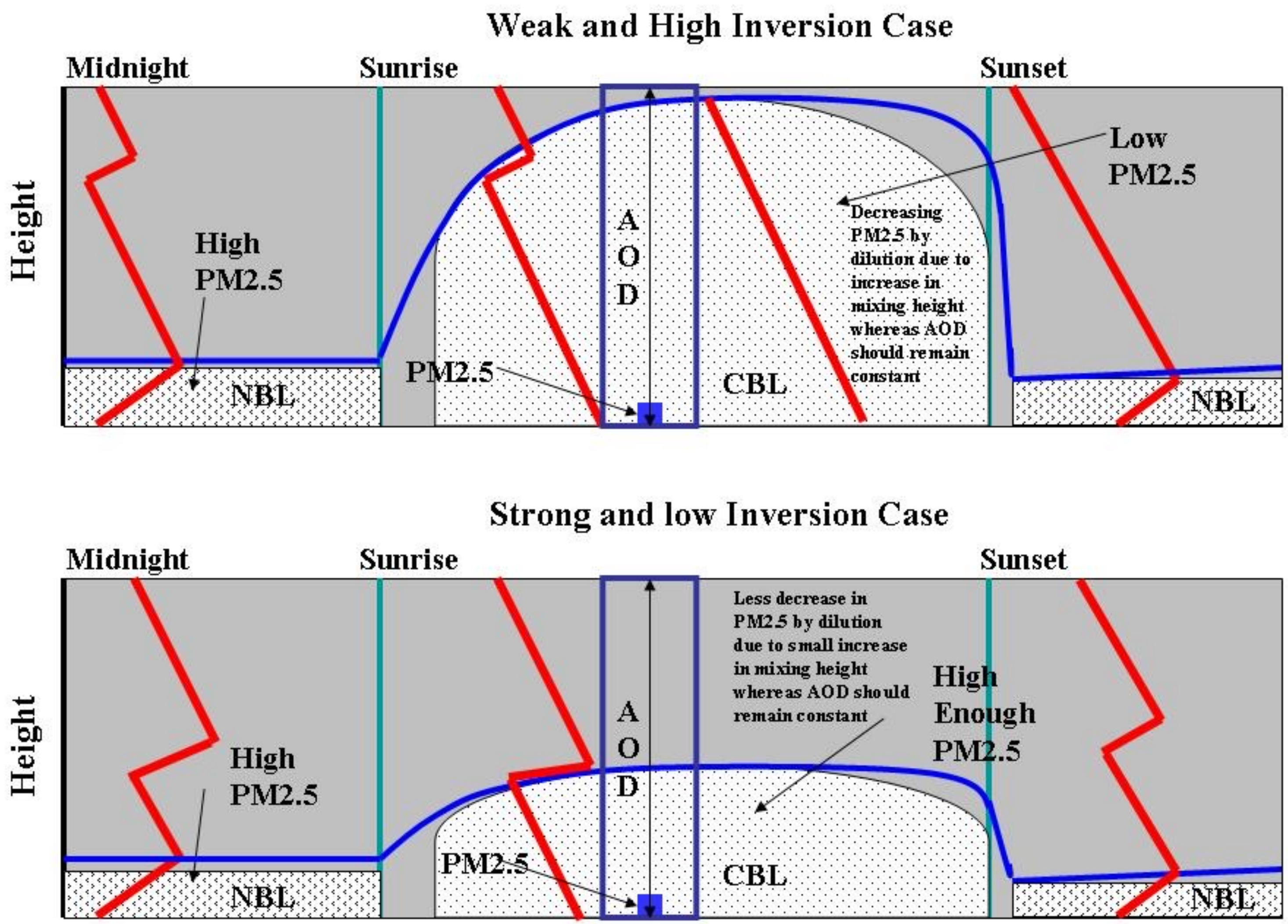
Assuming cloud-free skies, a well mixed boundary layer with no overhead aerosols, and aerosols that have similar optical properties*, AOD and $PM_{2.5}$ can be related by this equation:

$$\tau = PM_{2.5}\, \mathrm{H}\, \mathrm{f}(RH)\, \frac{3Q_{ext,dry}}{4\,\rho\, r_{eff}}$$

- τ: AOD at 550 nm
- ρ: Aerosol Mass Density
- r_e: Particle Effective Radius
- Q: Extinction Coefficient
- H: Mixing Height
- *ƒ(RH)*: How aerosol scattering changes with changing relative humidity

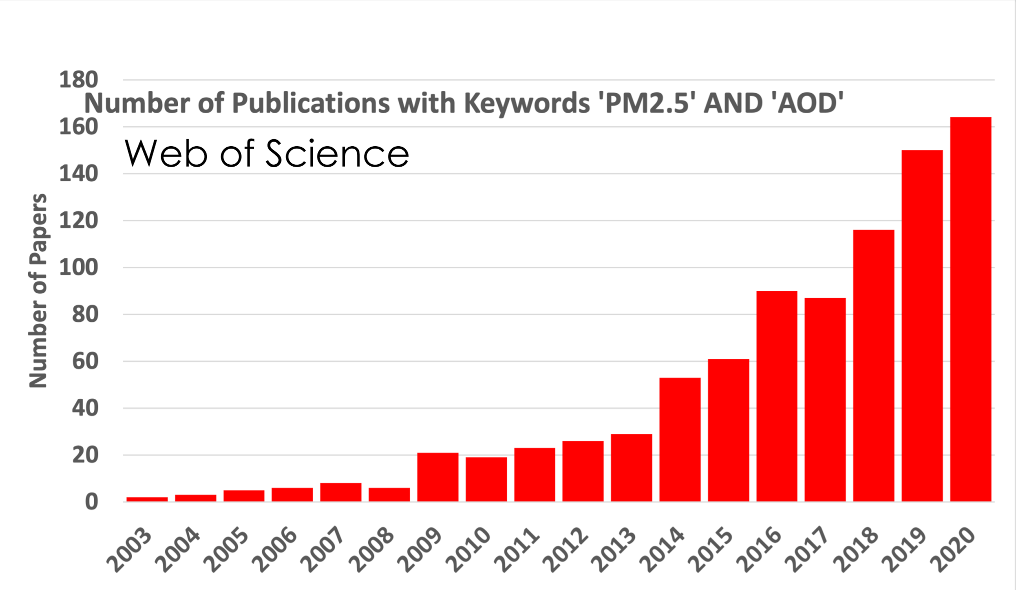
Source: Hoff, R. & Christopher, S., 2009

Vertical Mixing



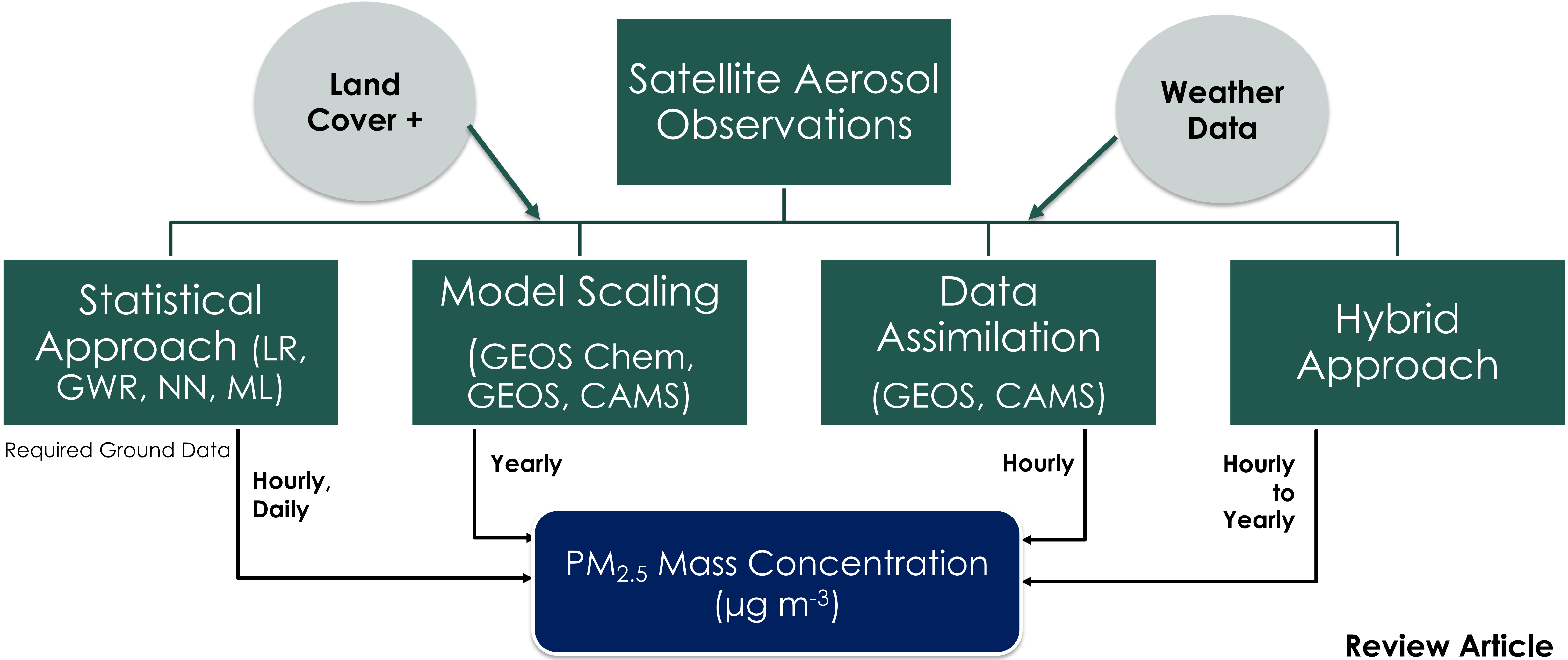
Particulate Matter (PM) from Satellites

- Kaufman and Fraser, 1983, Fraser et al., 1984
  - AOD and Sulfate from GOES-VISSR
- **Wang and Christopher, 2003, Chu et al., 2003**
  - AOD & $PM_{2.5}$ (and PM_{10}) relationship
- Liu et al., 2004, van Donkelaar et al., 2006
  - Used CTM to scale AODs to $PM_{2.5}$
- Gupta and Christopher, 2009
  - Used Artificial Intelligence to convert AOD to $PM_{2.5}$
- van Donkelaar et al., 2010, 2015, 2019, 2021
  - Global Product – Annual & Monthly Mean
- Shaddick et al., 2017, 2018
  - Bias corrected annual $PM_{2.5}$ data for WHO, SDGs
- Di et al., 2019 – Daily CONUS $PM_{2.5}$ (MAIAC)
- Hai and Kondragunta, 2021 – Hourly/Daily from VIIRS & GOES-R



Research on AOD to $PM_{2.5}$ conversion is growing exponentially, but we only have annual & monthly mean global products and no daily or sub-daily operational global products from satellites.

Almost Two Decades of Research and Learning



Review Article
Hoff and Christopher, 2009
Li et al., 2020
Lee, 2020

$PM_{2.5}$ Estimation: Popular Methods

Difficulty Level

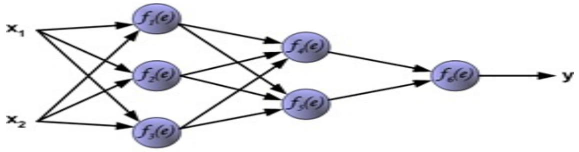
Two-Variable Method

$Y = mX + c$

Multivariable Method

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

Artificial Intelligence/ML/DL



MSC

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

$PM_{2.5}$ Estimation: Two Variable Method (TVM)

Difficulty Level

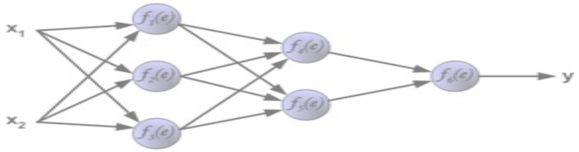
Two-Variable Method

$$Y = mX + c$$

Multivariable Method

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

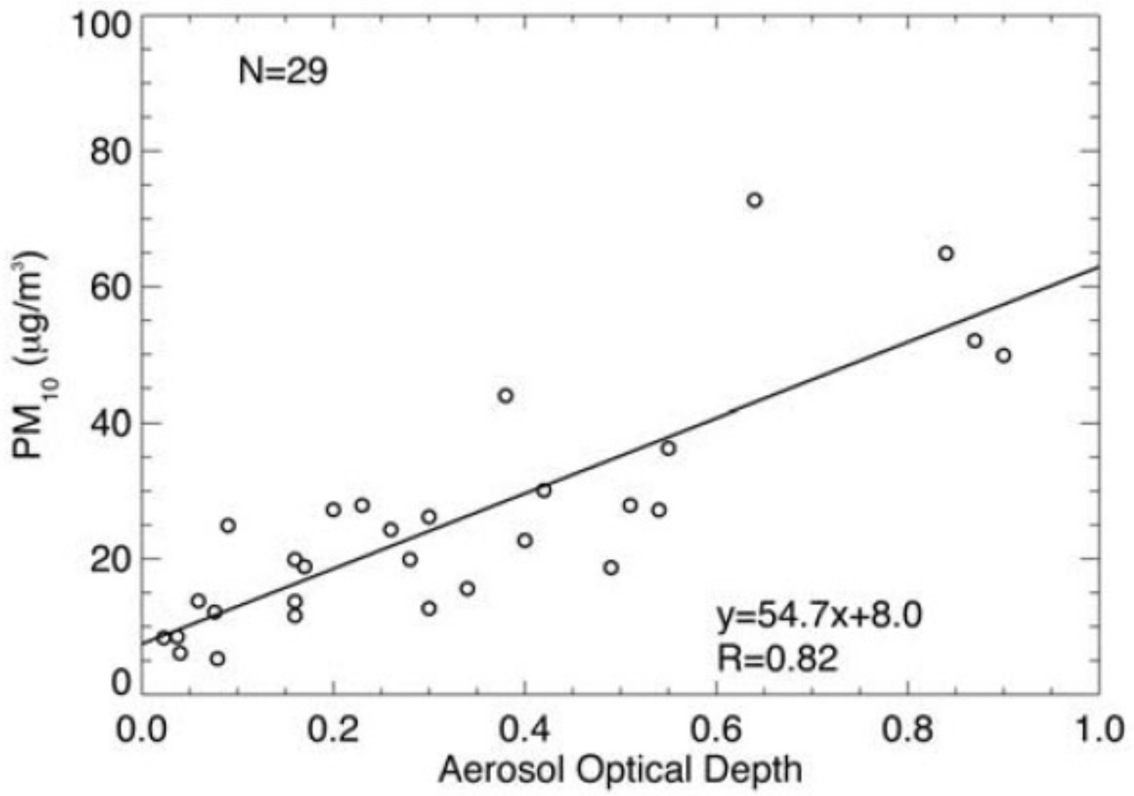
Artificial Intelligence

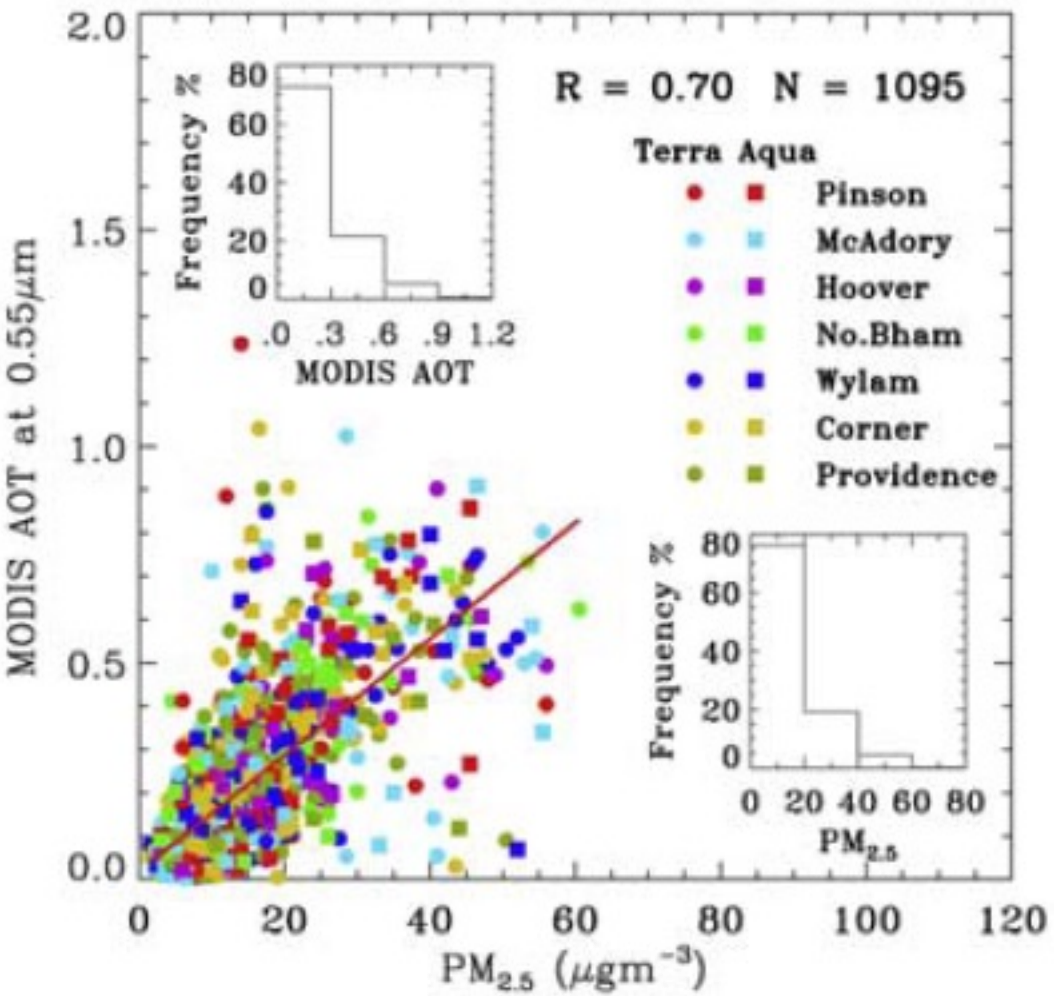


MSC

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

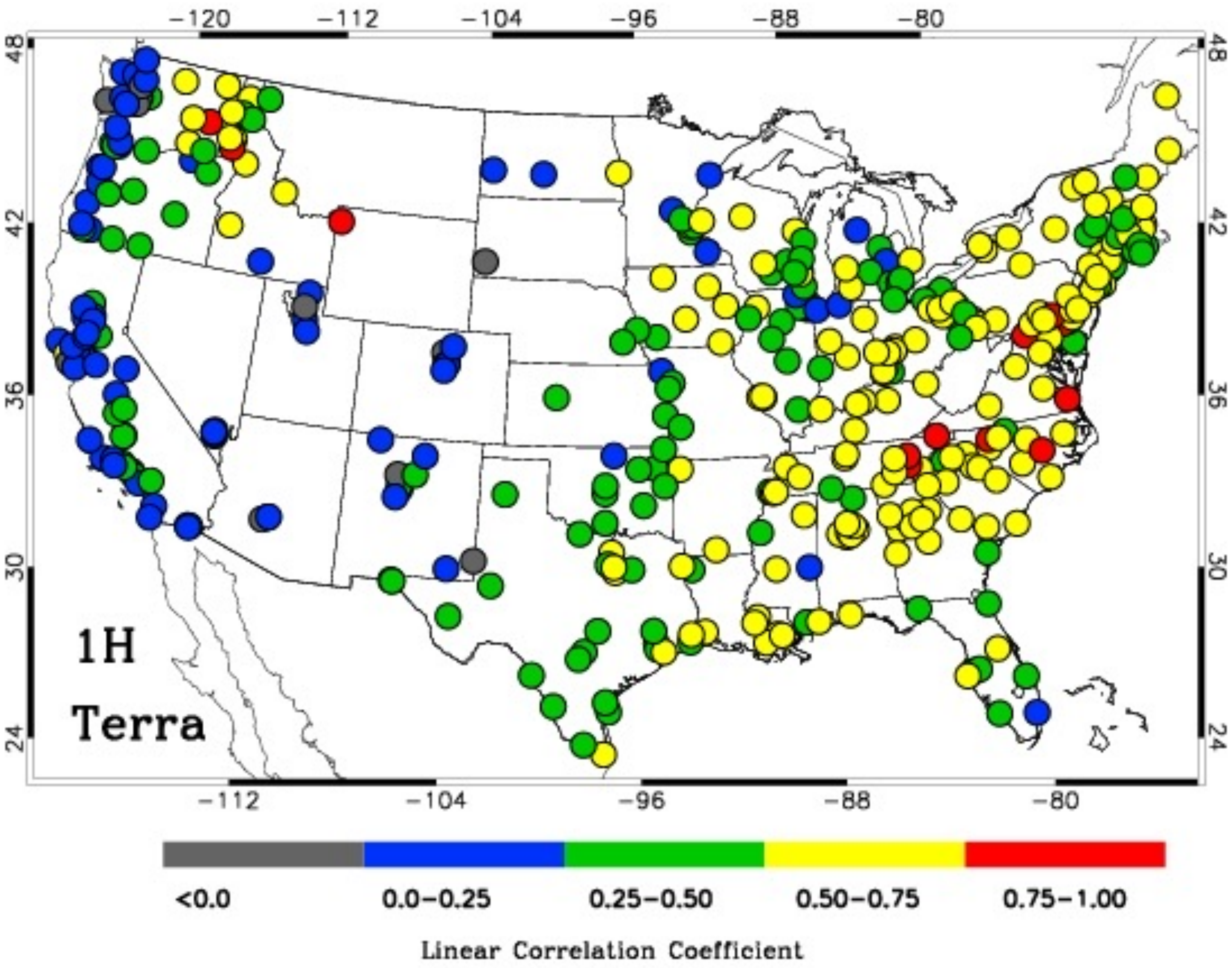
Simple Models from Early Days





(Left) Chu et al., 2003; (Right) Wang et al., 2003

AOD-$PM_{2.5}$ Relationship



Source: Gupta et al., 2008

$PM_{2.5}$ Estimation: Multivariable Method (MVM)

Difficulty Level

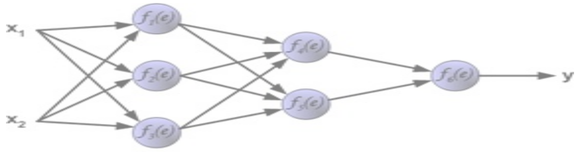
Two-Variable Method

$Y = mX + c$

Multivariable Method

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

Artificial Intelligence

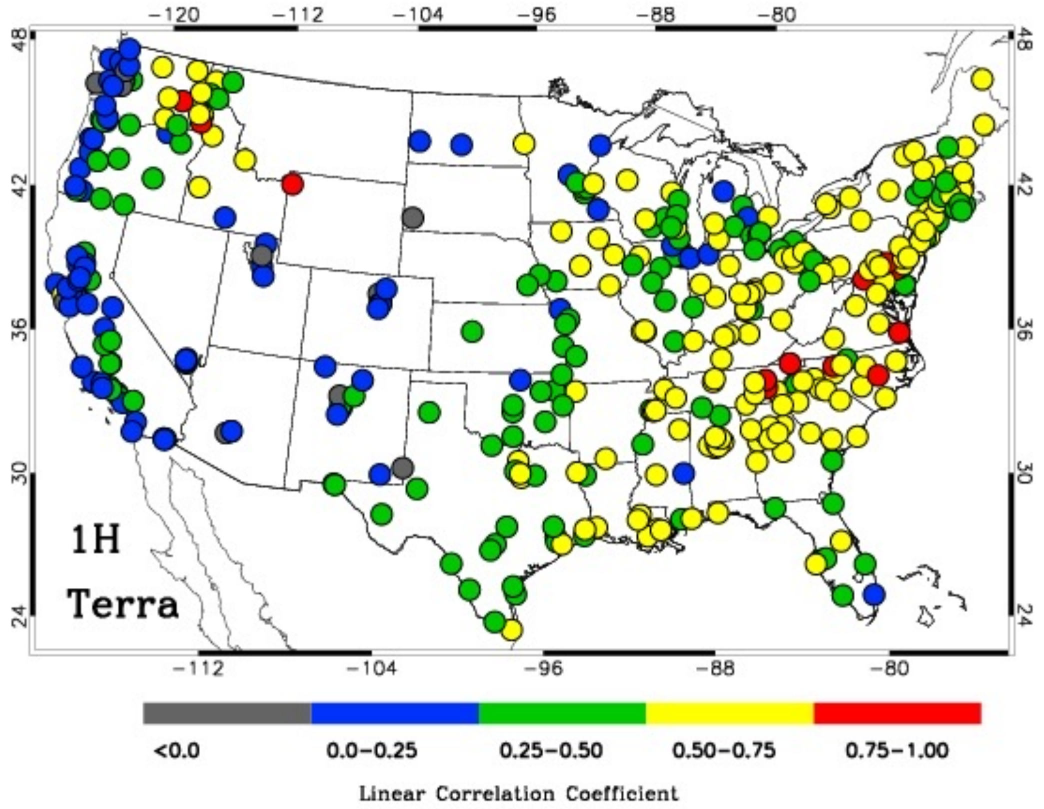


MSC

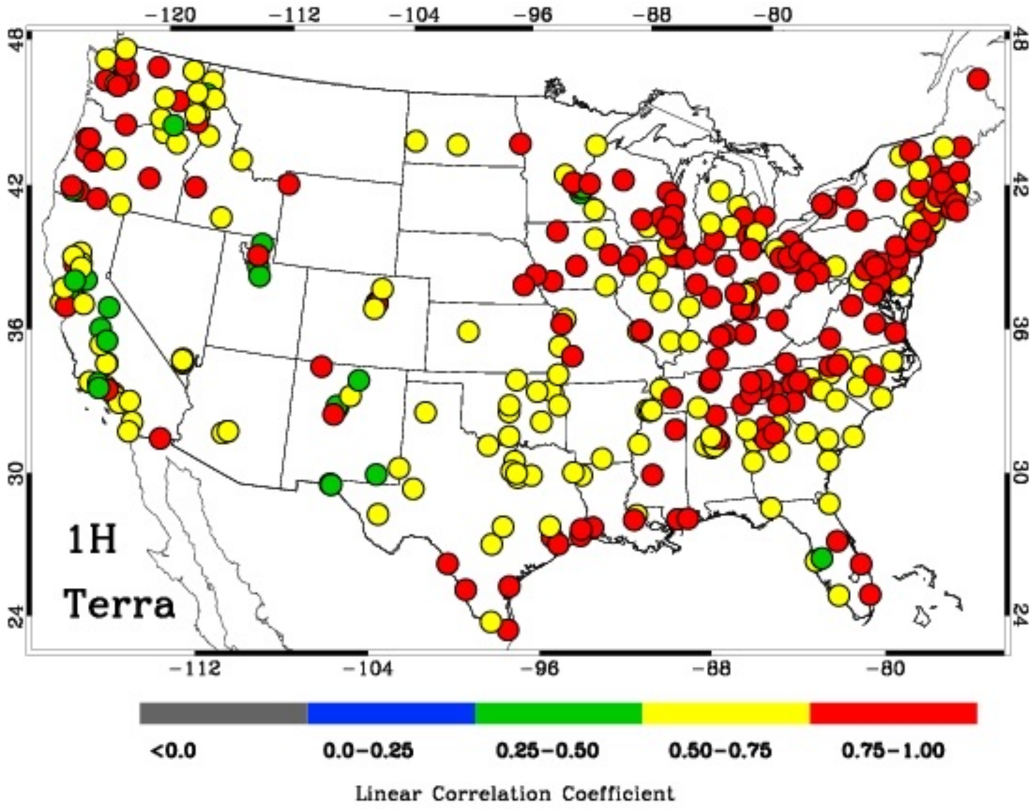
$$\text{Estimated } PM_{2.5} = \frac{\text{Model Surface Area Concentration}}{\text{Model AOD}} \times \text{Satellite AOD}$$

Multivariable Method (MVM)

Predictor: AOD



Predictor: AOD + Meteorology



Linear Correlation Coefficient Between Observed and Estimated $PM_{2.5}$

Source: Gupta et al., 2008

Multivariable Method – Beyond Meteorology

- Advanced Regression Analysis with More Input Parameters
  - Land Cover Type
  - Forest Cover, Shrub Cover
  - Urban %
  - DEM (Altitude)
  - Road Length
  - Population Density
  - Snow Fraction
  - Shortwave Radiation
  - NDVI

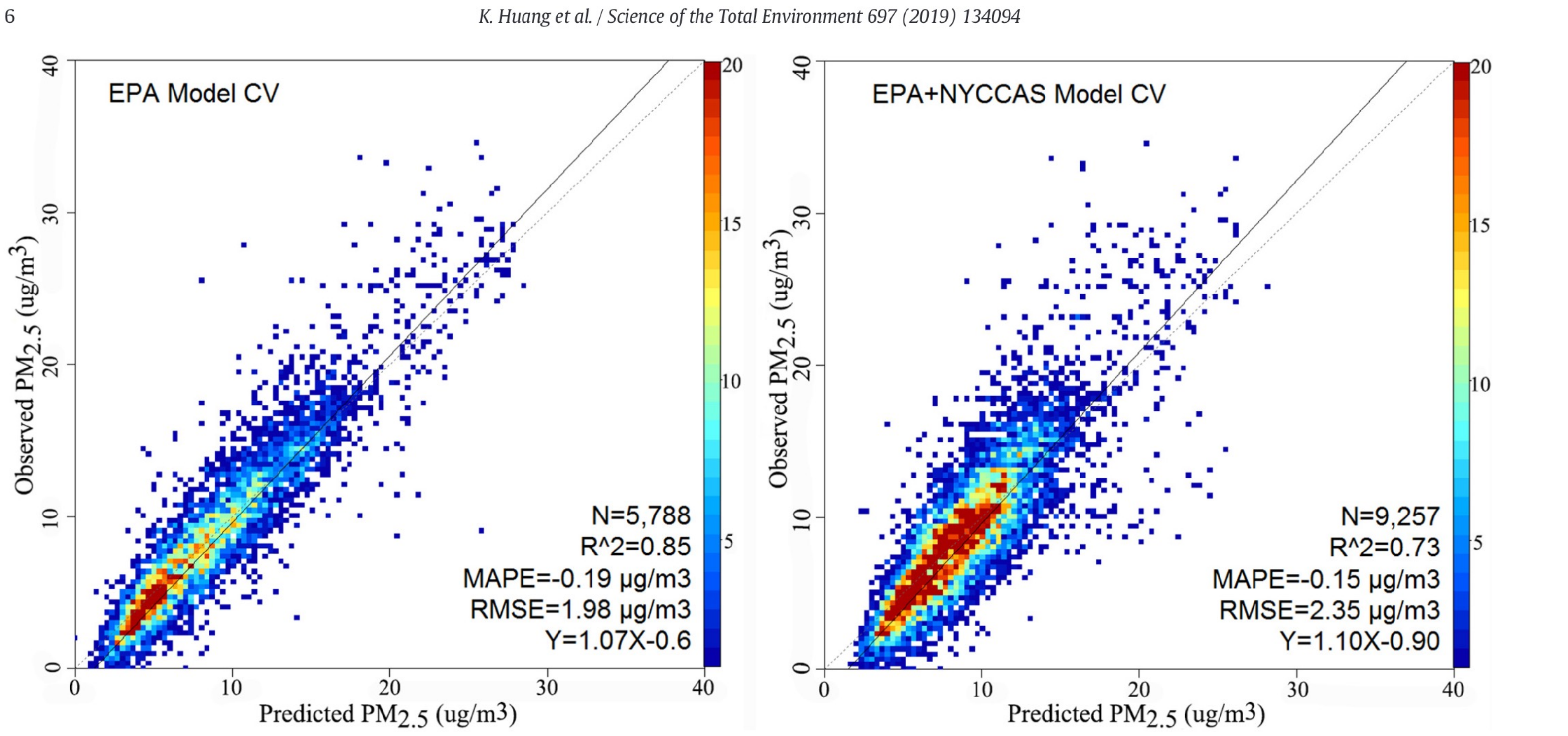


Fig. 2. Ten-fold cross-validation results for the EPA model and EPA + NYCCAS models.

https://www.sciencedirect.com/science/article/pii/S0048969719340719

$PM_{2.5}$ Estimation: Artificial Intelligence (or ANN)

Difficulty Level

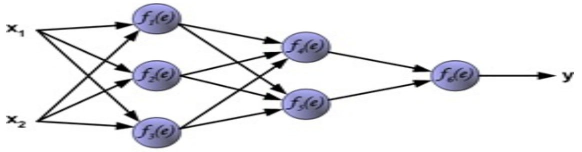
Two-Variable Method

$$Y = mX + c$$

Multivariable Method

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

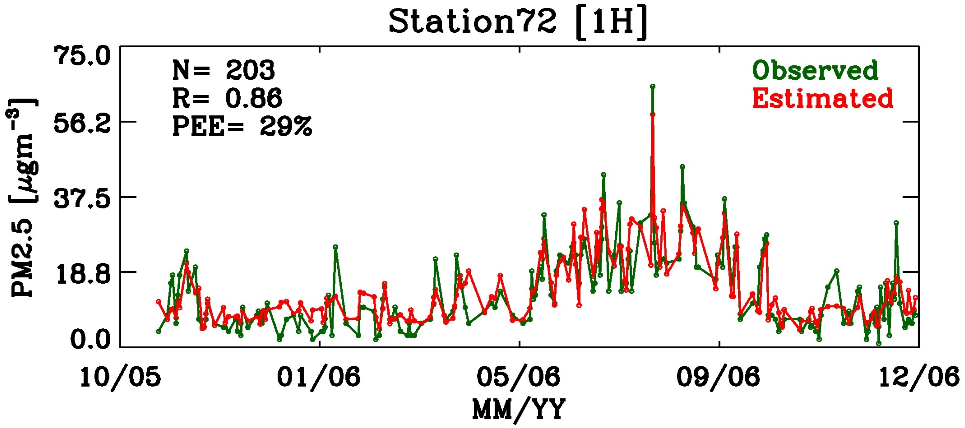
Artificial Intelligence

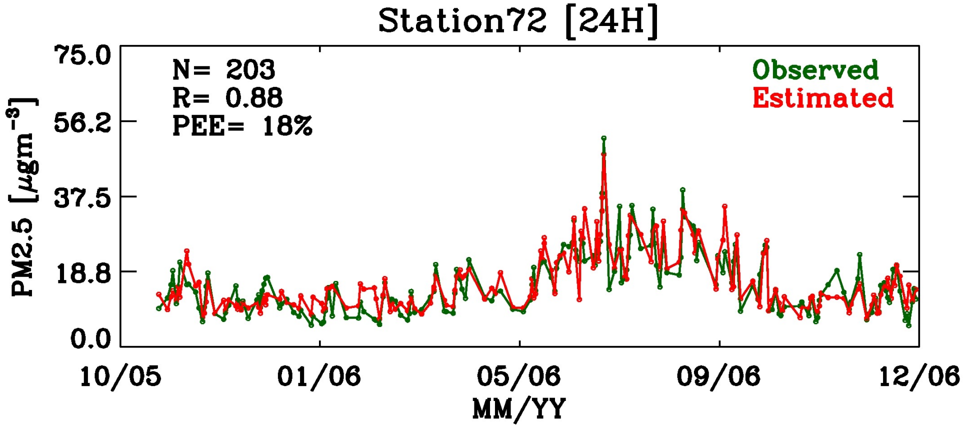


MSC

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

Examples of Results from ANN & RF





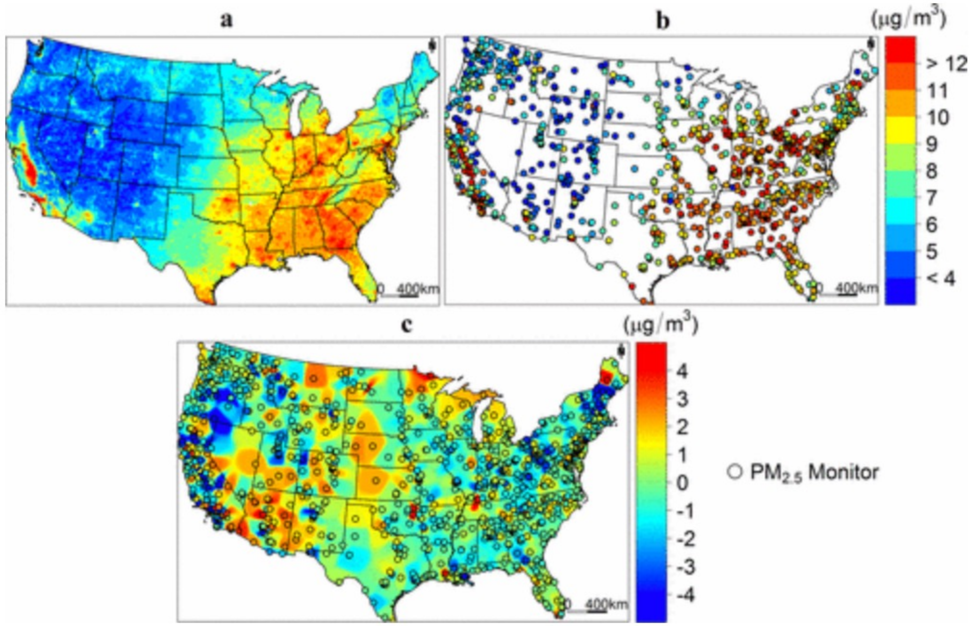


Figure 4. Annual mean predictions. (a) Annual mean $PM_{2.5}$ predictions over the continental United States for 2011; (b) annual mean $PM_{2.5}$ measurements at ground monitors; (c) difference between annual mean predictions and observations at ground monitors and difference interpolations over the continental United States.

Source: Gupta 2009, Hu et al., 2017

$PM_{2.5}$ Estimation: Model Scaling (MSC)

Difficulty Level

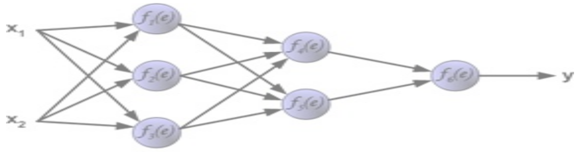
Two-Variable Method

$Y = mX + c$

Multivariable Method

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

Artificial Intelligence



MSC

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

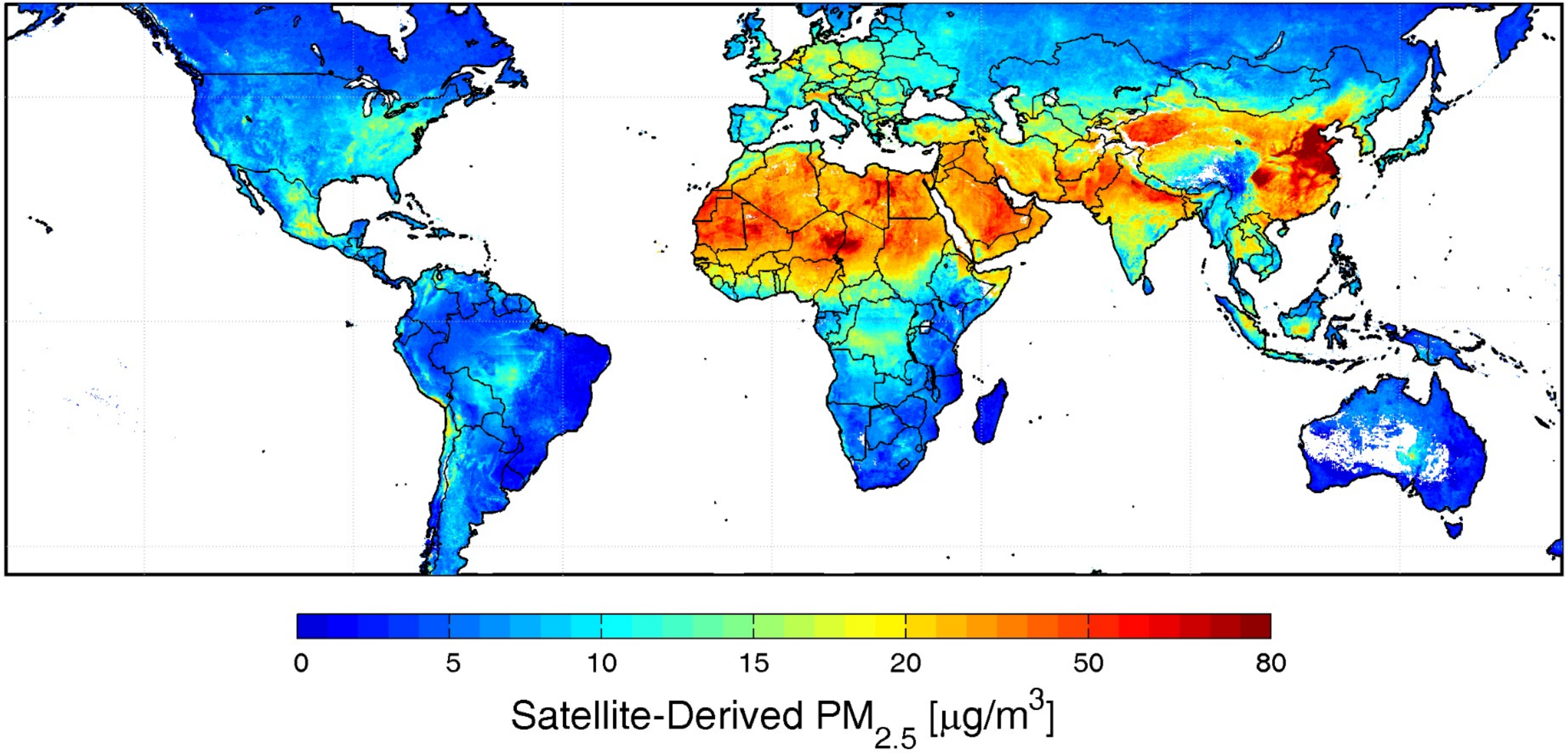
Scaling Approach

- Basic Idea:
  - Let an atmospheric chemistry model decide the conversion from AOD to $PM_{2.5}$.
  - Satellite AOD is used to calibrate the absolute value of the model-generated conversion ratio.

- Satellite-Derived $PM_{2.5}$ $= \left(\frac{PM_{2.5}}{AOD} \right)_{Model} \times$ Satellite AOD

Source: Liu et al., 2006

Annual Mean $PM_{2.5}$ from Satellite Observations

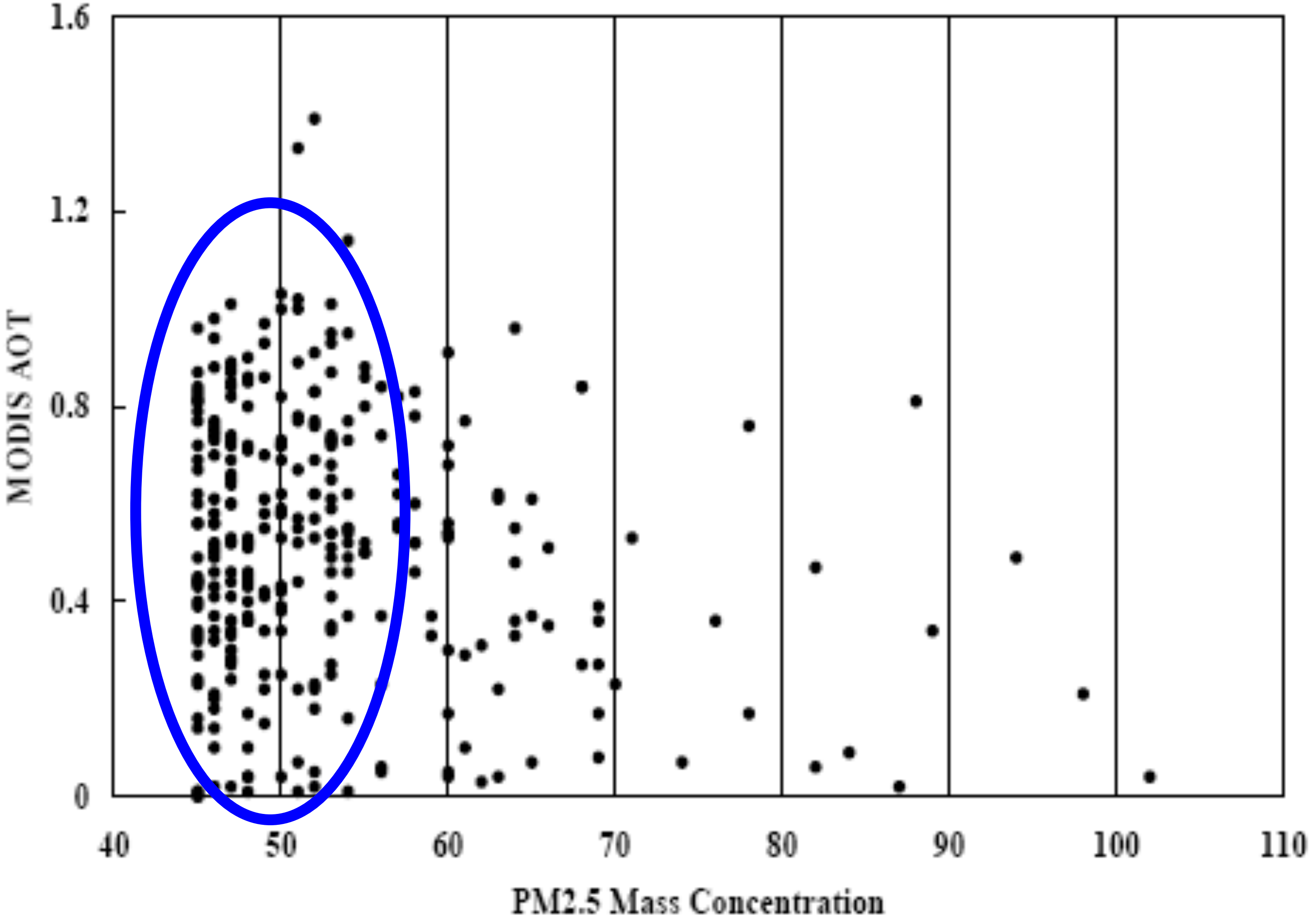


Source: von Donkelaar et al., 2006, 2009

Questions to Ask: Issues

- How accurate are these estimates?
- Is the $PM_{2.5}$ – AOD relationship always linear?
- How does AOD retrieval uncertainty impact estimation of air quality?
- Does this relationship change in space and time?
- Does this relationship change with aerosol type?
- How does meteorology drive this relationship?
- How does the vertical distribution of aerosols in the atmosphere impact these estimates?

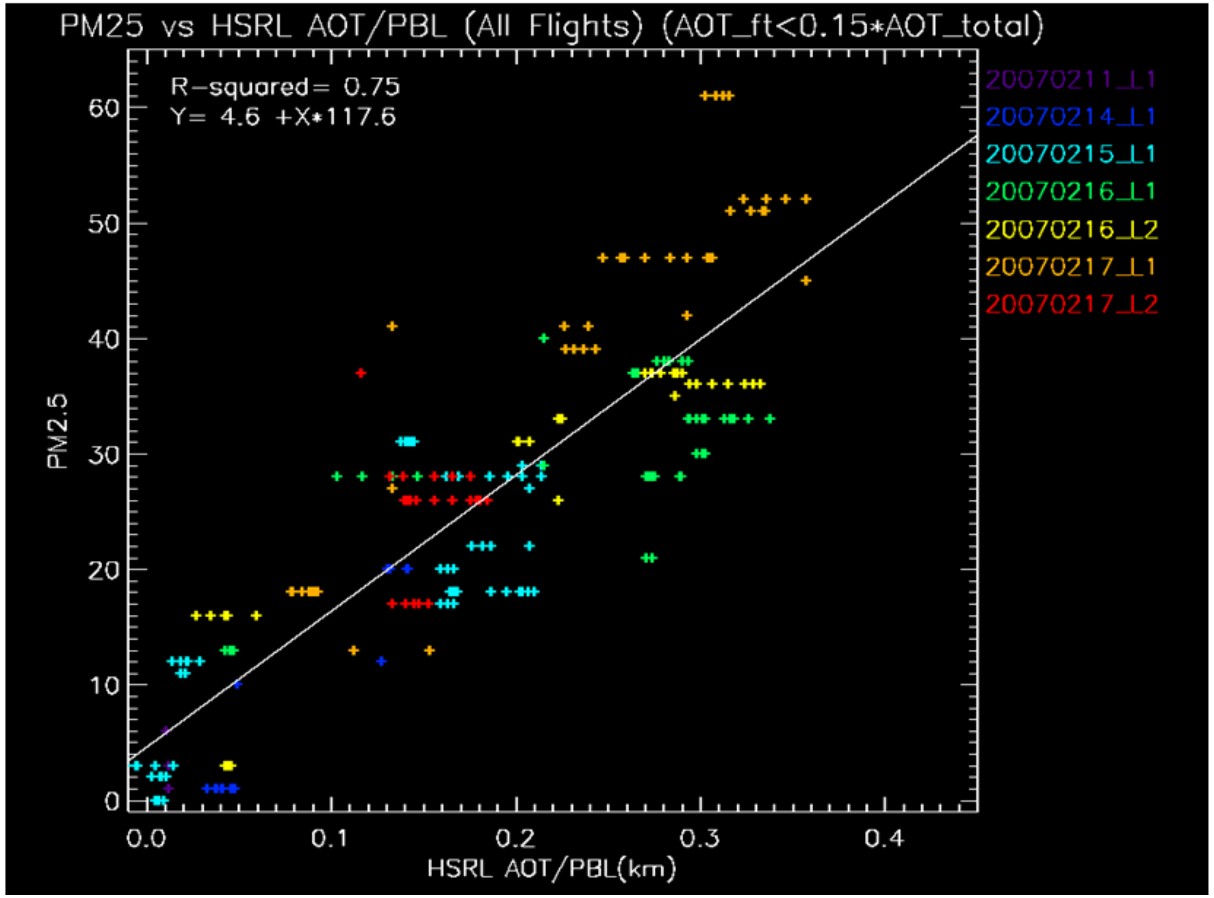
Limitation: Vertical Distribution of Aerosols



Source: Gupta et al., 2009

Vertical Distribution: Impact on AOD-$PM_{2.5}$

- Normalizing AOD with boundary layer height significantly improves the correlation with surface $PM_{2.5}$ (R^2 increases from 0.36 to 0.75).
- With accurate estimates of PBL height, AOD can be a good proxy for $PM_{2.5}$.



Source: Al-Saadi et al., 2008

Assumption for Quantitative Analysis

When most particles are concentrated and well mixed in the boundary layer, satellite AOD contains a strong signal of ground-level particle concentrations.

No Textbook Solution

Use of Satellite Data

- Currently for Research & Applications
  - Spatial distribution of $PM_{2.5}$ on a regional to national level
  - Long term trends of $PM_{2.5}$
  - Model calibration, data assimilation, and validation
  - Exposure assessments for health effect studies
  - Spatial trends at urban scales
  - Improved coverage and accuracy
  - Fused statistical-deterministic models
- For Regulation?

Suggested Reading

http://www.nsstc.uah.edu/sundar/papers/2009/AWMA-proof.pdf

2009 CRITICAL REVIEW

ISSN:1047-3289 *J. Air & Waste Manage. Assoc.* 59:645–675
DOI:10.3155/1047-3289.59.6.645

R.M. Hoff

S.A. Christopher

Remote Sensing of Particulate Pollution from Space: Have We Reached the Promised Land?

Raymond M. Hoff
Department of Physics and the Joint Center for Earth Syste... and Technology Center, University of Maryland, Baltimore ...

Sundar A. Christopher
Department of Atmospheric Sciences and Earth System Sc... Alabama–Huntsville, Huntsville, AL

IMPLICATIONS

Satellite measurements are going to be an integral part of the Global Earth Observing System of Systems. Satellite measurements by themselves have a role in air quality studies but cannot stand alone as an observing system. Data assimilation of satellite and ground-based measurements into forecast models has synergy that aids all of these air quality tools.

the "but for" provision in the rule makes the use of satellite data possible in significant exceedances only. Applications such as event identification, transport, and atmospheric composition determination are strengths of satellite measurements. Where high precision is required (compliance monitoring, the "but for" test, and quantitative measurement of visibility effects on Class I areas), satellite data are presently of limited utility.

The use of the AOD as a measure for mass concentration has skill in some regions but less in others and does not provide a uniform way to measure aerosols across the United States. We discussed in Table 4 the range of mea-

In 2007, the A&WMA Critical Review by Bachmann discussed the history of the National Ambient Air Quality Standards (NAAQS).[142] The 39-yr history of those standards parallels the time period that satellite meteorology and observations have developed and yet, to date, no satellite measurements have been used to quantitatively address the NAAQS. From the review conducted here, only one congres-

EPA has taken a satellite observations role for itself in the Exceptional Events Rule.[144] If a region can show conclusively that they are being impacted by an event (a fire, a dust storm, etc.) that is outside of their jurisdiction to regulate, the event can be flagged as a nonexceedance event. This provides a significant motivation for regional

Although the desire for the use of satellite data for air quality purposes is widely stated, the reality is that many of the measurements have not yet met the promise that they can be operationally used for today's air quality monitoring requirements. Precision in measuring AOD is

More Review Articles

Review

A Review on Predicting Ground $PM_{2.5}$ Concentration Using Satellite Aerosol Optical Depth

Yuanyuan Chu [1,2,†], Yisi Liu [1,†], Xiangyu Li [1,2], Zhiyong Liu [3], Hanson Lu [4], Yuanan Lu [2,5], Zongfu Mao [1,2], Xi Chen [1], Na Li [1], Meng Ren [1], Feifei Liu [1], Liqiao Tian [6], Zhongmin Zhu [6,7] and Hao Xiang [1,2,*]

1 Department of Epidemiology and Biostatistics, School of Public Health, Wuhan University, 115# Donghu Road, Wuhan 430071, China; 2014203050033@whu.edu.cn (Y.C.); roselewis@sina.com (Y.L.); 2015203050022@whu.edu.cn (X.L.); zfmao@126.com (Z.M.); aries_c_7@163.com (X.C.); 2012302170047@whu.edu.cn (N.L.); melodyrren@163.com (M.R.); 2015203050008@whu.edu.cn (F.L.)
2 Global Health Institute, Wuhan University, 115# Donghu Road, Wuhan 430071, China; yuanan@hawaii.edu
3 The National Environmental Satellite, Data, and Information Service (NESDIS), National Oceanic and Atmospheric Administration (NOAA), 5830 University Research Court, College Park, MD 20740, USA; Zhiyonglau@gmail.com
4 International Baccalaureate Diploma Program, Wuhan Foreign Languages School, Wan Song Yuan Road, Wuhan 430022, China; hansonlu_hl@hotmail.com
5 Environmental Health Laboratory, Department of Public Health Sciences, University of Hawaii at Manoa, 1960 East-West Road, Honolulu, HI 96822, USA
6 State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, 129# Luoyu Road, Wuhan 430079, China; tianliqiao@whu.edu.cn (L.T.); zhongmin.zhu@whu.edu.cn (Z.Z.)
7 College of Information Science and Engineering, Wuchang Shouyi University, Wuhan 430064, China
* Correspondence: xianghao@whu.edu.cn; Tel.: +86-27-6875-9118
† These authors contributed equally to this work.

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journal homepage: www.elsevier.com/locate/rse

Review

A review of statistical methods used for developing large-scale and long-term $PM_{2.5}$ models from satellite data

Zongwei Ma [a,*], Sagnik Dey [b,c], Sundar Christopher [d], Riyang Liu [a], Jun Bi [a], Palak Balyan [b], Yang Liu [e,*]

a State Key Laboratory of Pollution Control and Resource Reuse, School of the Environment, Nanjing University, Nanjing, Jiangsu, China
b Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, Hauz Khas, New Delhi, India
c Centre of Excellence for Research on Clean Air, Indian Institute of Technology Delhi, Hauz Khas, New Delhi, India
d Department of Atmospheric and Earth Science, University of Alabama in Huntsville, USA
e Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA, USA

ARTICLE INFO

Editor: Menghua Wang

Keywords:
Satellite remote sensing
Aerosol optical depth
$PM_{2.5}$ estimates
Statistical methods

ABSTRACT

Research of $PM_{2.5}$ chronic health effects requires knowledge of large-scale and long-term exposure that is not supported by newly established monitoring networks due to their sparse spatial coverage and lack of historical measurements. Estimating $PM_{2.5}$ using satellite-derived aerosol optical depth (AOD) can be used to fill the data gap left by the ground monitors and extend the $PM_{2.5}$ data coverage to suburban and rural areas over long time periods. Two approaches have been applied in large-scale and long-term satellite remote sensing of $PM_{2.5}$, i.e., the scaling and statistical approaches. Compared to the scaling method, the statistical approach has greater prediction accuracy and has been widely used. There is a gap in the current literature and review papers on how the statistical methods work and specific considerations to best utilize them, especially for large-scale and long-term estimates. In this critical review, we summarize the evolution of large-scale and long-term $PM_{2.5}$ statistical models reported in the literature. We describe the framework and guidance of large-scale and long-term satellite-based $PM_{2.5}$ modeling in data preparation, model development, validation, and predictions. Sample computer codes are provided to expedite new model-building efforts. We also include useful considerations and recom-

https://www.sciencedirect.com/science/article/pii/S0034425721005472

https://www.researchgate.net/profile/Hyung-Joo-Lee/publication/348104773_Advancing_Exposure_Assessment_of_PM25_Using_Satellite_Remote_Sensing_A_Review/links/60bc5ad6458515218f94cec3/Advancing-Exposure-Assessment-of-PM25-Using-Satellite-Remote-Sensing-A-Re

Review Article

Advancing Exposure Assessment of $PM_{2.5}$ Using Satellite Remote Sensing: A Review

Hyung Joo Lee*

California Air Resources Board, 1001 I Street, Sacramento, CA 95812, USA

*Corresponding author.
Tel: +1-916-323-1193
E-mail: hyungjoo.lee@arb.ca.gov

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ABSTRACT Epidemiological studies have reported the associations of adverse health outcomes with ambient particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$ ($PM_{2.5}$). While these studies have accumulated increasingly refined evidence on $PM_{2.5}$-health associations, the needs for more advanced $PM_{2.5}$ exposure models have also grown. For the last two decades, $PM_{2.5}$ estimation approaches using satellite remote sensing have been developed and advanced, taking advantage of quantitative aerosol data (e.g., aerosol optical depth; AOD), the development of satellite instruments and data retrieval algorithms, and the application of statistical and machine learning techniques. Subsequently, the satellite-based $PM_{2.5}$ concentrations have contributed to health effect studies by providing spatially resolved exposure estimates of ambient $PM_{2.5}$ and thus reducing exposure misclassification. This article summarizes previous development and recent advancement of satellite-based $PM_{2.5}$ exposure assessment in the context of satellite aerosol products and $PM_{2.5}$ estimation methodologies. Furthermore, this article deals with enhanced satellite capabilities of generating the exposure estimates of $PM_{2.5}$ composition and time-resolved $PM_{2.5}$. Finally, the future directions of satellite-based exposure assessment are discussed based on research needs and the satellite remote sensing technology of addressing them.

KEY WORDS AOD, Environmental epidemiology, Exposure assessment, $PM_{2.5}$, Public health, Satellite remote sensing

Remote Sensing of PM2.5 – White Paper

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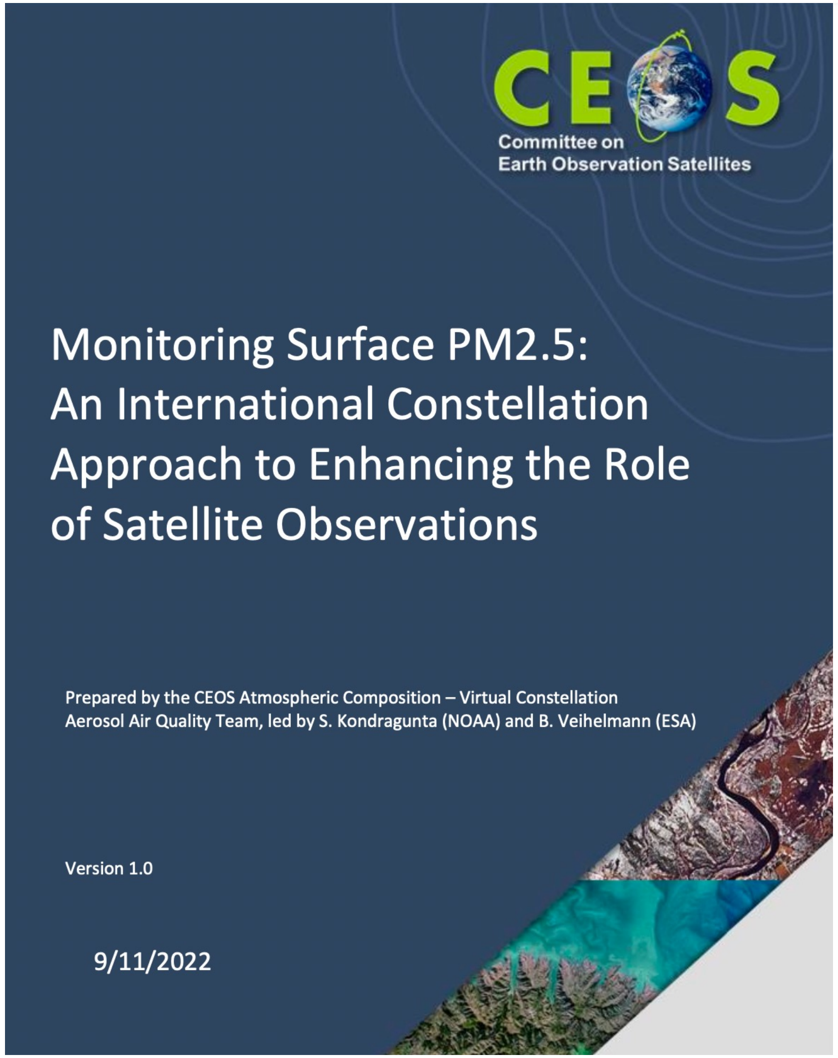

Lead Authors: Kondragunta, Shobha (NOAA) and Veihelmann, Ben (ESA)

Contributing Authors:
Chatfield, Robert (NASA)
Chin, Mian (NASA)
Christopher, Sundar (University of Alabama Huntsville)
Clements, Andrea (EPA)
Da Silva, Arlindo (NASA)
Delgado, Ruben (University of Maryland Baltimore County)
Dickerson, Phil (EPA)
Diner, David (JPL/Caltech)
Dubovik, Oleg (LOA)
Fougnie, Bertrand (EUMETSAT)
Garrigues, Sébastien (ECMWF)
Giles, David (NASA)
Goldberg, Mitch (NOAA)
Gupta, Pawan (NASA/USRA)
Hashimoto, Makiko (JAXA)
Henderson, Barron (EPA)
Holben, Brent (NASA)
Huff, Amy (IM Systems Group)
Kahn, Ralph (NASA)
Kim, Jhoon (Yonsei University)
Knowland, K. Emma (NASA/Morgan State University)
Koplitz, Shannon (EPA)
Laszlo, Istvan (NOAA)
Lefer, Barry (NASA)
Levy, Rob (NASA)
Liu, Hongqing (IM Systems Group)
Liu, Yang (Emory University)
Loyola, Diego (DLR)
Lyapustin, Alexei (NASA)
Martin, Randall (Washington University)
Mishra, Manoj (ISRO)
Muva, Ramana (ISRO)
Natraj, Vijay (NASA JPL)
Newchurch, Michael (University of Alabama Huntsville)
Pierce, Brad (University of Wisconsin – Madison)
Price, Julie (NOAA)
Saide, Pablo (University of California Los Angeles)
Szykman, James J (EPA)
Tanaka, Taichu (JMA)
Torres, Omar (NASA)
van Donkelaar, Aaron (Dalhousie University)
Wang, Jun (U of Iowa)
Welton, Judd (NASA)
Zhang, Hai (IM Systems Group)

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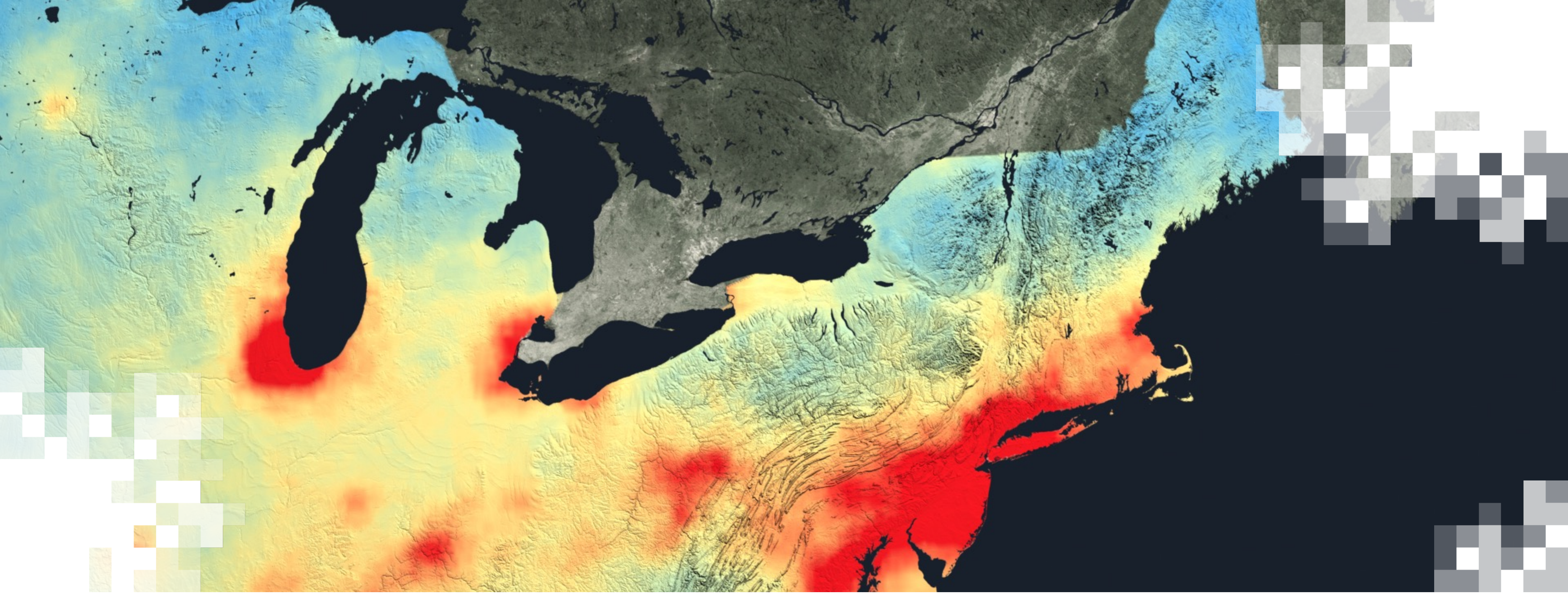

Questions?