Satellite aerosol products and PM2.5 - current state of the art

David J. Diner
Yang Liu

Jet Propulsion Laboratory
California Institute of Technology

EMORY
ROLLINS SCHOOL OF PUBLIC HEALTH

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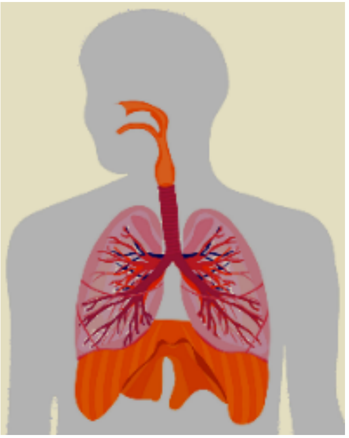
Airborne particulate matter (PM): a major risk to human health



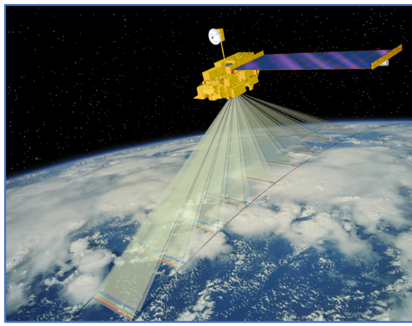
Airborne PM has been associated with

- premature deaths (>4 million per year globally)
- cardiovascular and respiratory disease
- pregnancy complications and low birth weight
- lung cancer
- many other adverse health outcomes

$PM_{2.5}$ = near-surface mass concentration of airborne particles < 2.5 μm in aerodynamic diameter

Surface monitors

- $PM_{2.5}$ determined in situ
- high accuracy
- sparsely distributed



Satellites

- $PM_{2.5}$ inferred indirectly
- moderate accuracy
- enable mapping

Relationship of aerosol parameters to PM

Satellite aerosol optical depth (AOD)	PM concentration
○ Column-averaged (passive sensors) ○ Dimensionless ○ Observed at time of overpass only (low Earth orbit) ○ Corresponds to ambient conditions	○ Surface level ○ Reported in μg m^{-3} ○ Sampled frequently and typically daily-averaged for health studies ○ Corresponds to dry mass

$$PM_{2.5} \approx \frac{4\rho r_{eff}}{3HQ_{ext,dry} f(RH)} \cdot AOD_{satellite}$$

- Aerosol parameters are particle type dependent

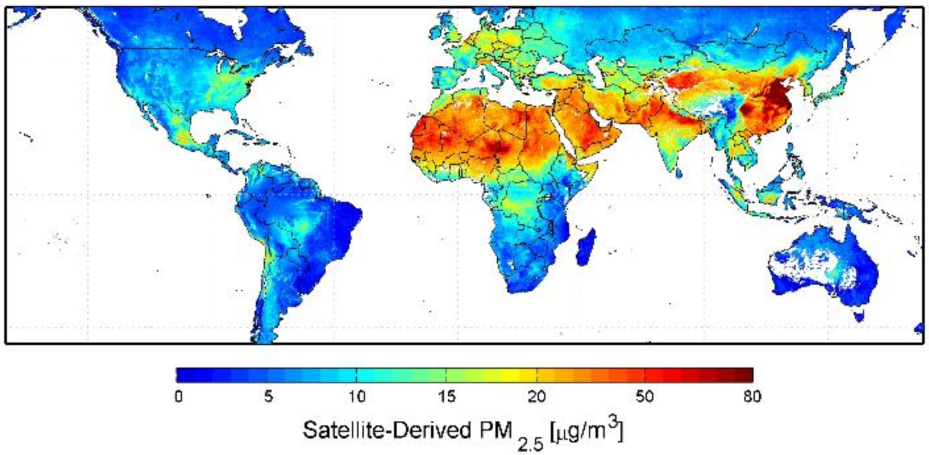
Koelemeijer et al., AE (2006),
Gupta and Christopher, JGR (2009)

- ρ = particle density
- r_{eff} = effective particle radius
- H = height of the aerosol layer
- $Q_{ext,dry}$ = extinction efficiency under dry conditions
- f(RH) = conversion factor from dry to ambient

Transformation of satellite aerosol to PM: Scaling with chemical transport models (CTMs)

$$PM_{2.5} = \eta \times AOD_{satellite} = \frac{PM_{2.5,CTM}}{AOD_{CTM}} \times AOD_{satellite}$$

- Used in the US by *Liu et al., JGR (2004)* using MISR, GEOS-Chem, GOCART
- Extended globally by *van Donkelaar et al., JGR (2006), EHP (2010, 2015)* using MODIS, MISR, SeaWiFs and GEOS-Chem

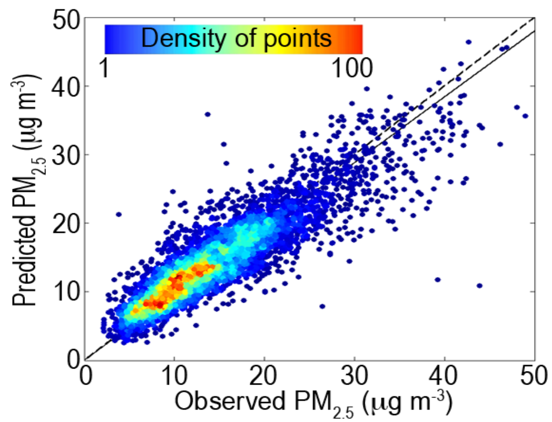


- Applied to many health impact studies including the Global Burden of Disease (*Brauer et al., ES&T, 2016; Gakidou et al., Lancet, 2017)*

Transformation of satellite aerosol to PM: Regression models

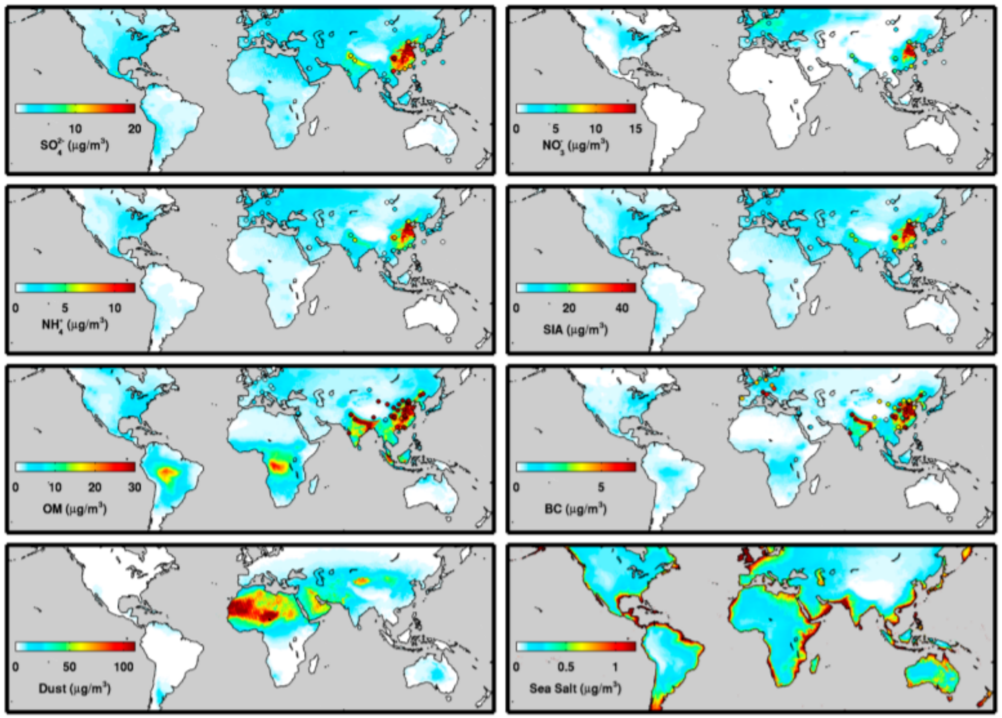
$$PM_{2.5} = \alpha\ \text{(Spatiotemporal offsets)} + \beta \cdot AOD_{satellite}$$
$$+\ \gamma \cdot \text{Geospatial predictors (road density, population, land use)}$$
$$+\ \delta \cdot \text{Spatiotemporal predictors (e.g., meteorological variables)}$$

- Coefficients calibrated using surface monitor measurements
- Bayesian statistical formulation (e.g., *Shaddick et al., Appl. Stat., 2018*)
- Linear (*Lee et al., ACP, 2011*), nonlinear (*Sorek-Hamer et al., Environ. Poll., 2013*), and machine learning approaches used (e.g., *Gupta and Christopher, JGR, 2009; Hu et al., ER, 2017*)
- Applied to many health impact studies, e.g., birth outcomes (*Kloog et al., EH, 2012)* and pediatric respiratory infections *(Strickland et al., EHP, 2016*)



Transformation of satellite aerosol to *speciated* PM: CTM scaling approach

- Extension to speciated $PM_{2.5}$ (e.g., SO_4, NO_3, OC, EC/BC, dust)
  - Species-specific values of η derived from GEOS-Chem (*Philip et al., ES&T, 2014*)

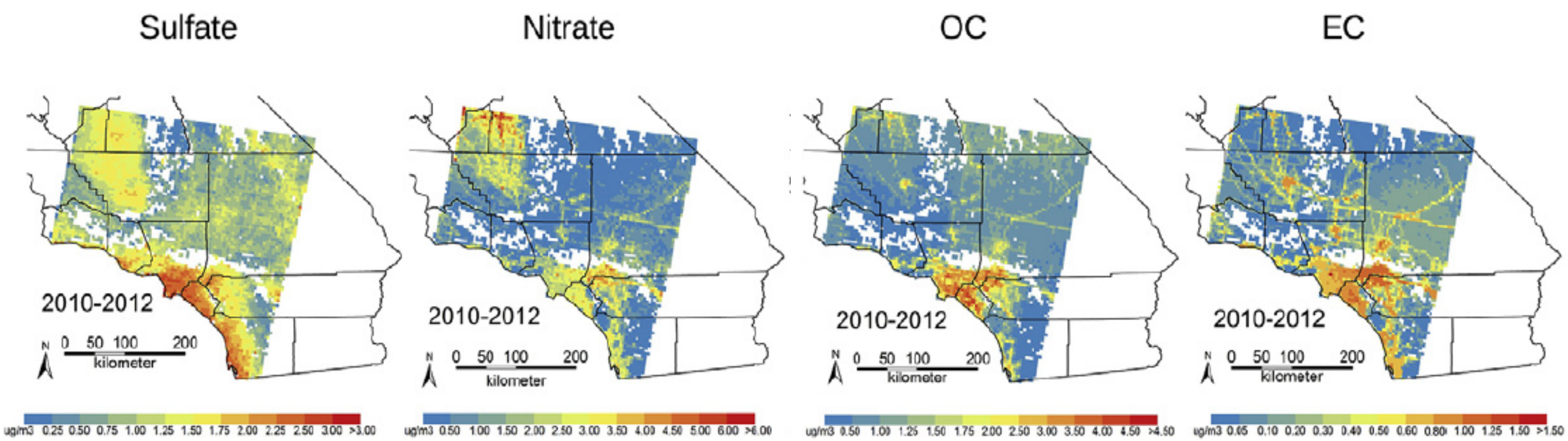


Philip et al., ES&T (2014)

No ground observation involved

Transformation of satellite aerosol to *speciated* PM: Regression approach

- Extension to speciated $PM_{2.5}$ (e.g., SO_4, NO_3, OC, EC/BC, dust)
  - Fractional AODs of different particle types from MISR (*Franklin et al., RSE, 2017; Meng et al., AE, 2018*), calibrated using speciated $PM_{2.5}$ from CSN/IMPROVE (*Solomon et al., JAWMA, 2014), SPARTAN (*Snider et al., AMT 2015*)



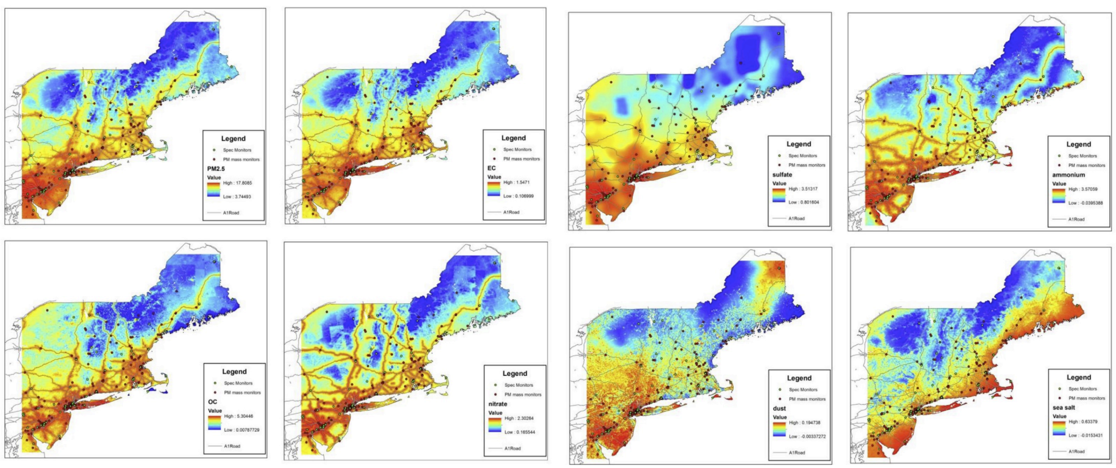
Meng et al., AE (2018)

Requires ground $PM_{2.5}$ speciation measurements

Transformation of satellite aerosol to PM:
Advanced models

- Integration of CTM and regression approaches
  - CTM-based scaling terms used as spatiotemporal predictors in regression models and bias-corrected using surface monitors (*Dey et al., RSE, 2012*)

- Parameters other than total or fractional AOD as predictors
  - Particle effective radius, phase function asymmetry from AERONET inversion products show good skill (*Sorek-Hamer et al., AGU, 2019*)

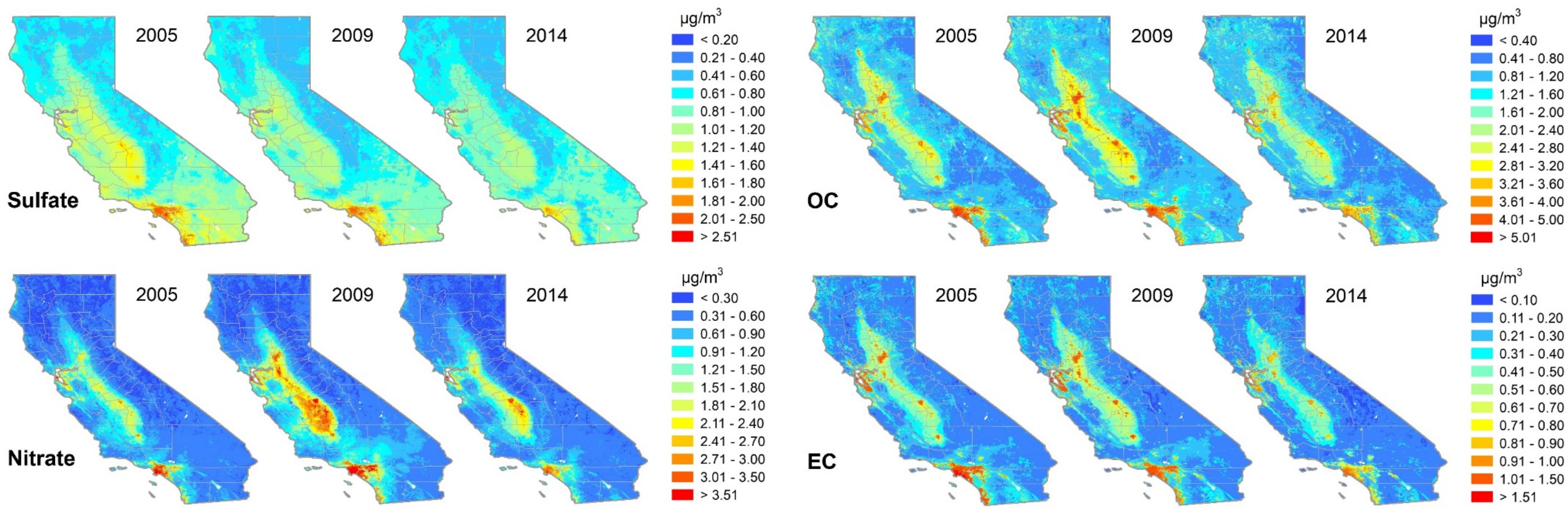


Di et al., AE (2016)

Land use regression using GEOS-Chem simulation results, no AOD involved

MISR aerosol microphysical properties as predictors in machine learning models

- ML models often make more accurate predictions than statistical models, but they require a large training dataset, difficult to collect
- High quality model simulations, meteorological fields, and land use variables are important predictors in addition to satellite retrievals



Geng et al., ERL (2020)