

Overcoming Barriers in Applying Satellite-Derived $PM_{2.5}$ to Health



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HAQAST4

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HEALTH

July 16 – 17, 2018

EMORY

Madison, WI

Motivation

- $PM_{2.5}$: airborne particles with an aerodynamic diameter of $2.5\text{ }\mu\text{m}$ or less
- $PM_{2.5}$ is one of most important public health concerns worldwide.
- Associated with **4.2** million deaths in 2015 (GBD, 2016)
- Associated with **2.7-3.4** million preterm births in 2010 (Malley et al., 2017)

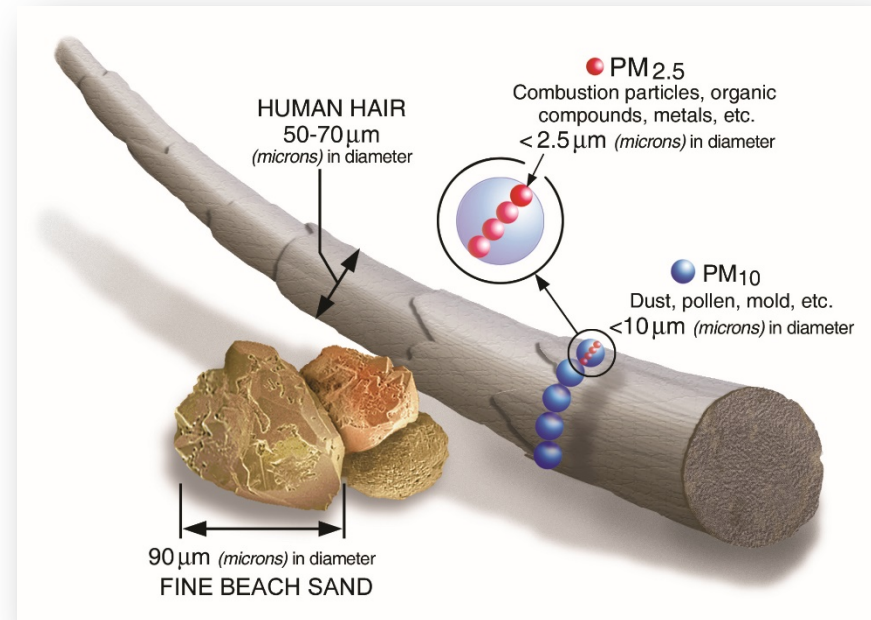
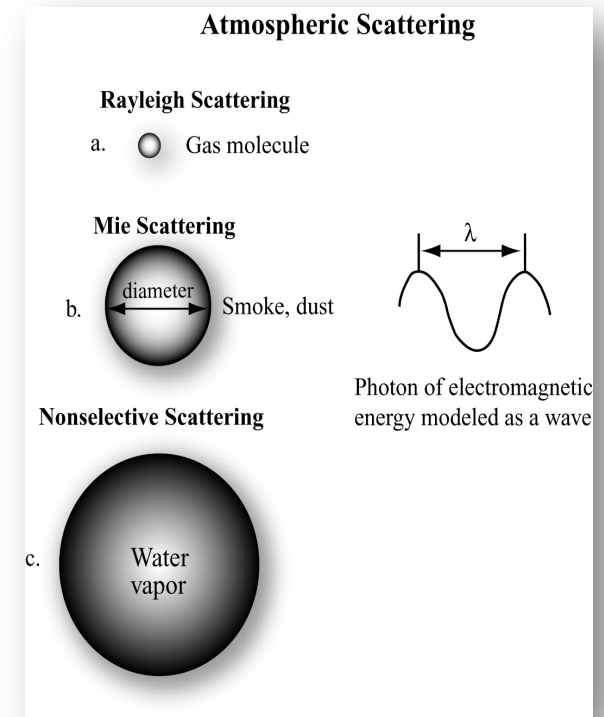


Image courtesy of USEPA

PM2.5 and Satellite AOD



- Aerosol Optical Depth (AOD)
 - The integral of aerosol extinction coefficients along the atmospheric column
 - Broad coverage, high spatial resolution, long data record
 - Satellite AOD retrieved at visible wavelengths is most sensitive to PM 0.1-2 μm . AOD is dominated by near-surface emissions sources so it is a good indicator of PM2.5 most of the time.



Satellite-based PM_{2.5} models are being used to estimate exposure in health effects research



THE LANCET

Articles

Estimates and 25
attributable to ar
from the Global B

Aaron J Cohen*, Michael Brauer*, Richard
Lalit Dandona, Rakhi Dandona, Valery Fei
Lidia Morawska, C Arden Pope III, Hwashi
Theo Vos, Christopher J L Murray, Mohan

The NEW ENGLAND JOURNAL of MEDICINE

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Air Pollution an

Qian Di, M.S., Yan Wang, M.S.
Christine Choirat, F



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Associations between birth outcomes and maternal PM_{2.5} exposure in Shanghai: A comparison of three exposure assessment approaches

Qingyang Xiao^{a,1}, Hanyi Chen^{b,c,1}, Matthew J. Strickland^d, Haidong Kan^e, Howard H. Chang^f, Mitchel Klein^a, Chen Yang^{g,c}, Xia Meng^a, Yang Liu^{a,*}

Current Barriers

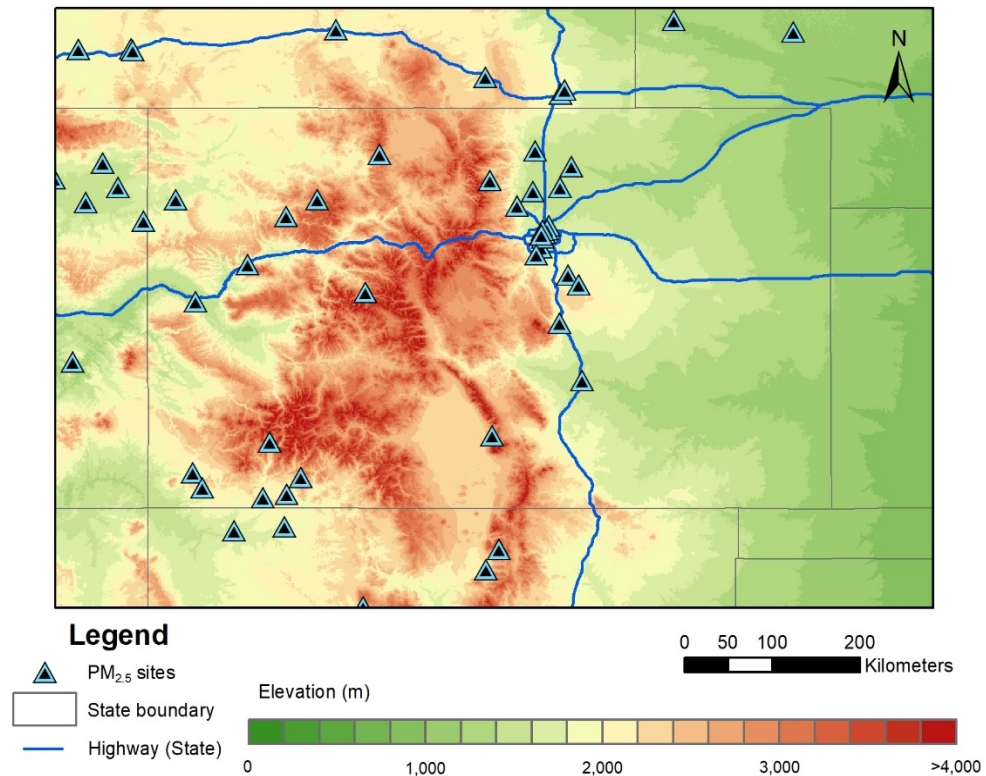


1. Almost every health study needs a custom PM_{2.5} exposure model to meet its study design, period, and resolution requirements
2. Epidemiologists and other health researchers need the support of exposure modelers and NASA satellite experts
3. Satellite data are difficult to handle and not made with health applications in mind

Barrier 1 & 2 example: Associations of wildfire-specific PM_{2.5} exposure on cardiorespiratory events in Colorado



Study Objective:
estimate respiratory and cardiovascular health effects of wildfire PM_{2.5} in Colorado during the fire seasons of 2011-2014 using wildfire PM_{2.5} separated from background ambient PM_{2.5} levels



Study co-authors & collaborators



- Emory: G. Geng, X. Hu, X. Meng, E. Saikawa, N. Murray, H. Chang, Y. Liu
- NOAA Air Resources Lab: D. Tong, P. Lee
- University of Tennessee: J. Fu
- University of Nevada Reno: M. Strickland
- CDPHE: K. Bol

Two-stage Bayesian PM_{2.5} exposure Model



Stage 1: Bayesian downscaler

Monitoring
measurements

MAIAC or CMAQ value at grid
cell s and time t

$$PM_{2.5}(s,t) = \alpha(s,t) + \beta(s,t) X(s,t) + \gamma Z_{st} + \varepsilon(s,t)$$

Additive and
multiplicative calibration

Z_{st} depends on met and
land use parameters.

Independent
Normal error

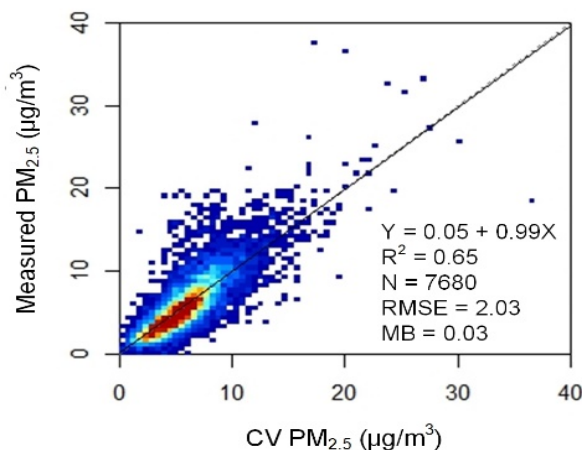
Stage 2: Bayesian ensemble weighting

$$PM_{2.5}(s,t) = (1 - w_s) PM_{s,t}^{AOD} + w_s PM_{s,t}^{CMAQ}$$

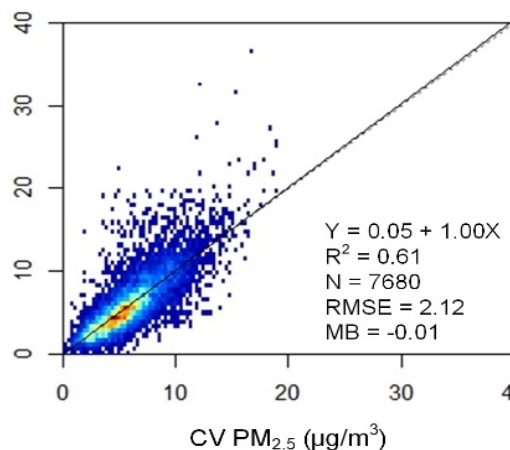
Model Performance



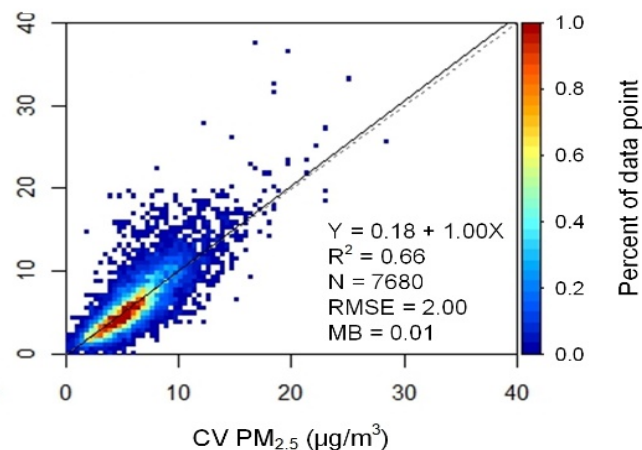
(a) AOD downscaler



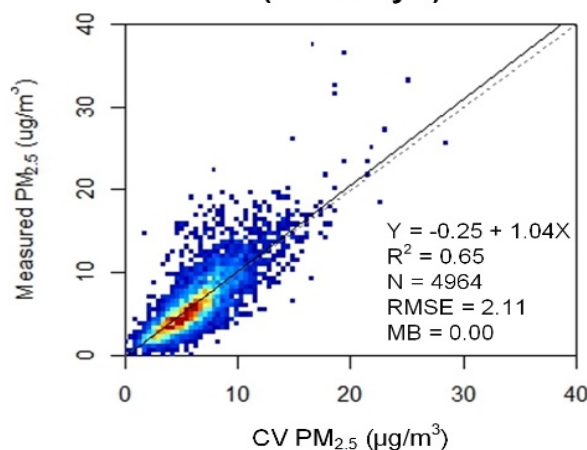
(b) CMAQ downscaler



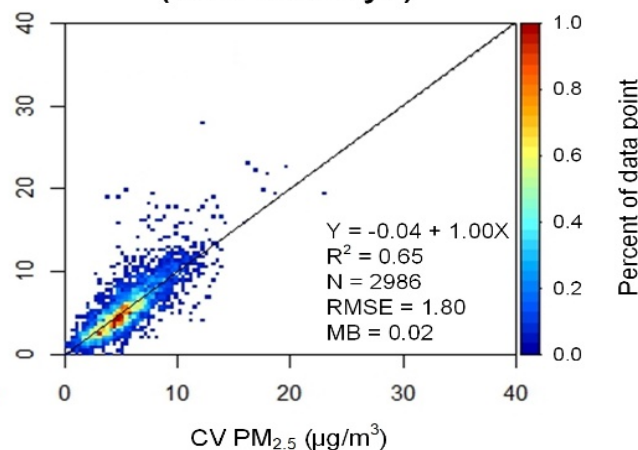
(c) Bayesian ensemble model



(d) Bayesian ensemble model (Fire days)



(e) Bayesian ensemble model (Non-fire days)

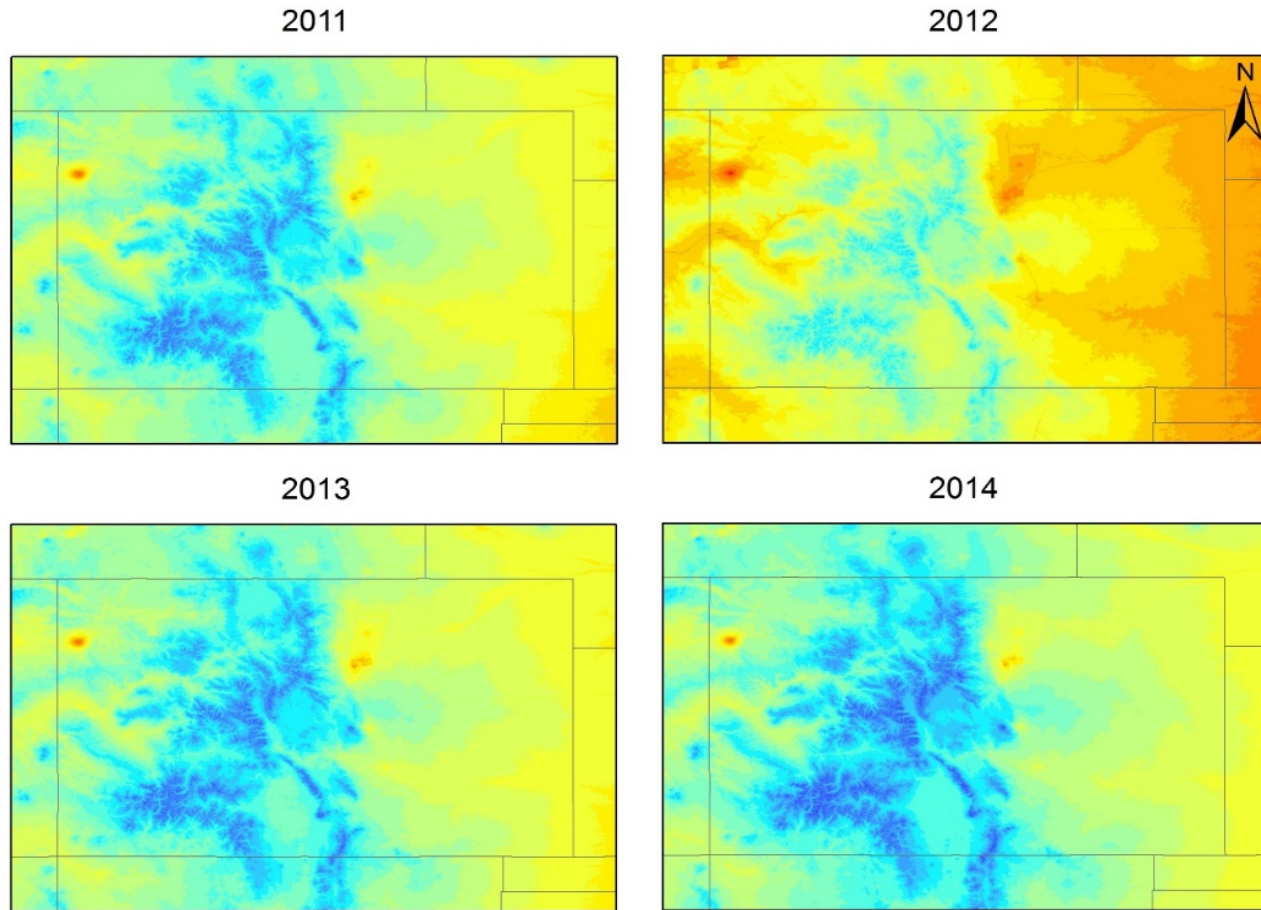


Model predicted total PM_{2.5} with full daily coverage at 1 km resolution



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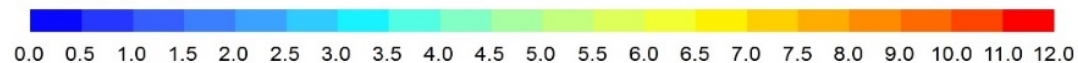
EMORY



Legend

State Boundary

PM_{2.5} (μg/m³)



0 40 80 160 240 320
Kilometers

19 Jun, 2012

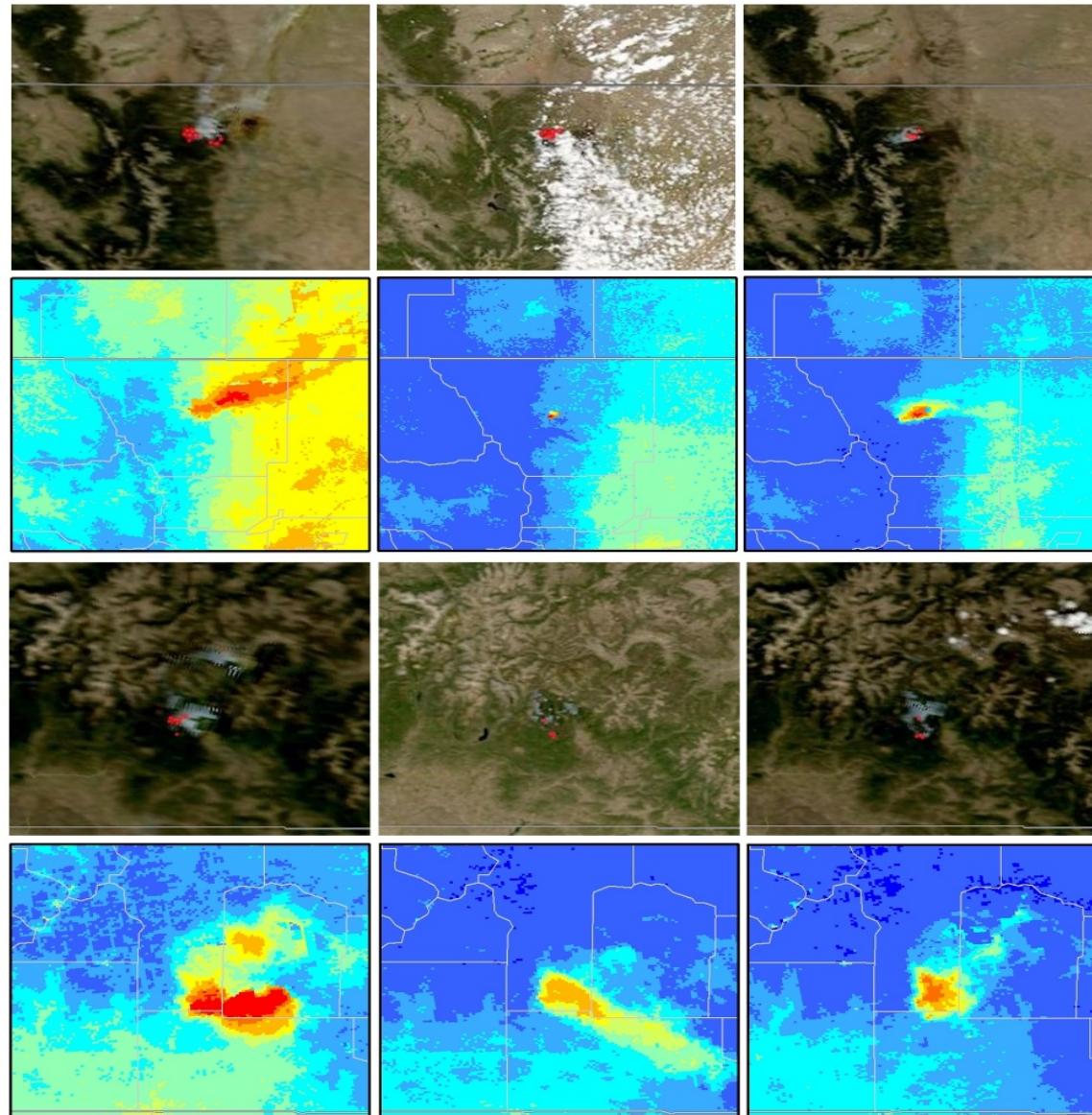
20 Jun, 2012

21 Jun, 2012

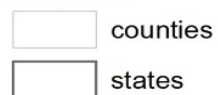


High Park fire

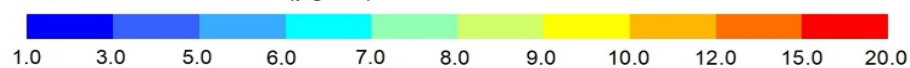
Little Sand fire



Legend



PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$)

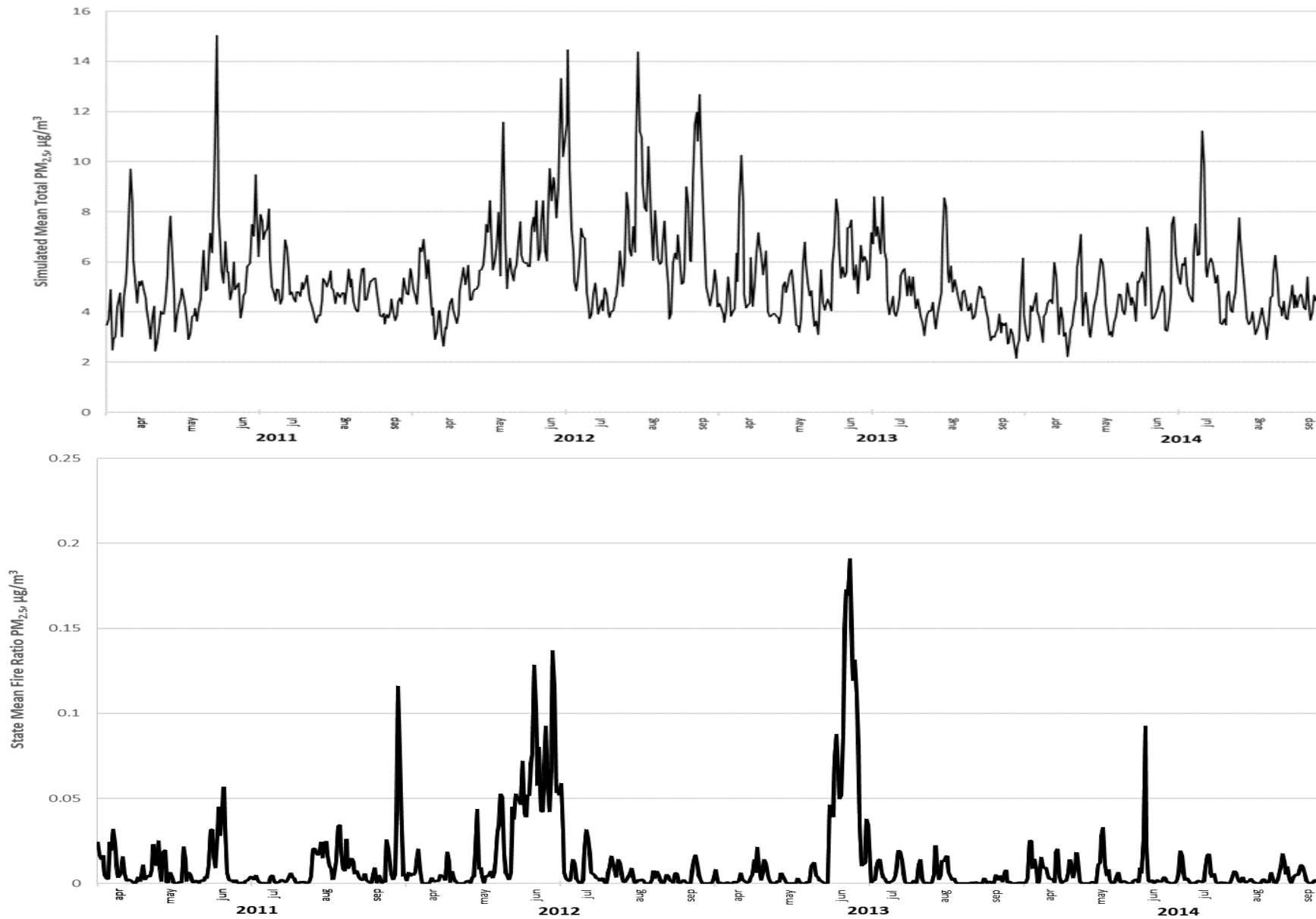


Further processing for epidemiologic modeling

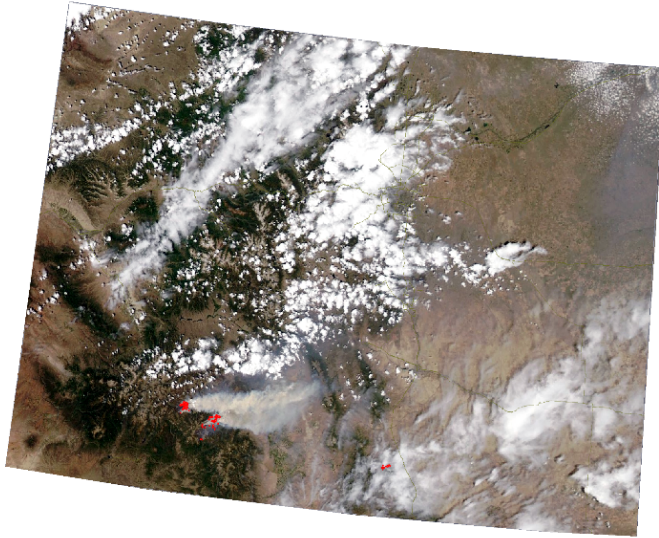


- Aggregated to a 4km grid to match the resolution of the health data
- MODIS active fire count data was obtained to specify fire days for each grid cell
- Fire-specific $PM_{2.5}$ concentrations were calculated by taking the difference between CMAQ models run with and without fire emissions

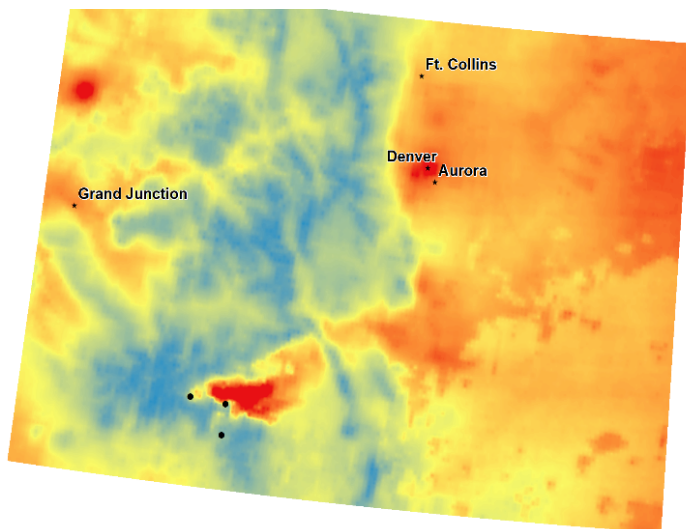
Predicted daily PM_{2.5} and smoke contribution



Ratios of fire $\text{PM}_{2.5}$ to total $\text{PM}_{2.5}$ ranged from 0 to 99.56%, with a mean ratio of 0.006%.

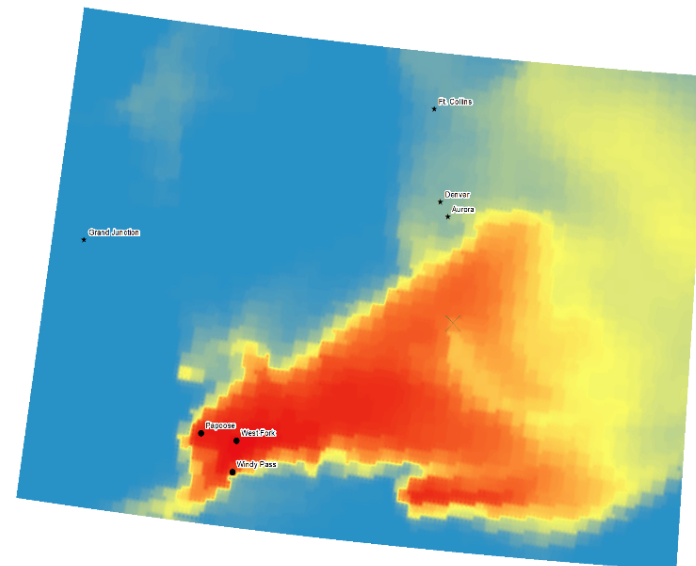


Satellite Smoke Plume, Modeled Total $\text{PM}_{2.5}$ and Fire $\text{PM}_{2.5}$ for West Fork Fire Complex, June 22, 2013



**Total PM
June 22, 2013**

High: 12
Low: 2



**Fire PM Ratio
June 22, 2013**

High : 99%
Low : 0%

Epidemiologic Models



Reference model with total PM_{2.5} as exposure controlling for temperature and time trend

$$\text{logit } P(X) = \beta(\text{total } \downarrow 3 \text{ day } PM_{2.5}) + \beta(\text{temp } \downarrow 3 \text{ day } PM_{2.5}) + ns(\text{doy})$$

Fire smoke PM_{2.5} model controlling for temperature, time trend, and non-fire PM_{2.5}

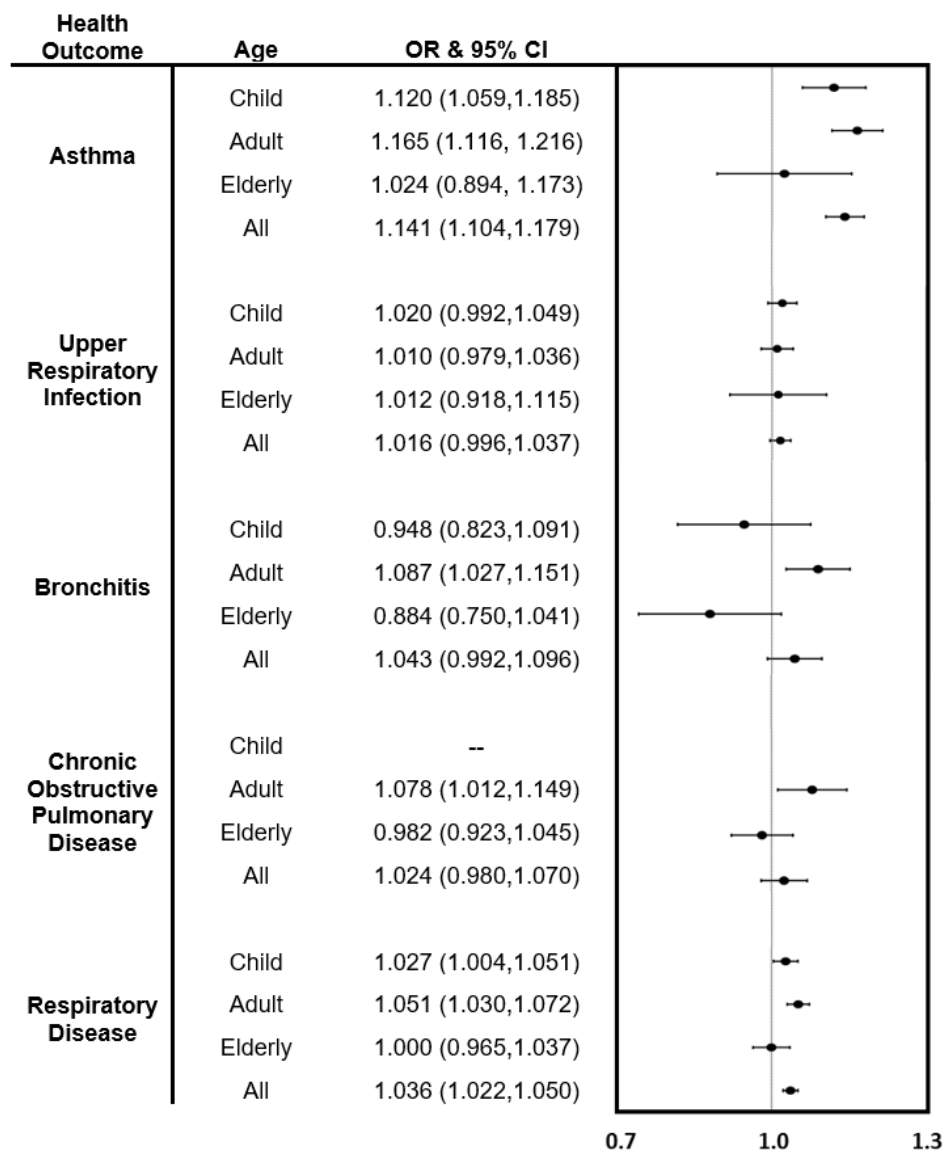
$$\text{logit } P(X) = \beta(\text{fire } \downarrow 3 \text{ day } PM_{2.5}) + \beta(\text{non-fire } \downarrow 3 \text{ day } PM_{2.5}) + \beta(\text{temp } \downarrow 3 \text{ day } PM_{2.5}) + ns(\text{doy})$$

Preliminary results, don't quote



- 446,106 geocoded ED visit and hospitalization events
- Using 3-day average total $PM_{2.5}$ as the exposure variable, ORs for respiratory outcomes were null
- Significant associations between $1\mu g/m^3$ increase in 3-day moving average fire $PM_{2.5}$ exposures and asthma (OR 1.141, 95% CI (1.104, 1.179)) and combined respiratory disease (OR 1.036, 95% CI (1.022, 1.050))

Age stratified results





MAIA

Associating airborne particle types with adverse health outcomes

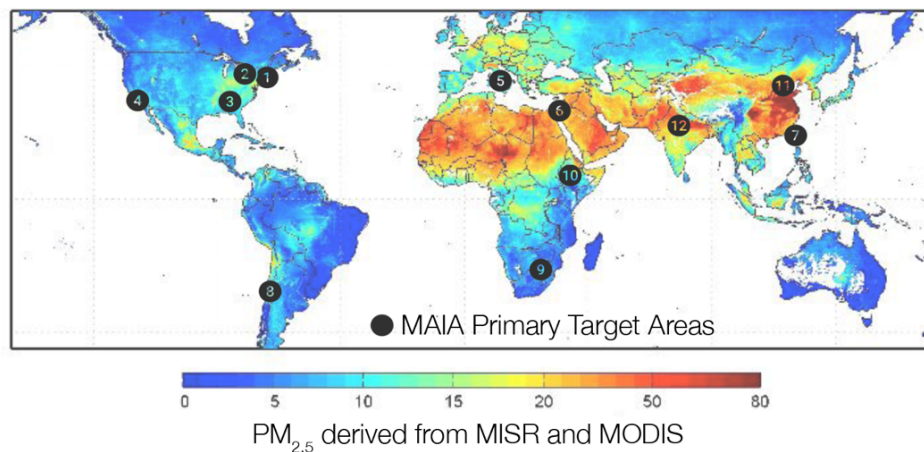
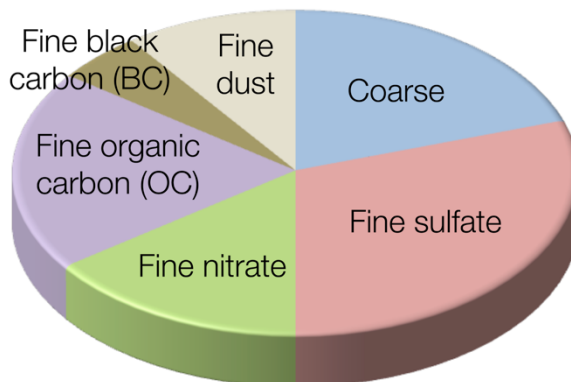


Advances against Barrier 3: Multi-Angle Imager for Aerosols (MAIA)

Modified from slides of David J. Diner, MAIA PI

MAIA's primary objective is to link exposure to different types of PM—mixtures of particles of various sizes, shapes, and compositions—with human health.

PM type and concentration



Exposure timescale
Health outcomes

Acute (days to weeks)
Emergency room visits,
premature deaths

Subchronic (months)
Adverse birth outcomes,
pregnancy complications

Chronic (years)
Cardiovascular and
respiratory diseases

Principal Investigator

David Diner	JPL
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Co-Investigators: Instrument Characterization

Carol Bruegge	JPL
Russell Chipman	Univ. of Arizona
Veljko Jovanovic	JPL

Co-Investigators: Aerosol Remote Sensing, CTM Modeling, Validation

Larry Di Girolamo	University of Illinois
Michael Garay	JPL
Edward Hyer	Naval Research Lab.
Olga Kalashnikova	JPL
Alexei Lyapustin	GSFC
Randall Martin	Dalhousie University
Jun Wang	University of Iowa
Feng Xu	JPL

Co-Investigators: PM Exposure, Epidemiology

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Michael Jerrett	UCLA
Yang Liu	Emory University
Bart Ostro	UC Davis
Beate Ritz	UCLA
Joel Schwartz	Harvard University

Collaborators: Air Quality and Public Health

Bert Brunekreef	Utrecht University
Sagnik Dey	IIT Delhi
Sina Hasheminassab	SCAQMD
Kembra Howdeshell	NIH
John Langstaff	EPA
Pius Lee	NOAA
Fuyuen Yip	CDC

- Primary Target Areas (PTAs) are chosen by the MAIA Science Team for conducting epidemiological studies.
 - Candidate list currently includes 12 sites based on:
 - Science value to the MAIA investigation
 - Identification of sources of surface monitor data, complexity of interfaces, requirements for supplementary monitor deployments, and associated costs
 - Establishment of health study objectives, health data sources, and local collaborators
 - Cloud cover
 - Observability from orbit

Data level	Description
0	Downlinked instrument telemetry
1	Calibrated and georectified radiance and linear polarization imagery View and solar geometry, latitude, longitude
2	Cloud-screened total and fractional aerosol particle properties at time of satellite overpass 24-hr averaged concentrations of coarse PM, fine PM, and fine PM components on days and locations coincident instrument observations
4	Spatially and temporally gap-filled 24-hr averaged concentrations of daily coarse PM, fine PM, and fine PM components



Year 2 Progress Update, PI Liu

Using Earth Observations to Support Regional and National Environmental Health Surveillance

- Age-specific associations between ambient air pollution and respiratory emergency department visits
 - Baseline paper using EPA data in preparation. Will work with CDC on replacing exposure with satellite-based data.
 - Completed national Bayesian fusion modeling.
- Effect of Wildfire Smoke on ED Visits in Colorado
 - Satellite data fusion model completed. Epidemiologic study near completion.
 - Completed epidemiologic study on the effect of wildfire-specific PM2.5 exposure on acute health outcomes in Colorado.

Tiger Team Participation

- Pat Kinney: High Resolution Satellite-Based Assessments of Community Health
 - Completed 100 m satellite PM2.5 modeling in New York City. Delivered data to Anenberg for multi-city HIA.
 - Completed 1 km PM2.5 modeling in Imperial Valley.
 - Complete preliminary 1 km PM2.5 modeling in Southern California.
- Bryan Duncan: Demonstration of the Efficacy of Environmental Regulations in the Eastern U.S..
 - Completed the New York State long-term PM2.5 modeling. Data delivered to Fiore for cross-comparison with other methods.

- 2 conference talks, 3 stakeholder talks
- 2 paper published, 2 submitted, 4 in preparation

- 1 NE US (Boston, Providence, Hartford, New York)
- 2 NE Canada (Toronto, Hamilton)
- 3 SE US (Atlanta Metro)
- 4 SW US (Fresno, Bakersfield, LA, Riverside, San Bernardino)
- 5 Italy (Rome, Bologna)
- 6 Israel (Haifa, Tel Aviv, Jerusalem, Beer Sheba)
- 7 Taiwan (Taipei, New Taipei, Taichung, Tainan, Kaohsiung)
- 8 Chile (Santiago, Concepción)
- 9 South Africa (Johannesburg, Pretoria)
- 10 Ethiopia (Addis Ababa, Adama)
- 11 China (Beijing)
- 12 India (Delhi)



Candidate target areas

PTA

STA

CVTA

- | | | |
|------------------------|-------------------------|----------------------------|
| 1 Cloud field | 8 Nigeria (Lagos) | 1 Nevada (Railroad Valley) |
| 2 Arizona (Phoenix) | 9 Spain (Barcelona) | 2 Libya-4 desert site |
| 3 Mexico (Mexico City) | 10 Kuwait (Kuwait City) | |
| 4 Peru (Lima) | 11 Bangladesh (Dhaka) | |
| 5 Brazil (São Paulo) | 12 Vietnam (Hanoi) | |
| 6 Senegal (Dakar) | 13 South Korea (Seoul) | |
| 7 Cloud field | 14 Australia (Sydney) | |