

Fusing surface and satellite-derived PM observations to determine the impact of international transport on coastal $\text{PM}_{2.5}$ concentrations in the western U.S.

Neha Bora Tuo Chen Dana Cochran Kelly Dougan Gautam Sabnis
Chuanping Yu

Industrial Math/Stat Modeling Workshop
Environmental Protection Agency

May 8, 2017

Outline

- 1 Introduction
- 2 Data Sources and methods
- 3 Experiments
 - PM_{2.5} time series
 - AOD and PM_{2.5} fitting
- 4 Conclusions

Health Impacts



Figure: Donora, PA at noon on October 29, 1948

- 20 people died, thousands were sickened by smog from a steel mill.
- $PM_{2.5}$ one of the most harmful pollutants, can get lodged in lungs and cause respiratory problems

PM and AOD

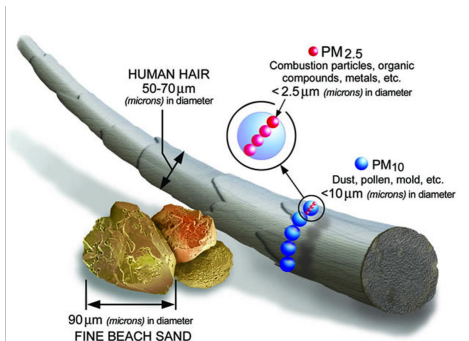


Figure: Size of PM_{2.5} compared to other particulate matter

- PM_{2.5} is a particulate matter that is less than 2.5 micrometers in diameter.
- Aerosol Optical Depth (AOD) measures the amount of light from the sun blocked by dust and pollutants.

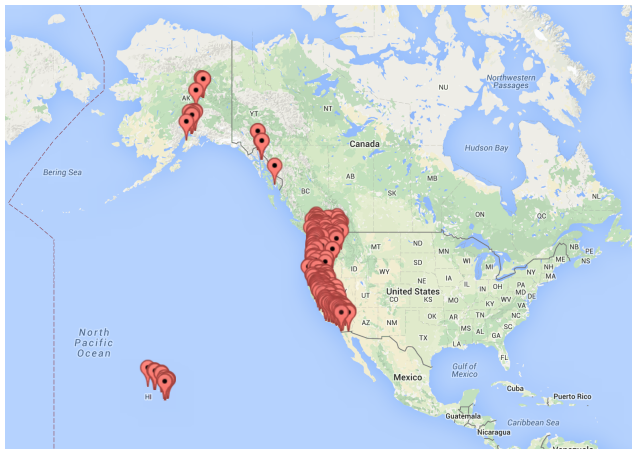
Pollution in Western U.S.



- The Clean Air Act imposes a national standard of permissible amount of $\text{PM}_{2.5}$.
- Sites in California, such as in the Los Angeles area consistently violate this standard.
- Want to investigate the possibility of external impact by international air travel of $\text{PM}_{2.5}$.

Outline

- 1 Introduction
- 2 Data Sources and methods
- 3 Experiments
 - PM_{2.5} time series
 - AOD and PM_{2.5} fitting
- 4 Conclusions

PM_{2.5}

- Ground sites of PM_{2.5} measurements, as collected by EPA
- Data collected either daily, every three days or every six days.

AOD

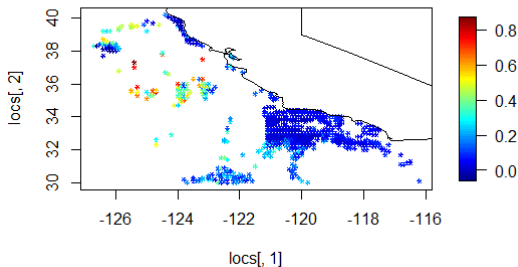


Figure: AOD readings on Jun 6, 2009

- AOD data collected over Pacific Ocean, near coast of California.
- Satellites travel around the Earth once every 16 days.
- AOD data is collected at each location least twice a month.

Data Cleaning

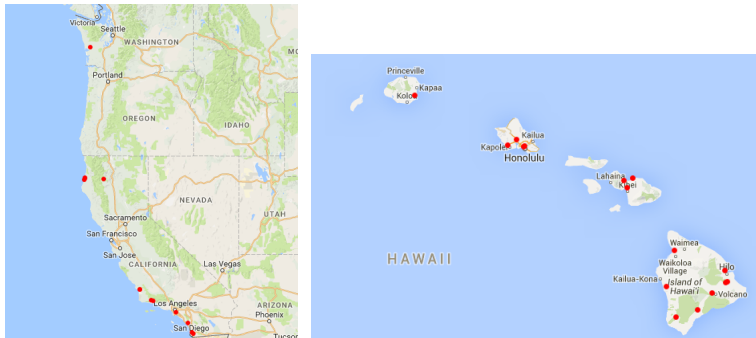


Figure: (left) CA PM_{2.5} sites we compared with AOD data, (right) Hawaii PM_{2.5} sites we compared with AOD data

- Picked PM sites closest to coast (13 in California, 9 in Hawaii)
- Found closest locations of AOD measurements to these sites
- Matched data by date of AOD/PM readings

Using additional data

Challenges

- AOD and PM_{2.5} datasets are quite sparse in space-time.
- Need additional information to improve fits and predictions.

Covariates used in this analysis

- wind speed and direction
- humidity
- planetary boundary layer height
- air temperature
- added values of these measures at each location at each date

Overall big picture

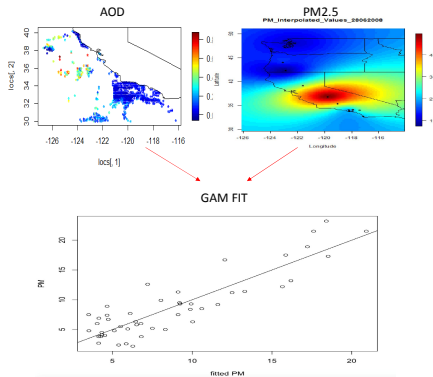
Fuse AOD and PM_{2.5} datasets to

- Understand their quantitative relationships,
- Predict PM measurements from years 1991 – 2000.

Overall Goal

Methods:

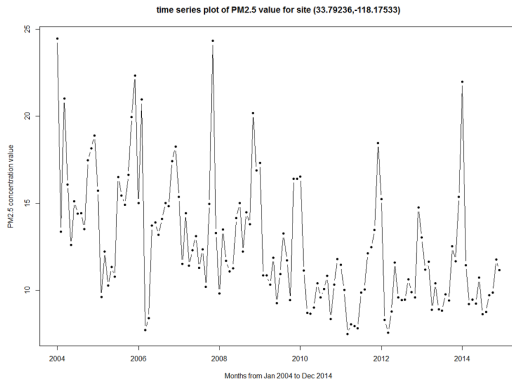
1. *Time Series*
2. *Spatial Interpolation*
3. *Multivariate Regression*



Outline

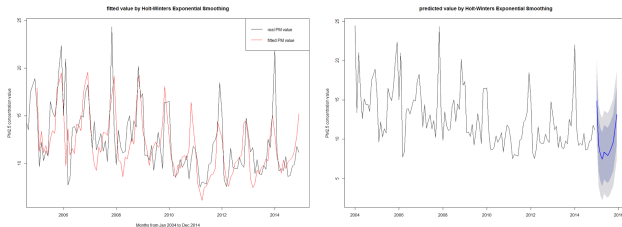
- 1 Introduction
- 2 Data Sources and methods
- 3 **Experiments**
 - PM_{2.5} time series
 - AOD and PM_{2.5} fitting
- 4 Conclusions

PM_{2.5} Time Series



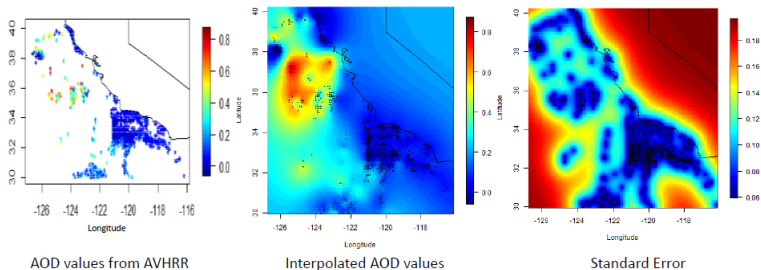
- Goal is to make predictions about PM_{2.5} in 2015.
- Overall pollution appears to be decreasing.
- Seasonal variations are observed.
- Two methods used – Holt-Winter Exponential smoothing and ARIMA model

Holt-Winters Exponential Smoothing



- Mean square error is 5.5 but the mean of PM_{2.5} values is 12.6
- Similar result observed using different method - ARIMA.
- PM_{2.5} dataset itself not sufficient to make predictions
- This motivates using covariates and AOD data.

Spatial interpolation of AOD data

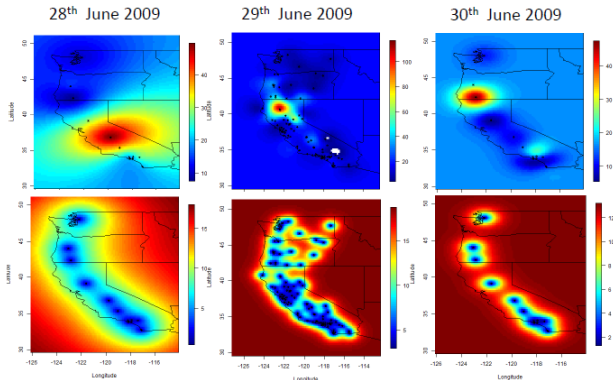


- Interpolation using Ordinary Kriging.
- The quality of interpolation depends on availability of data.
- Understand the transport of pollutants to inform regression models.

Spatial interpolation of PM_{2.5} data

Spatial Interpolation
PM_{2.5}

Standard Error
PM_{2.5}



Need further validation with satellite data to confirm plume tracking.

PM_{2.5} vs AOD

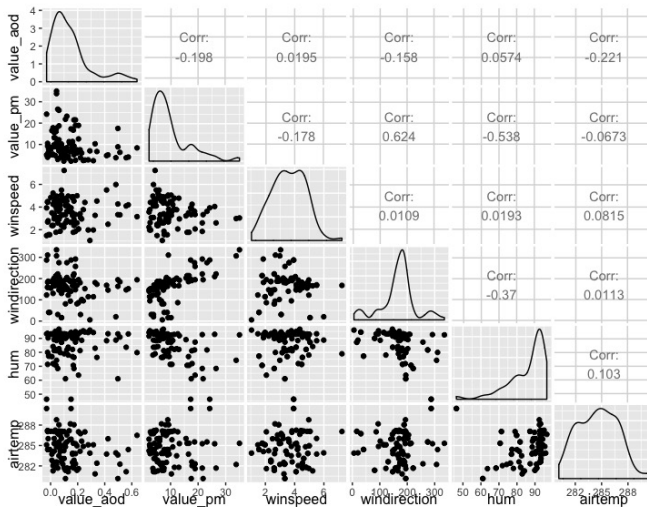
- Goal - relationship between PM_{2.5} and AOD in presence of other meteorological variables.
- Response variable - PM_{2.5} - “What we want to predict”
- Covariates - “What we use to predict”
 - continuous variables: wind direction, wind velocity, relative humidity, air temperature
 - factors: season – a discrete variable that models seasonality.
- Model the relationship at a particular PM_{2.5} site or combine data from two nearby PM_{2.5} sites along the west coast of United States.

Snapshot of the dataset

date	value_aod	value_pm	winspeed	windirection	hum	airtemp	season
2006-12-28	0.01794	17.8	4.25	193.17	71.9	283	4
2007-01-12	0.10983	21.8	3.33	194.59	61.1	281	4
2007-01-21	0.04382	17.7	3.83	190.70	81.1	283	4
2007-03-28	0.17270	7.2	4.53	173.31	76.3	283	1
2007-04-18	0.13014	3.6	4.97	122.07	78.0	282	1
2007-05-18	0.01794	5.2	2.38	130.32	93.2	283	1
2007-06-05	0.24137	2.5	3.78	95.29	95.4	285	2
2007-06-11	0.10983	5.1	4.74	163.40	92.0	285	2
2007-08-10	-0.02195	4.0	4.44	158.96	93.4	287	2
2007-09-21	0.06187	8.2	2.91	188.68	92.6	288	3

- PM_{2.5} sites' coordinates near Eureka, CA - (40.8, -124) and (40.9, -123)
- This site was chosen since it provides best fits.

Preliminary Analysis I



- Shows nonlinear relationships between covariates and responses.
- skewed data, outliers.

Multiple Linear Regression Model

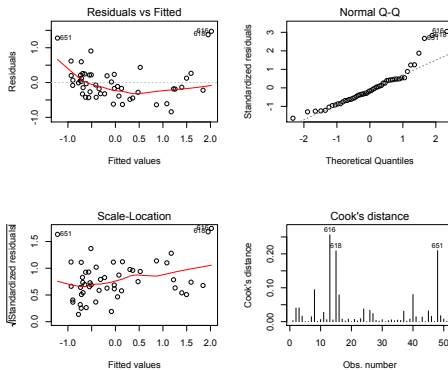
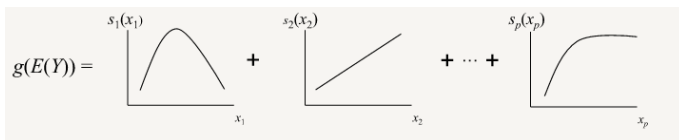


Figure: Some model diagnostics

Multiple linear regression does not provide good fits.

Generalized Additive Model



- Regression splines:

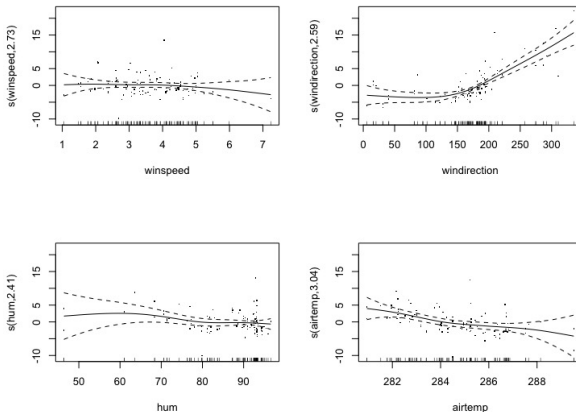
$$s_j(x) = \sum_{j,k} \beta_{jk} \phi_{jk}(x) = \beta' \phi_j$$

- Estimate β by minimizing the penalized least squares objective function.

Results I

- **Formula:** $\text{PM}_{2.5} \sim \text{AOD} + \text{s}(\text{windspeed}) + \text{s}(\text{winddirection}) + \text{s}(\text{hum}) + \text{s}(\text{airtemp}) + \text{season}$
- **Coefficient** = 4.085, $\beta_{\text{AOD}} = -2.283$ ($t = 3.84$, $p\text{-value} = 0.0023$).
- $R^2 = 0.782$, **Deviance** = 81.4%
- We compared various models using a subset of covariates and chose the model with the smallest **AIC** (Akaike's Information Criterion).

Results II



- Equivalent degrees of freedom = (2.69, 2.54, 2.37, 3.00)

Outline

- 1 Introduction
- 2 Data Sources and methods
- 3 Experiments
 - PM_{2.5} time series
 - AOD and PM_{2.5} fitting
- 4 Conclusions

Conclusions and future work

Conclusions

- AOD has a linear relationship with the $PM_{2.5}$ measurements.
- Meteorological information is also important in predicting $PM_{2.5}$ (particularly wind speed).
- GAM model better than multivariate linear regression model better than mixed effects model.

Future work

- Perform analysis on Hawaii sites.
- Use data from more years to train our model.
- Performing spatio-temporal analysis.

Acknowledgments

- Faculty mentors
- EPA – Brett Gantt and Elizabeth Mannshardt
- NOAA, specifically Jessica Matthews for help with satellite data
- IMSM
- NSF

References



Lee, H. J., et al. "A novel calibration approach of MODIS AOD data to predict PM_{2.5} concentrations." *Atmos. Chem. Phys.* 11.15 (2011): 7991-8002.



van Donkelaar, Aaron, et al. "Use of satellite observations for long-term exposure assessment of global concentrations of fine particulate matter." Diss. University of British Columbia, 2015.



Li, Jing, Barbara E. Carlson, and Andrew A. Lacis. "How well do satellite AOD observations represent the spatial and temporal variability of PM_{2.5} concentration for the United States?." *Atmospheric Environment* 102 (2015): 260-273.



Liu, Yang, Christopher J. Paciorek, and Petros Koutrakis. "Estimating Regional Spatial and Temporal Variability of PM_{2.5} Concentrations Using Satellite Data, Meteorology, and Land Use Information." *Environmental health perspectives* 117.6 (2009): 886.



National Centers for Environmental Information. National Oceanic and Atmospheric Administration. Department of Commerce, n.d. Web. 23 July 2016. <https://www.ncdc.noaa.gov/cdr/atmospheric/avhrr-aerosol-optical-thickness>.



United States Environmental Protection Agency. AirData. EPA, 5 July 2016. Web. 23 July 2016. <https://www3.epa.gov/airdata/>.