

DOES REMOTELY-SENSED AEROSOL HELP PREDICT GROUND-LEVEL PM_{2.5} CONCENTRATIONS IN THE EASTERN U.S.?

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INTRODUCTION

- Remote sensing observations of aerosol hold promise for adding information about PM_{2.5} concentrations beyond that from monitors, particularly in suburban and rural areas with limited monitoring.
- AOD (aerosol optical depth) observations are frequently missing, and noisy and biased relative to PM_{2.5}.
- Bayesian statistical modeling holds promise for integrating AOD, PM_{2.5}, and GIS and weather information to predict monthly PM_{2.5} concentrations on a fine grid (4 km).
- Here we assess the potential of AOD to improve predictions of PM_{2.5} concentrations.
- This work is part of a larger project seeking to estimate monthly PM_{2.5} concentrations at fine spatial scale as a data product for use in chronic health studies.

KEY QUESTIONS

- Do spatial patterns in AOD reflect true patterns in PM_{2.5}?
 - Statistical formulation: Should we model spatially-correlated (systematic) bias in AOD as a proxy for PM_{2.5}?
- Does AOD help to improve monthly and longer-term predictions of PM_{2.5}?
 - Statistical formulation: Does including AOD in a statistical prediction model improve PM_{2.5} concentrations when other information is included in the model?
 - GIS-based covariates
 - Meteorological covariates
 - Spatial smoothing to estimate large-scale variation

SUMMARY OF RESULTS

- Systematic, spatially-correlated error in AOD as a proxy for PM_{2.5} suggests that spatial patterns in AOD do not reflect patterns in PM_{2.5}.
 - Differences may be due to missing retrievals as well as errors from retrieval algorithm that are spatially-correlated.
- Inclusion of AOD in statistical prediction models for PM_{2.5} has little impact on PM_{2.5} predictions.
 - Raw correlation between AOD and PM_{2.5} reflects patterns in PM_{2.5} that can be predicted using other sources of information.

ONGOING WORK

- Full cross-validated assessment of statistical models with and without AOD to quantify effect of AOD on PM_{2.5} prediction.
- Full development of monthly-scale Bayesian statistical models for PM_{2.5} prediction, accounting for spatio-temporal structure.
- Monthly model predictions of PM_{2.5} on a four-km grid over the eastern U.S. for 2000-2006.

DATA SOURCES

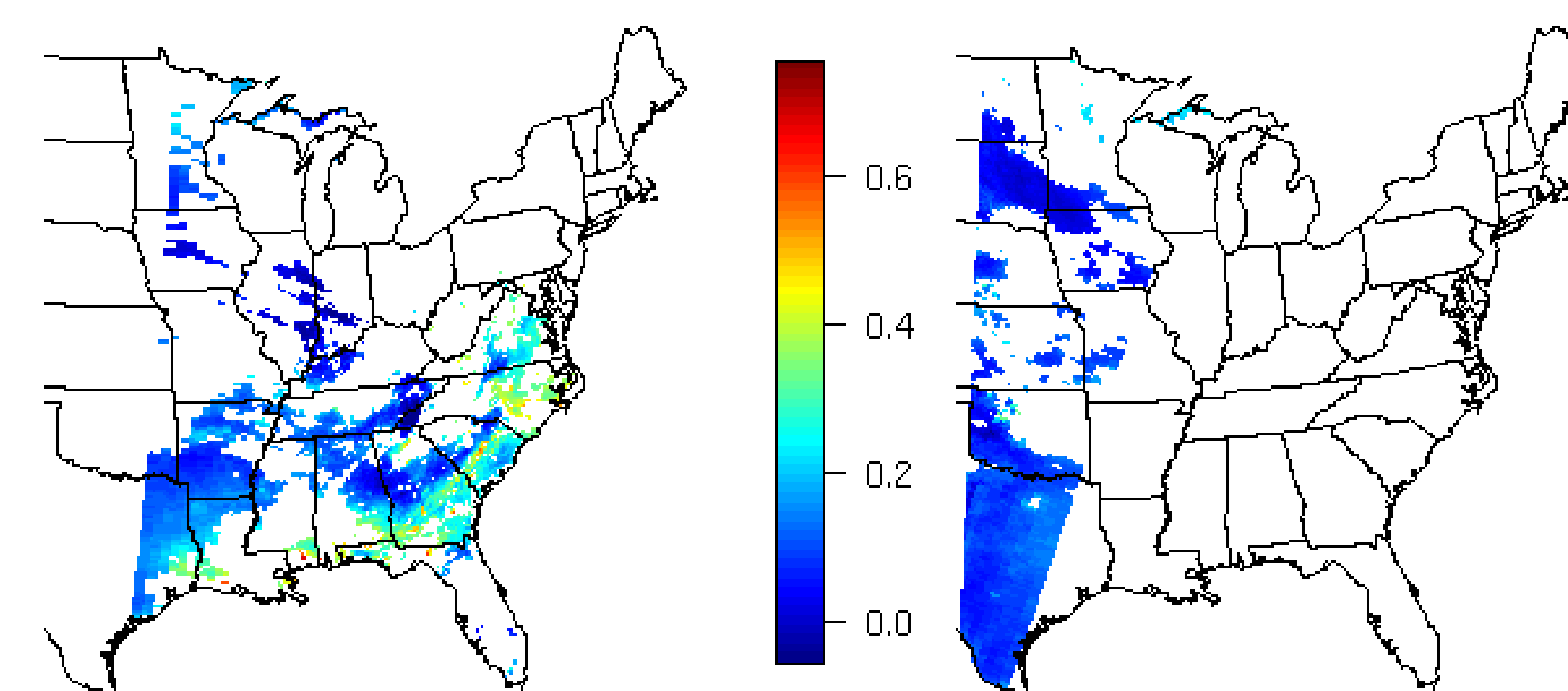
Remote Sensing Observations

- MISR AOD: 16 day orbit repeat, observations every 4-7 days at 10:30 am for a given location, 17.6 km nominal resolution
- MODIS AOD: 16 day orbit repeat, observations every 1-2 days at 10:30 am for a given location, 10 km nominal resolution
- GOES AOD: observations every half hour, 4 km nominal resolution

PM_{2.5} and Covariate Information

- PM_{2.5} measurements from AQS and IMPROVE: daily average, every 1, 3, or 6 days
- Weather data at 32 km, 3 hour resolution from North American Regional Reanalysis
- GIS-derived information: distance to roads (and road density) by road class, population density, land use
- NEI point source and county-level area emissions

Example: MODIS orbits, July 14, 2004



White indicates areas outside swath or with missing retrievals.

Key Question: Are such spatial patterns reflective of patterns in PM_{2.5}?

RAW ASSOCIATIONS OF AOD AND PM_{2.5}, EASTERN U.S.

DAILY ASSOCIATION

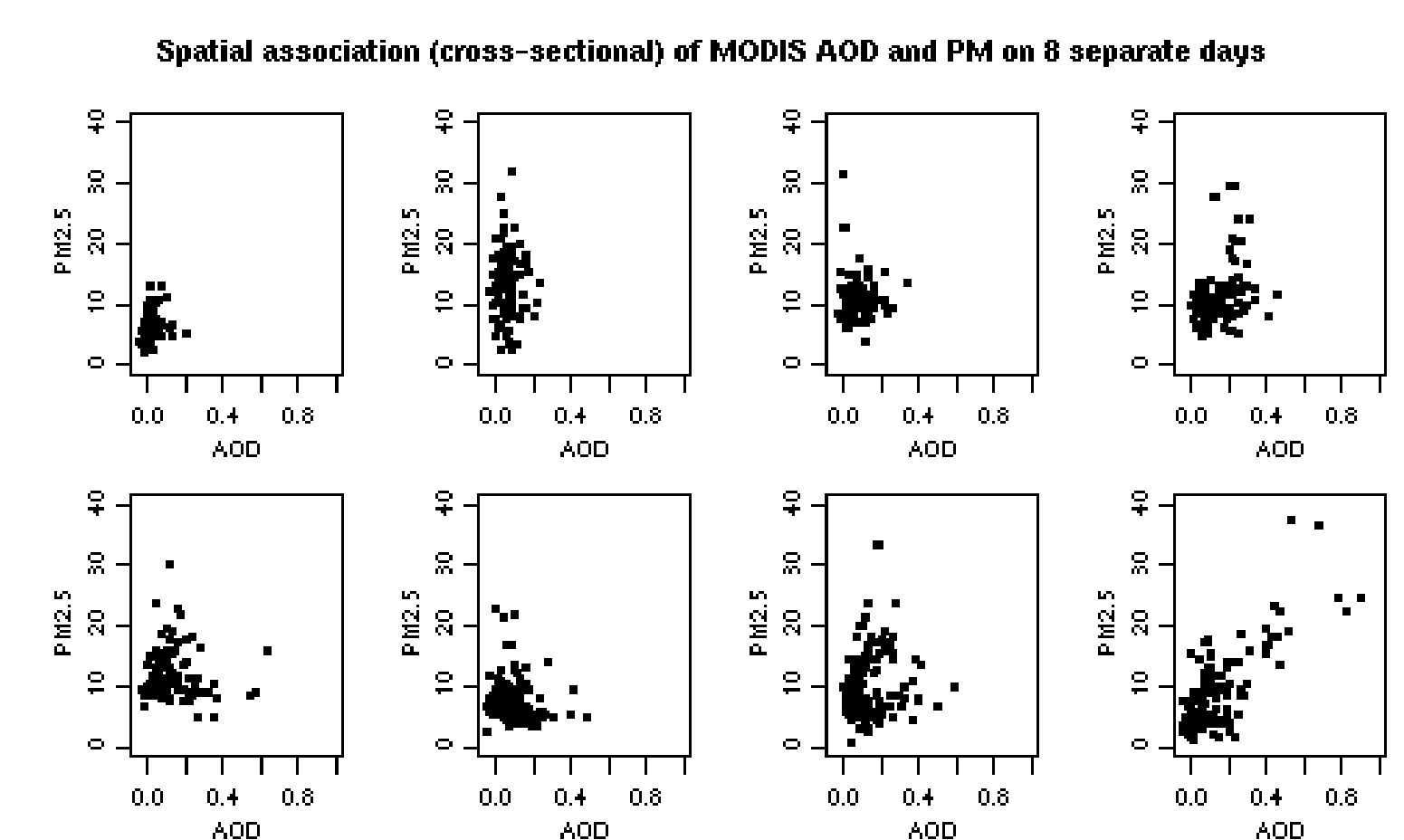
Associations of matched (time and space) daily AOD retrievals and PM_{2.5} concentrations

	Raw AOD			Calibrated AOD		
	MODIS	MISR	GOES	MODIS	MISR	GOES
Overall correlation (longitudinal plus cross-sectional)	0.60	0.50	0.38	0.64	0.57	0.40
Average of daily (cross-sectional) correlations	0.35	0.30	0.23	0.45	0.32	0.29
Average of daily, April-October only	0.42	0.34	0.30	0.50	0.38	0.40

LONG-TERM ASSOCIATION

Associations (cross-sectional) of yearly average PM_{2.5} with average of available AOD retrievals (not matched by day, matched in space)

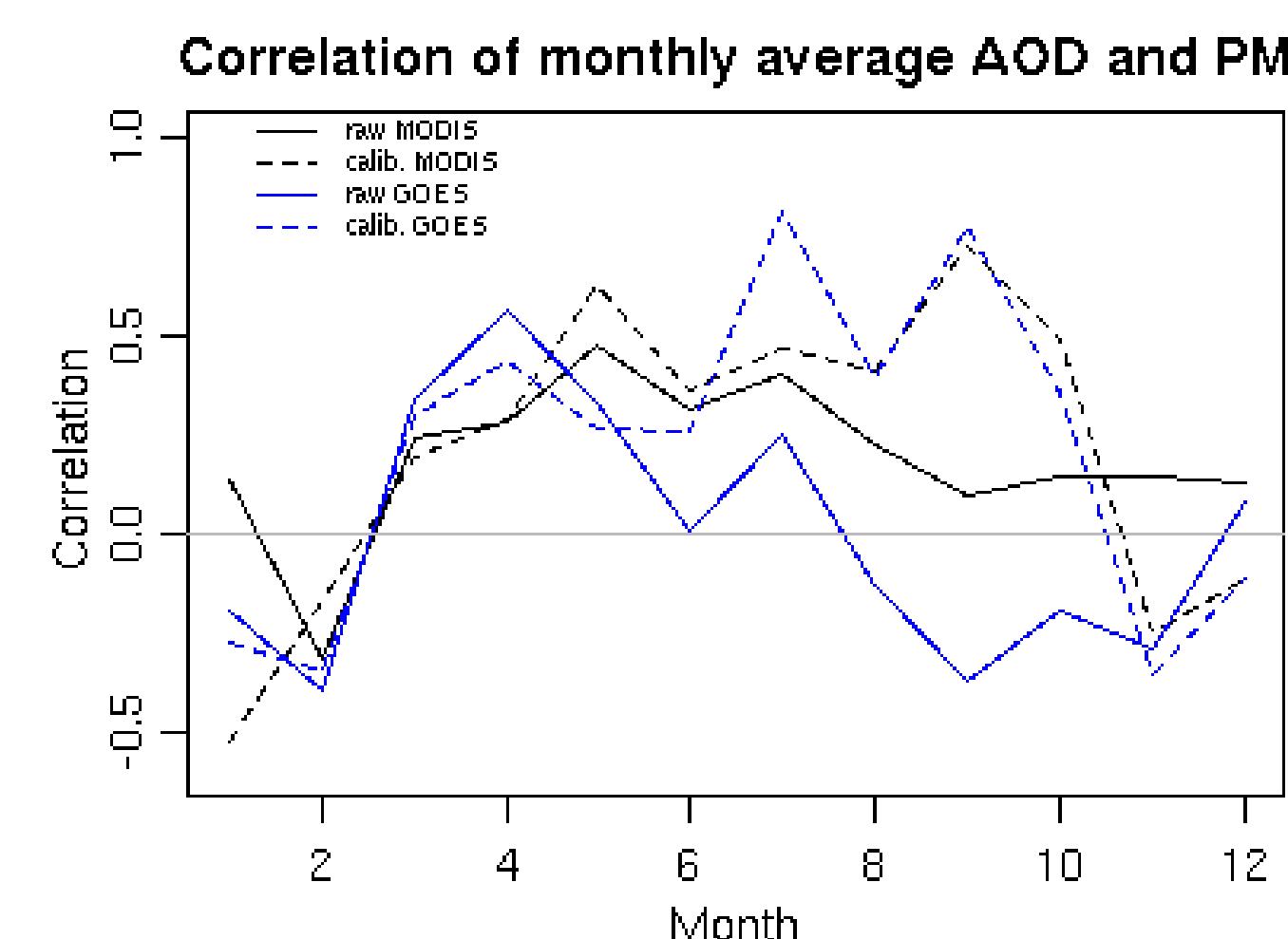
	Raw AOD			Calibrated AOD		
	MODIS	MISR	GOES	MODIS	MISR	GOES
Overall correlation	0.09	0.25	-0.06	0.49	0.22	0.57
April-October only	-0.11	0.17	-0.24	0.41	0.13	0.64



CALIBRATION

Involves adjusting AOD for relative humidity, planetary boundary layer, day of year, and regional spatial effects based on regression model of AOD on PM_{2.5} for matched daily data from 2004.

Spatial (cross-sectional) associations of monthly average PM_{2.5} with smoothed average of available AOD retrievals (not matched by day, matched in space)



Note: spatial smoothing of AOD done to interpolate areas with no retrievals in a month (this is primarily for MODIS and primarily in the winter).

SUMMARY

Moderate correlations are seen when comparing daily AOD and PM_{2.5} matched in time and space, which includes both longitudinal and cross-sectional (spatial) association. Adjustment (calibration) for meteorology and regional spatial variation in the relationship improves correlations. However, when considering only cross-sectional association and comparing long-term average PM_{2.5} concentrations with the average of available AOD retrievals, correlations are not strong. In interpreting the correlations that do exist, one possibility is that these represent large-scale associations such that AOD included in a full statistical model for PM_{2.5} may not help improve PM_{2.5} predictions because large-scale patterns can be estimated solely from spatial smoothing of the available PM_{2.5} data.

This research is supported by HEI 4746-RFA05-2/06-7.

STATISTICAL MODELLING: MID-ATLANTIC CASE STUDY

Question 1: Do AOD patterns reflect PM_{2.5} patterns?

MODEL FRAMEWORK: USE AOD AS DATA

- AOD and PM_{2.5} treated as two separate datasets and both related to latent 'true' PM_{2.5}.
- Naturally deals with missing AOD – doesn't require imputation.
- Model structure for bias of AOD is critical – must model any systematic error (spatially-correlated bias) in AOD as a proxy for PM_{2.5}.

MODEL

Likelihoods for monthly average data:

$$PM_i = y_i \sim \mathcal{N}(\mu + P(s(i)) + \sum_k f_k(z_{k,i}), \sigma_{y,i}^2)$$

$$AOD_m = a_m \sim \mathcal{N}(\beta_0 + \phi(s_m) + \beta_1(\mu + P(s_m)), \sigma_{a,m}^2)$$

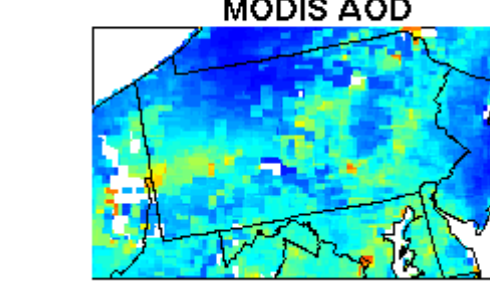
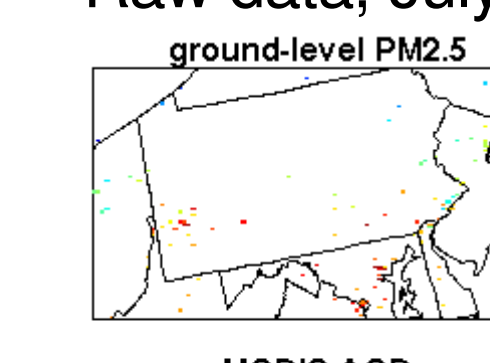
- $f_k(\cdot)$, $k = 1, \dots, K_f$ are nonparametric regression functions of within-grid cell covariates.
- $\phi(s)$ is spatially-correlated additive bias.

Latent PM_{2.5} process, $P(s)$, on 4 km grid:

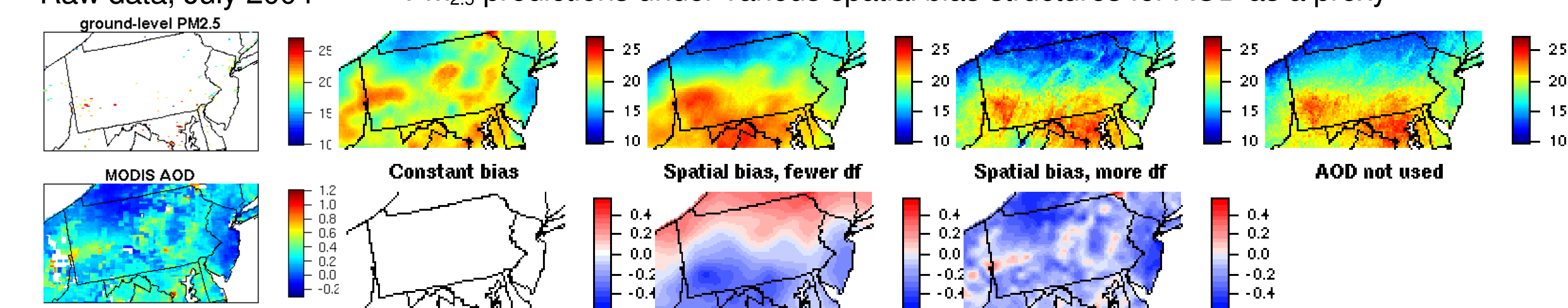
$$P(s_m) = \sum_k h_k(w_k(s_m)) + g(s_m)$$

- $h_k(\cdot)$, $k = 1, \dots, K_h$ are nonparametric regression functions of grid cell-scale covariates.
- $g(s)$ is Gaussian spatial process.

Raw data, July 2004



PM_{2.5} predictions under various spatial bias structures for AOD as a proxy



Estimated spatial bias (systematic error) of AOD as a proxy for PM_{2.5}

SUMMARY

Model predictions are very sensitive to the assumptions about the nature of the bias in AOD as a proxy for PM_{2.5}. If no spatial (i.e., no systematic) bias is assumed, spatial patterns in AOD are reflected in PM_{2.5} predictions. If systematic bias is parameterized in the model, the model estimates that the spatial pattern in AOD is distinct from spatial pattern in PM, discounting AOD as a proxy for PM_{2.5}. This suggests caution in interpreting spatial patterns in AOD as patterns in PM_{2.5}.

Question 2: Does AOD improve PM_{2.5} predictions?

MODEL FRAMEWORK: USE AOD AS A PREDICTOR

- AOD treated as a regression predictor.
- Treats PM observations as gold standard with inherent calibration of AOD to PM_{2.5}.
- Missing AOD needs to be imputed.

MODEL

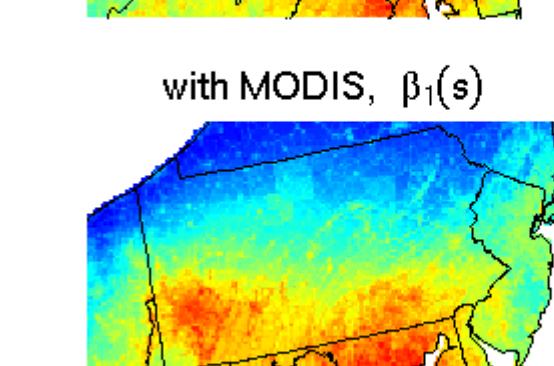
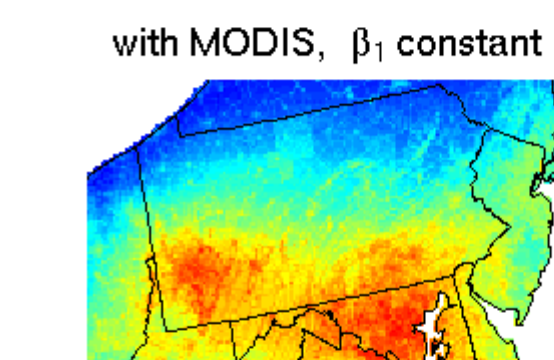
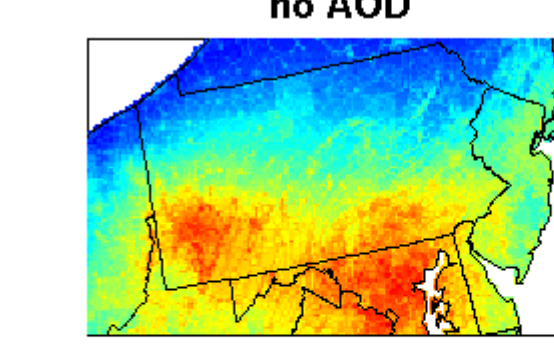
Likelihood for monthly average PM_{2.5}:

$$PM_i = y_i \sim \mathcal{N}(\mu + P(s(i)) + \sum_k f_k(z_{k,i}), \sigma_{y,i}^2)$$

Latent PM_{2.5} process, $P(s)$, on 4 km grid:

$$P(s_m) = \beta_1(s_m)A(s_m) + \sum_k h_k(w_k(s_m)) + g(s_m)$$

PM_{2.5} MODEL PREDICTIONS, JULY 2004



Note: Predictions based on GOES AOD as predictor are similar.

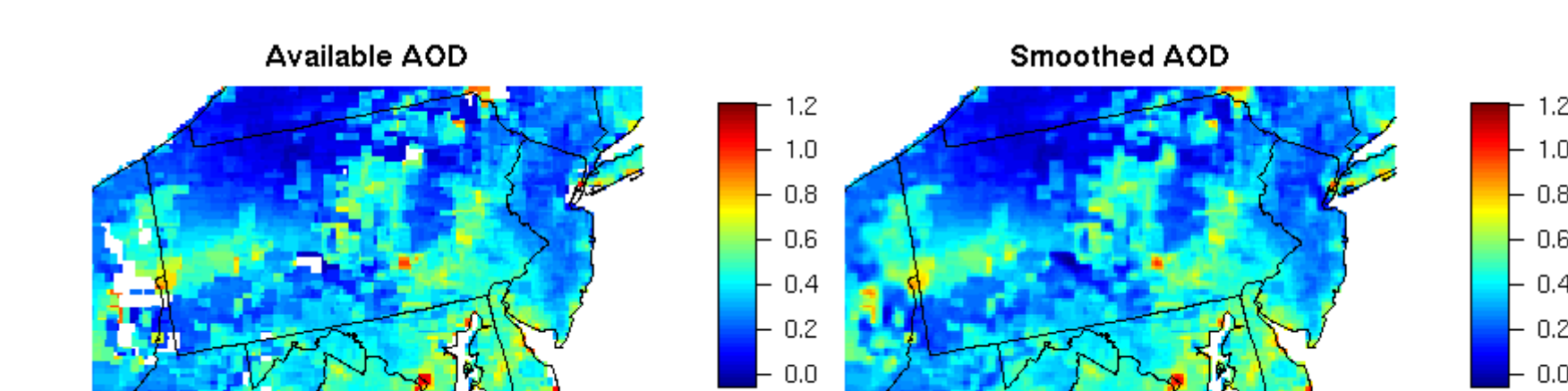
Imputation of AOD via spatial smoothing model, using a thin-plate spline-based GMRF model:

$$a_m \sim \mathcal{N}(\gamma_0 + A(s_m), \sigma_{a,m}^2)$$

$$A(s) \sim \text{GMRF}(\tau^2)$$

where $A(s)$ is smooth AOD process estimated everywhere.

EXAMPLE OF AOD IMPUTATION



SUMMARY

Estimate of beta1 (the AOD regression coefficient) is small. Including AOD as a predictor has little impact on model predictions of PM_{2.5}.