Connecting U.S. PM$_{2.5}$ means and extremes with regional meteorology and global change

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Motivating Questions

• How does climate change affect the overall U.S. air pollution distribution and extremes in the context of projected air pollutant emission changes?

• How does climate variability affect regional air pollution?

• When and where will climate change signals be detectable relative to climate variability?

• What regional feedbacks influence the air pollutant response to climate change and variability?
GOAL: Quantify risks from changing U.S. PM$_{2.5}$ distributions

$$\text{RISK} = \text{HAZARD} \times \text{VULNERABILITY}$$

Time-evolving (5 decades) PM$_{2.5}$ distributions:
- Daily PM$_{2.5}$
- Annual PM$_{2.5}$
- Visibility
- Health endpoints
- Probabilistic return levels

Probability that meteorological events conducive to high PM will occur, e.g.:
- Temperature
- Precipitation
- Stagnation
- Ventilation

Probability of high PM conditioned on hazard occurring; varies with:
- Anthropogenic emissions
- Climate Feedbacks
  - wildfires
  - biogenic emissions

Evaluate hazards, vulnerability, and overall risks in the context of climate variability and change, plus future PM$_{2.5}$ emission scenarios.
APPROACH: Large multi-chemistry-climate-model ensembles and high-res downscaling, evaluated with observations

**2 CMIP5/IPCC AR5 Chemistry-climate models**

- CM3 model \[\text{e.g., Donner et al., 2011}\]
- 3-member ensembles for **2006-2100** RCP4.5, RCP8.5; **RCP8.5_WMGG** (climate change from WMGHGs but PM + precursor emissions held at 2005)
- 400 years from “2000 Control” to examine climate variability
  → **Select targeted years in ~6 U.S. regions for downscaling with CMAQ**

**CESM | COMMUNITY EARTH SYSTEM MODEL** \[\text{e.g., Neale et al., 2012}\]

- 40-member large ensemble with monthly PM\(_{2.5}\) components archived
- ~15-member medium ensembles with daily PM\(_{2.5}\) components archived
- 400 years from “2000 Control” to examine climate variability
  → **Provide statistical context for GFDL-CMAQ simulations + climate variability**

**Targeted high-resolution downscaling with CMAQ**

- CONUS, multiple selected years (**mid-century**)
- Examine sensitivities (vulnerability) to meteorologically-sensitive emissions
  → **Combine fine-scale information with statistical power of large ensemble**
Observed year-to-year variability:
Similar spatial patterns in annual mean and high-PM$_{2.5}$ events

**ANNUAL MEAN $\mu g\ m^{-3}$**

2004 2005 2006

0 2 4 6 8 10 12 14 16 18 20

**FRACTION OF DAYS > 25 $\mu g\ m^{-3}$**

2004 2005 2006

0 0.02 0.04 0.06 0.08 0.1 0.12 0.14 0.16 0.18 0.2

J. Guo, LDEO/Columbia
Approach: Characterizing variability and change in high-PM$_{2.5}$ events with EOF analysis [see also Eder et al., 1993]

1°x1° observed summertime (JJA) 1999-2013 daily PM$_{2.5}$ from U.S. AQS from Schnell et al., PNAS, 2017

Varimax-rotated Midwest U.S. EOF (21% total variance)

Principal Component (PC): Time-varying strength of EOF spatial pattern

→ ~55% decrease in U.S. anthrop. SO$_2$ emissions 1999-2003 vs 2009-2013
→ Approach captures improved air quality from precursor emission controls [e.g., Boys et al., 2014; Murphy et al., 2011]
Empirical Orthogonal Function (EOF) analysis reveals underlying modes of spatiotemporal variability

5 EOFs capture >75% of the total variance

EOFs (Varimax-rotated) derived from standardized anomalies of 1999-2013 summer daily surface PM$_{2.5}$ 1°x1° gridded observations [Schnell et al., PNAS, 2017]
EOF analysis can be used as a rapid-screening tool for gauging changes in frequency & duration of pollution events.

- **Daily fields archived from the GFDL CM3 global chemistry-climate model**

- **EOF analysis on GFDL CM3 daily PM$_{2.5}$**
  - Identify regions that vary coherently
  - Reduces size of dataset for analysis

- **Time series analysis:** identify changes in frequency and duration of regional-scale events

Information relevant for air quality (and climate) management

An approach to tap spatial coverage and statistical power of large-ensemble coarse-resolution models to investigate air quality-climate linkages
GFDL CM3 can broadly capture the sign of observed monthly (de-trended, de-seasonalized) PM-meteorology relationships

- PM$_{2.5}$-T relationship captured in EUS and Midwest (US avg 0.09 µg m$^{-3}$ K$^{-1}$ vs. 0.07 observed)
- PM$_{2.5}$-precipitation sensitivities underestimated (-0.06 vs -0.41 µg m$^{-3}$ mm$^{-1}$ d observed)
- PM$_{2.5}$-wind speed sensitivities captured in EUS (-0.294 vs. -0.286 µg m$^{-3}$ m$^{-1}$ s)

Westervelt et al., Atm. Environ., 2016
A chemistry-climate model (GFDL CM3) represents observation-derived EOFs (spatial modes of variability). This evaluation approach does not require exact space-time matching.

Observation-derived (1999-2013 daily PM$_{2.5}$) Midwest EOF

Midwest EOF derived from GFDL CM3 2006-2100 RCP8.5_WMGG

Ensemble member #1: 18.1%

Ensemble member #2: 17.8%

Ensemble member #3: 17.6%
Analyze principal components for changes in the frequency at which each EOF is expressed (high regional events)

Midwest EOF in GFDL CM3 Ensemble member #1

Upper Quartile: More excursions in later decades?
The Midwest principal component shows more excursions into the upper quartile later in the 21\textsuperscript{st} century.

Occurs across GFDL CM3 RCP8.5_WMGG ensemble members #1, #2, and #3, implying a forced climate signal.

Slope=0.20 days/yr; $r^2=0.30$
Slope=0.16 days/yr; $r^2=0.22$
Slope=0.21 days/yr; $r^2=0.36$
Increase in duration over 21st century of upper quartile PM$_{2.5}$ events in the Midwest region in RCP8.5_WMGG

GFDL CM3 3-member ensemble average
Climate change from well-mixed greenhouse gases (RCP8.5_WMGG)
Analyze GFDL CM3 2000 Control Simulation (400 years) for insights to PM$_{2.5}$ response to climate variability.

Is U.S. PM$_{2.5}$ coupled to known modes of atmospheric variability?
Linking summertime (JJA) mean surface PM$_{2.5}$ variability to known modes of variability.

Sea-level pressure anomalies (hPa) (Index defined as 1$^{st}$ EOF)

PM$_{2.5}$ regressed onto ENSO index

El Niño (20°S-20°N)

PM$_{2.5}$ regressed onto NAM index

Northern Annular Mode (20°N-90°N)

Previdi
Aerosols aren’t simple passive responders to climate! What role might they play in the observed SE US ‘warming hole’?

Recent studies attribute to:
-- aerosols (various aspects)
-- internal climate variability
-- land-use

[e.g., Kumar et al., 2013; Leibensperger et al, 2012; Meehl et al, 2012, 2015; Misra et al., 2012; Pan et al., 2013; Portmann et al., 2009; Yu et al., 2012]

But focus on different regions, seasons, and time periods

Hartmann et al., 2013 Fig 2.21(IPCC AR5 WG1 Ch2)
A systematic look at summertime temperature trends over the SE USA (25-35N; 80-95W)

A forced component (aerosols) for trends from 1930s until mid-1970s

Note: multiple ‘holes’ that vary by region, season, timing leaves room to reconcile prior conflicting interpretations

Mascioli et al., ERL, 2017
Tap statistical power of large-ensemble global models plus high-res CMAQ to estimate time-evolving PM$_{2.5}$ risks

**Daily fields archived from existing GFDL & NCAR chemistry-climate model simulations**

**EOF analysis:** Apply to other scenarios in GFDL CM3 for downscaling + NCAR CESM LENS/MENS
- Identify regions that vary coherently
- Reduces size of dataset for analysis

**Time series analysis:** identify changes in frequency and duration of regional-scale events

**Evaluation with observations** (meteo, chem, relationships)

**Select periods for CMAQ downscaling; investigate vulnerabilities**

**bias correction?** metrics for health, visibility, NAAQS, extreme value theory methods (return levels)...
[e.g., Rieder et al., 2015]

**Information relevant for U.S. air quality (and climate) management**

**Statistical downscaling? NCAR LENS/MENS GFDL CM3 scenarios**