Uncovering spatiotemporal drivers of urban ozone in changing NO_x regimes: A data-driven case study of Los Angeles and Chicago

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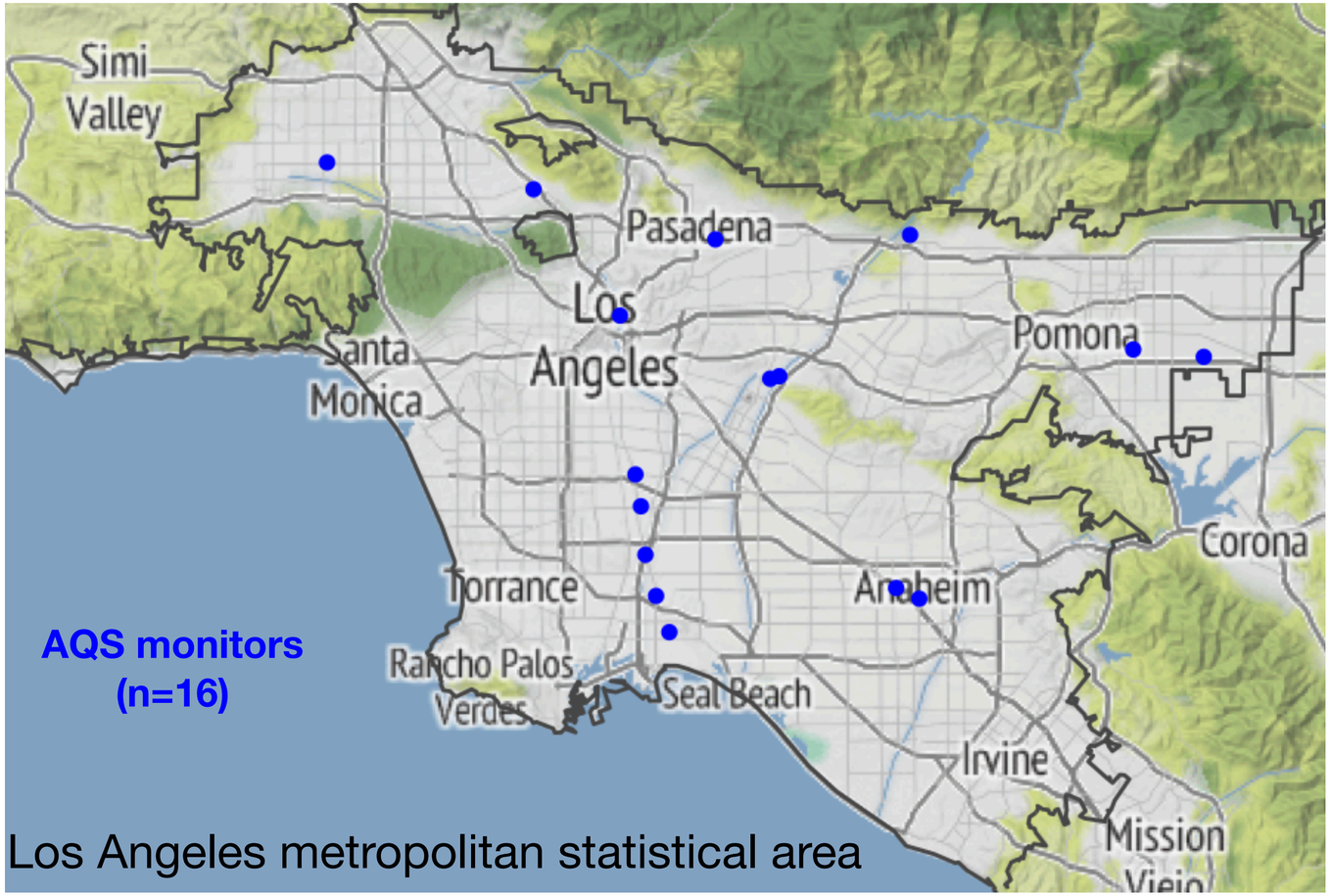
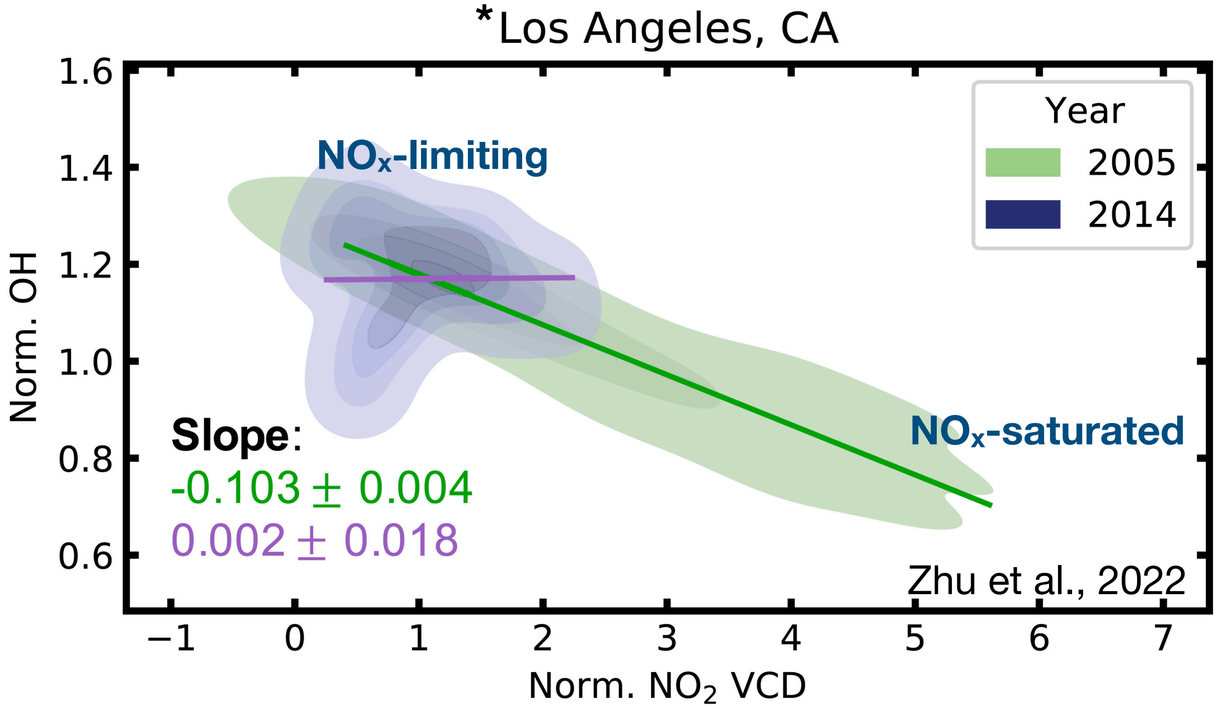
Through emission controls, Los Angeles has transitioned from a NO_x-saturated toward a NO_x-limited chemical regime in the 2010s

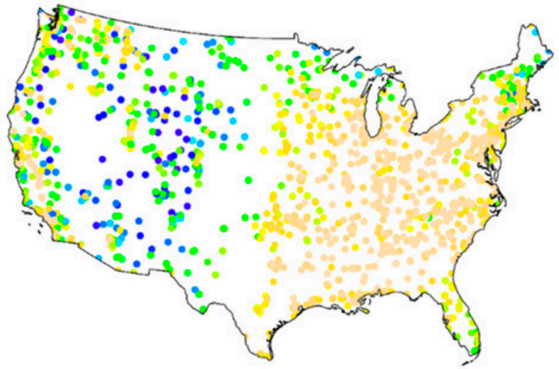




*Current understanding of spatiotemporal patterns are limited

Machine-learned data fusion datasets provide the most representative air pollution concentration fields today

Surface Monitor Data



Traffic ~ Population

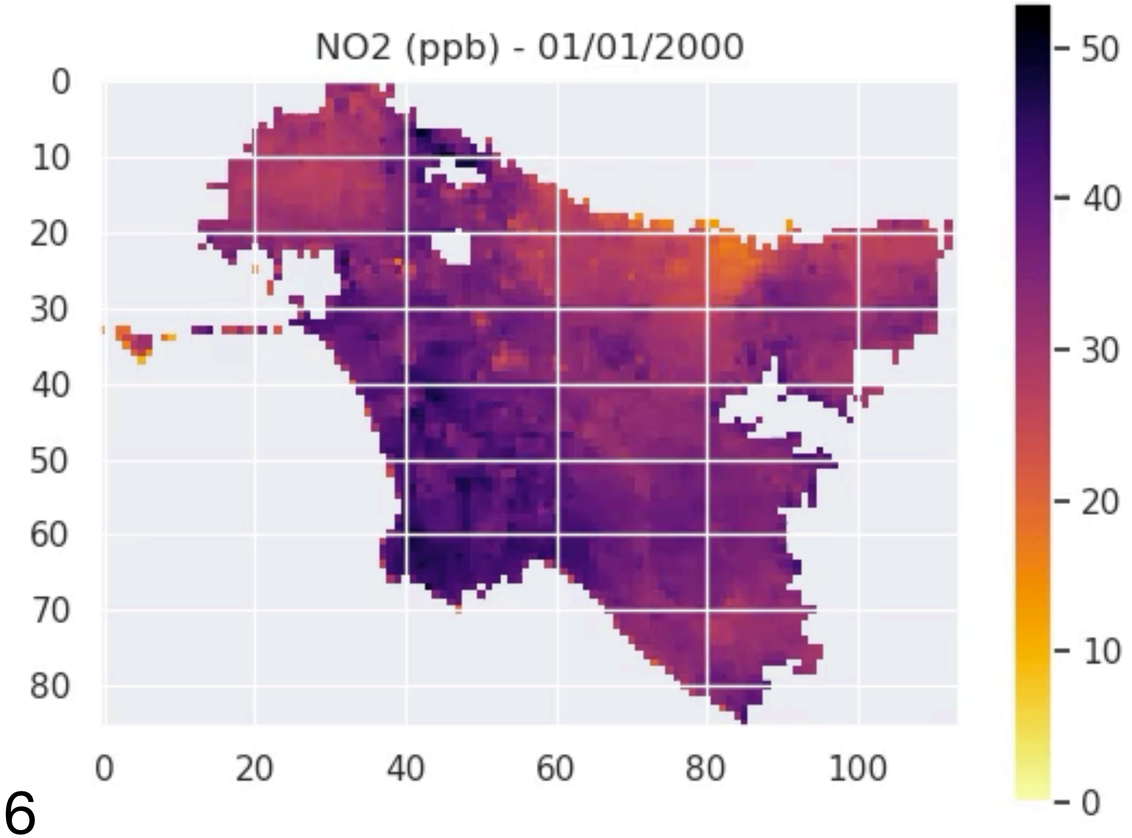
GEOS-Chem CMAQ

- Land-use Terms
- Chemical Transport Model Predictions
- Meteorological Variables
- Satellite Measurements

Predictor Variables

ML prediction

Predicted Daily Concentrations
1 km x 1 km grid cells



We use 2005-2016

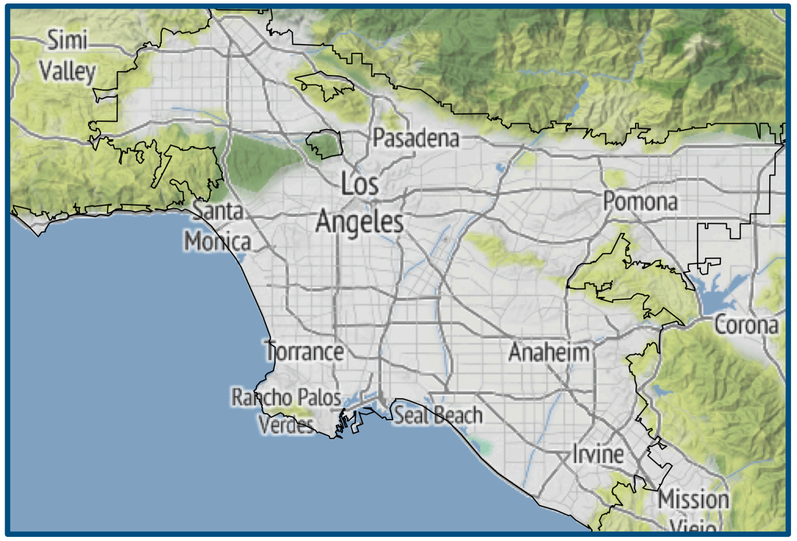
Data Products: NO_2, $PM_{2.5}$, and Ozone

Di et al., 2019, 2022

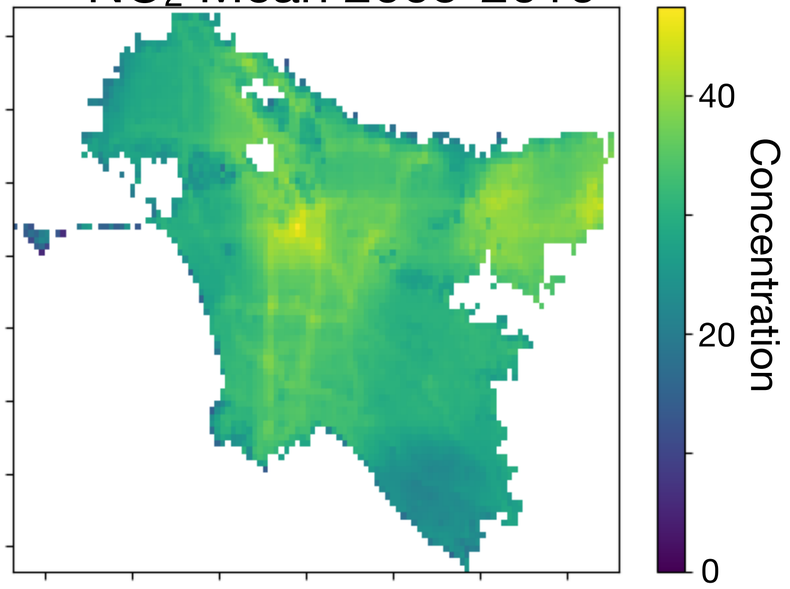
Classic statistics agree with our understanding of LA: NO_2 declining, ozone increasing

1. Mean and standard deviations have **same** spatial patterns
2. NO_2 and $PM_{2.5}$ concentrations **decline** over 2005-16
3. Ozone concentrations **increase** over 2005-16
4. **Mean/std. dev. used to evaluate chemical regimes and policy controls**

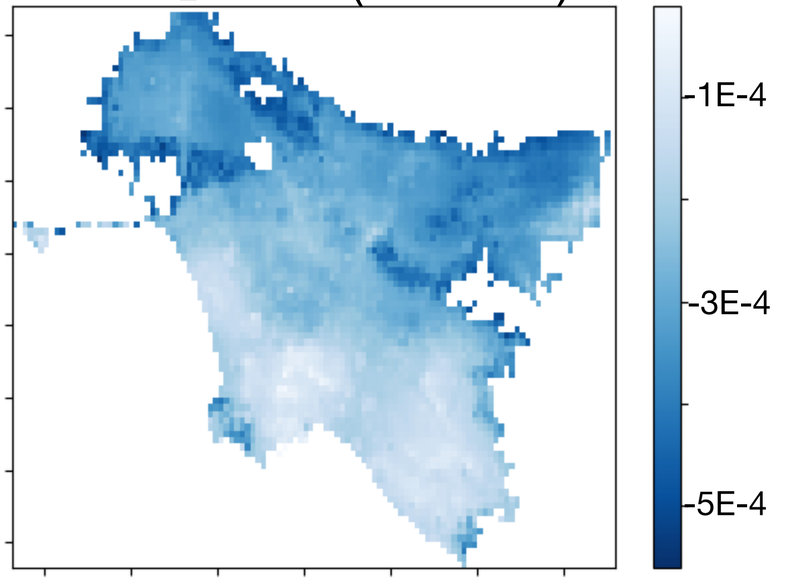
Los Angeles Metropolitan Statistical Area



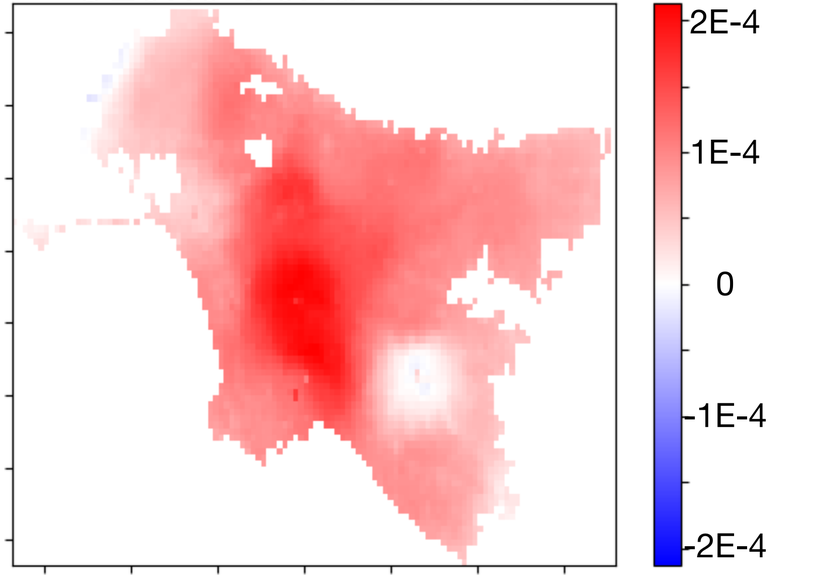
NO_2 Mean 2005-2016



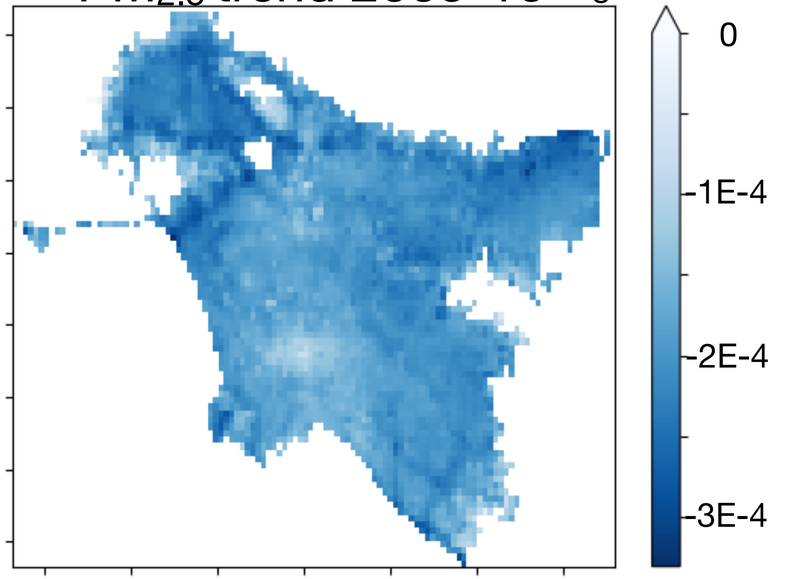
NO_2 trend (2005-16) ppb^{-1} $month^{-1}$



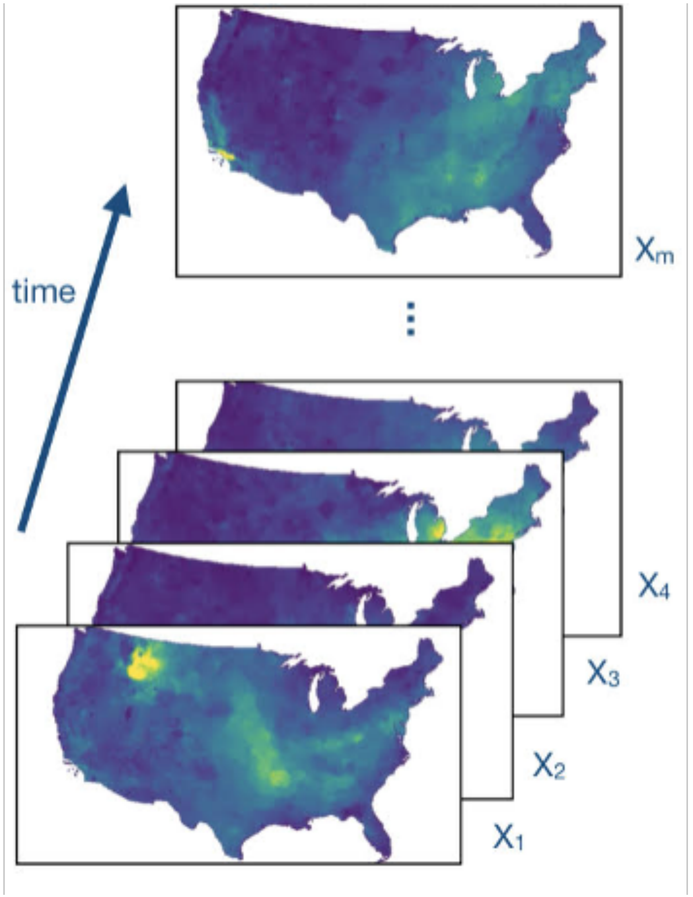
Ozone trend 2005-16 ppb^{-1} $month^{-1}$

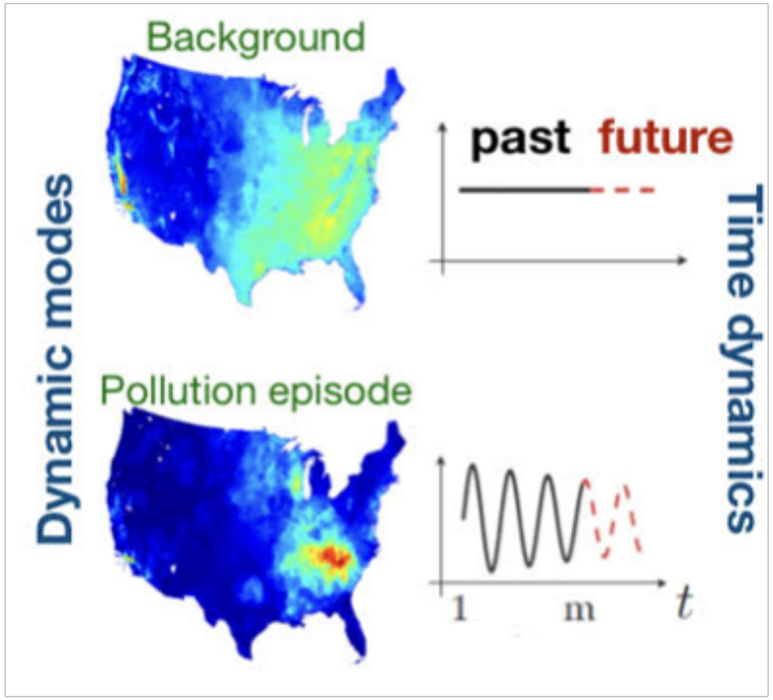


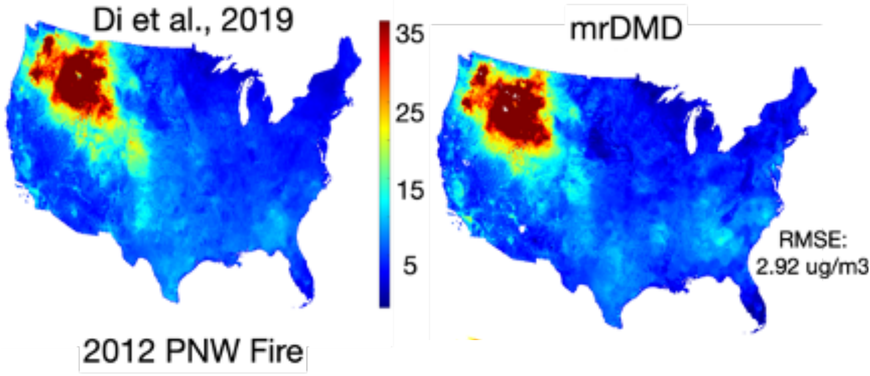
$PM_{2.5}$ trend 2005-16 $ug/m3^{-1}$ $month^{-1}$



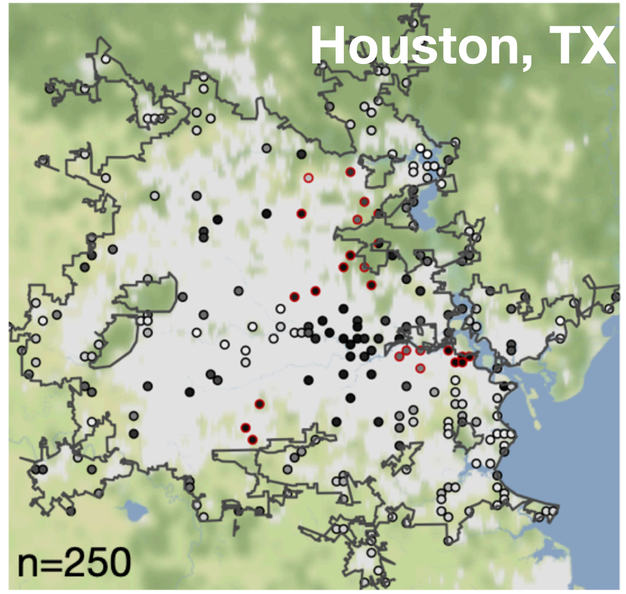
Multi-resolution dynamic-mode decomposition (mrDMD) can extract dynamic modes at varying spatiotemporal scales, which can serve to isolate pollutant events.







Identification of wildfire modes



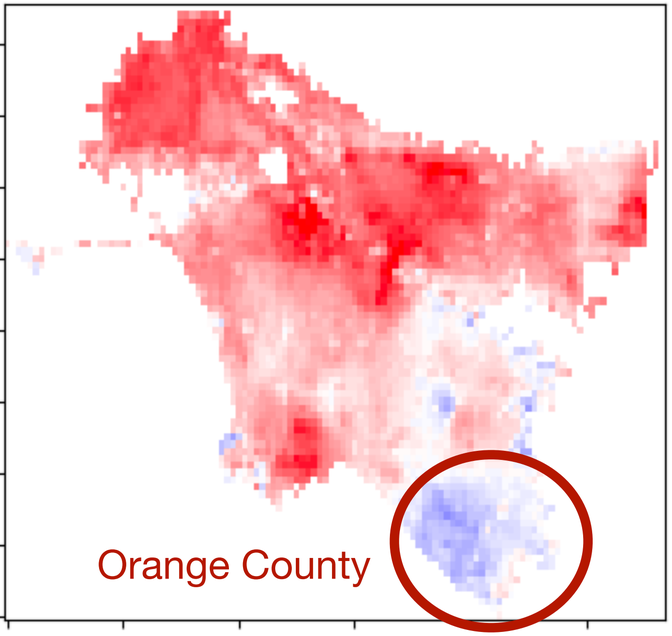
Data-driven urban air pollution networks

Kelp et al., 2022, 2023

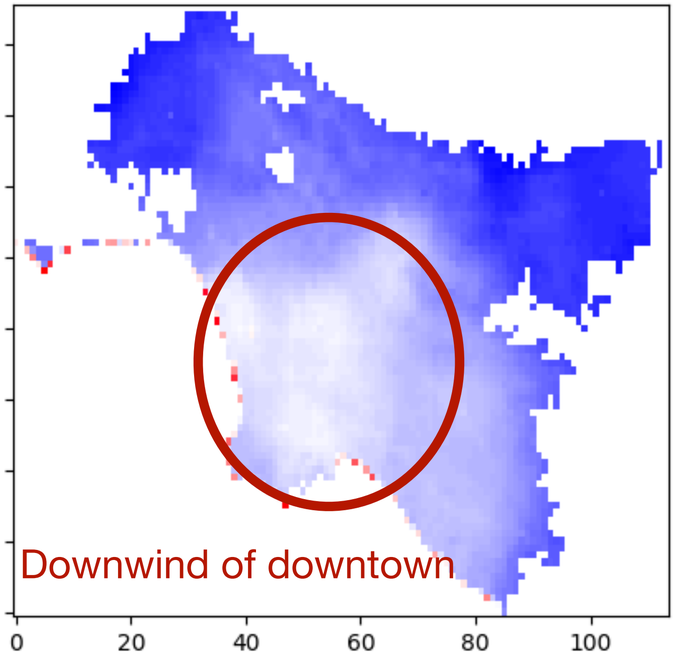
Long-term dynamic modes suggest an opposite relationship

DMD modes provide information about the structural changes in air pollution concentrations over time. Positive modes indicate growing air pollutant variability, while negative modes indicate decaying air pollutant variability.

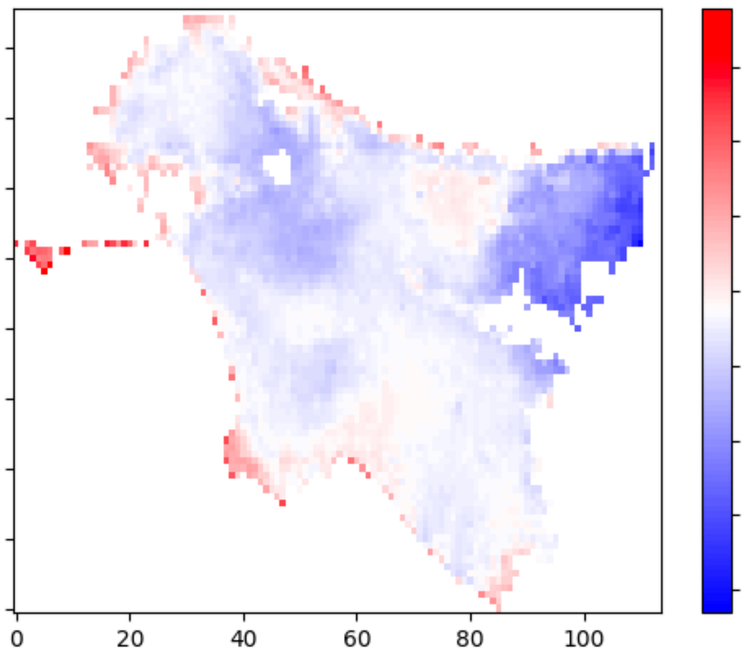
NO_2 Mode over 2005-2016

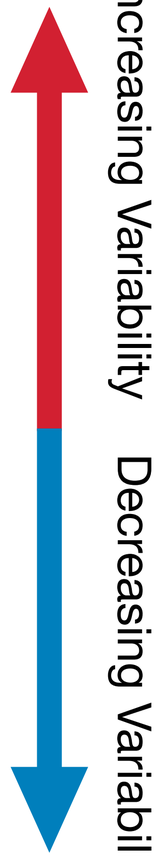


Ozone Mode over 2005-2016



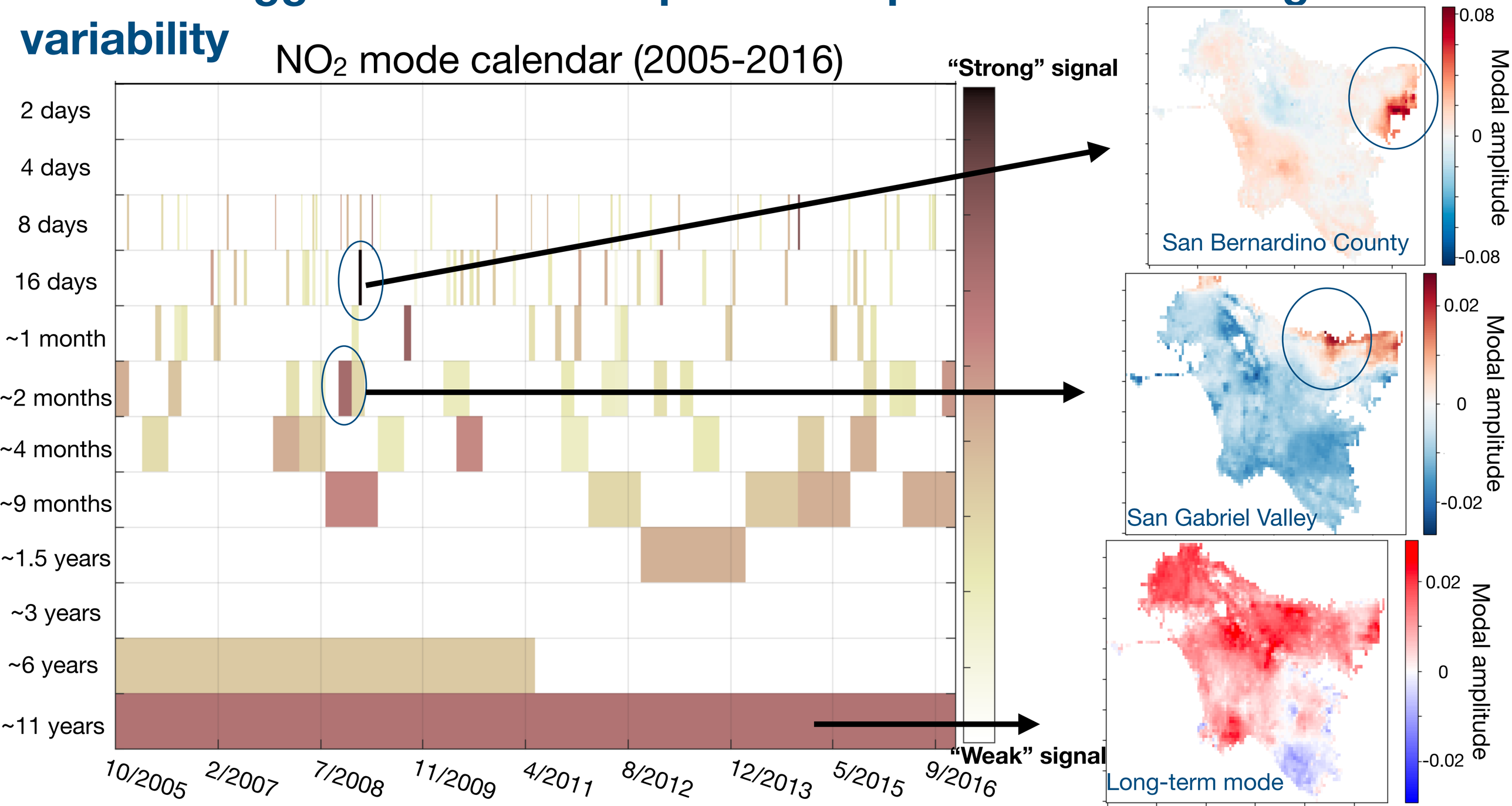
$PM_{2.5}$ Mode over 2005-2016





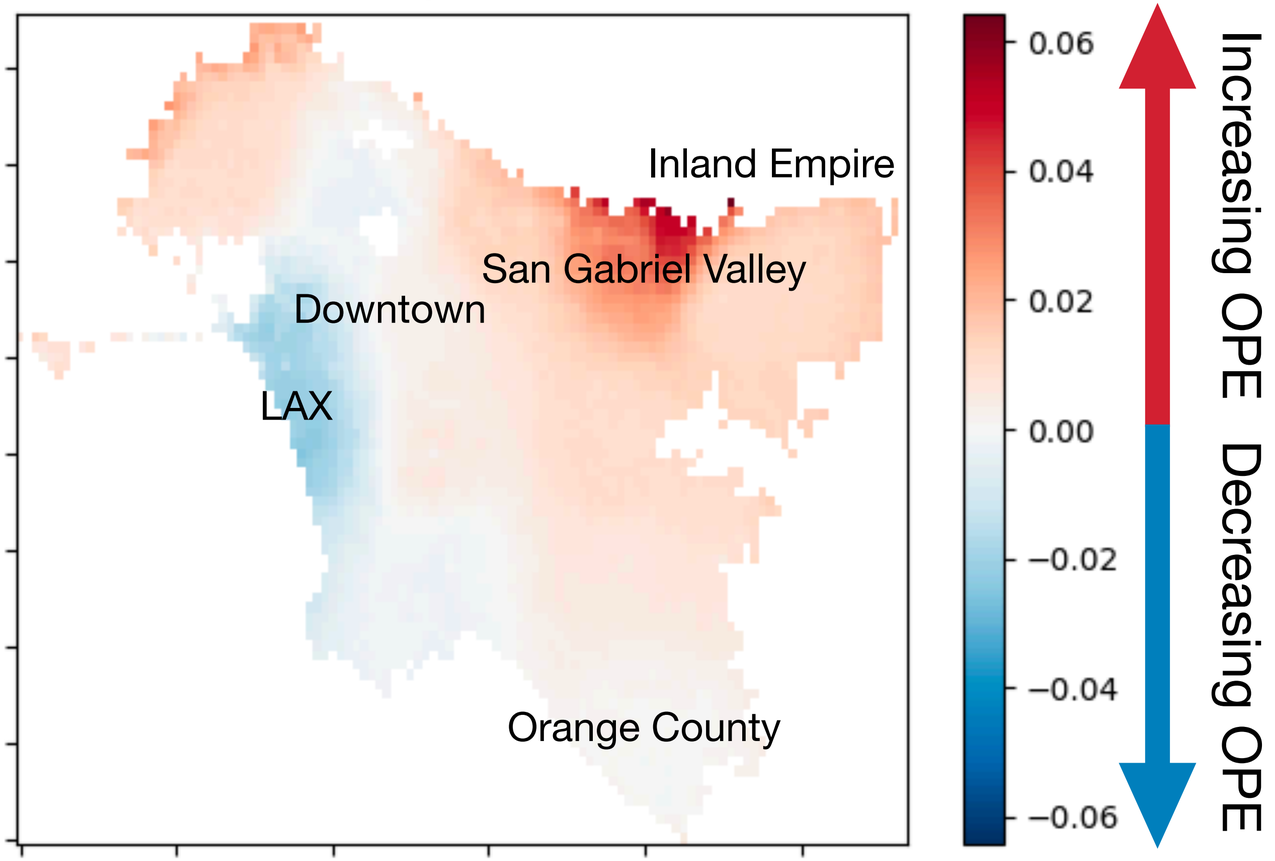
Increasing Variability Decreasing Variability

mrDMD suggests short-term pollution episodes drives long-term variability



San Gabriel Valley and the Inland Empire are increasing in OPE and more likely NO_x-saturated

Ozone/NO_2 Representative Mode



-Ozone/NO_2 can show information about ozone production efficiency (OPE) or NO_x-limited vs. NO_x-saturated regimes.

- LAX, downtown, near coast decreasing OPE

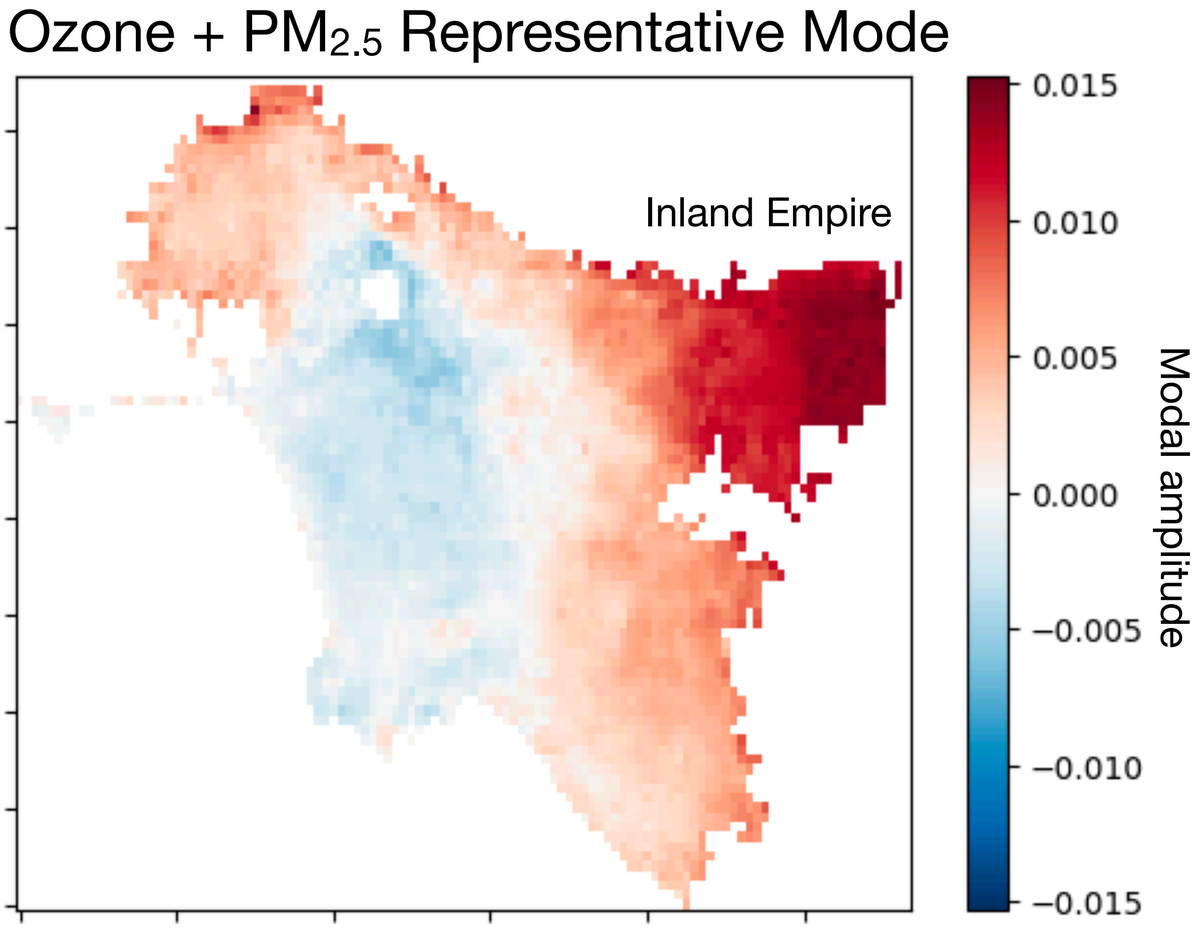
- San Gabriel Valley, Inland Empire increasing OPE

- Orange County increasing, but is NO_x-limited

Adding $PM_{2.5}$ and Ozone modes can highlight joint patterns or behaviors in the data

-Summing modes can capture co-occurring high variability of both pollutants.

-San Gabriel Valley/Inland Empire are a target area for high concentrations and high variability.



2021 in Los Angeles: c.f. Pfannerstill et al., 2023, *submitted*

Takeaways

-Los Angeles transitioning into a NO_x-limited regime, but some areas are more NO_x-limited than others

-Classic statistics may be misleading

-Short-term pollution episodes **dominate** long-term variability

-San Gabriel Valley/Inland Empire are a target area for high concentrations and high variability

-ML datasets with mrDMD may be a promising method to investigate pollution dynamics without running chemical transport models (CTMs)

Makoto Kelp

Website QR code

Next Steps: Incorporate temperature data, examine emissions over 2005-2016

NO_2 variability is increasing and spatiotemporal patterns are changing