

Long-Term Changes in Contributions of Anthropogenic and Natural Perturbations to Atmospheric Mercury in the United States

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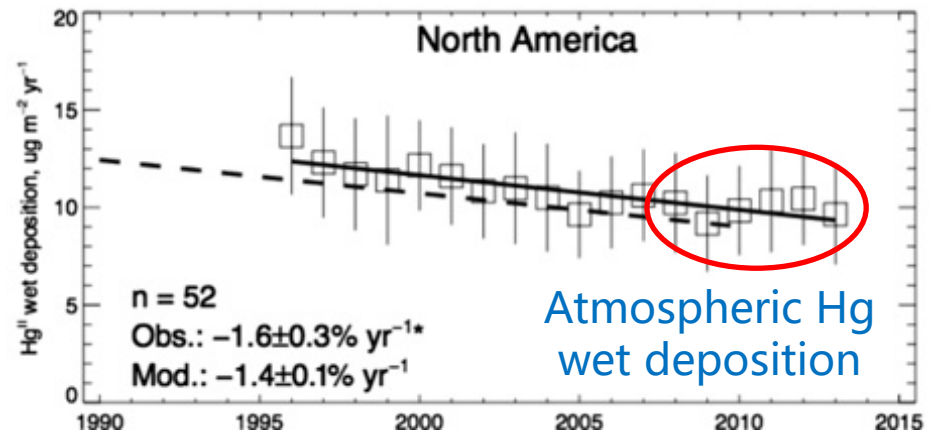
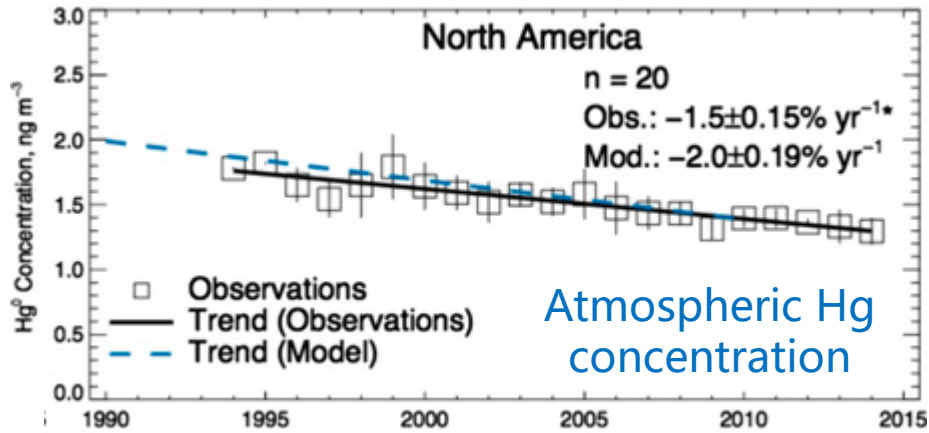
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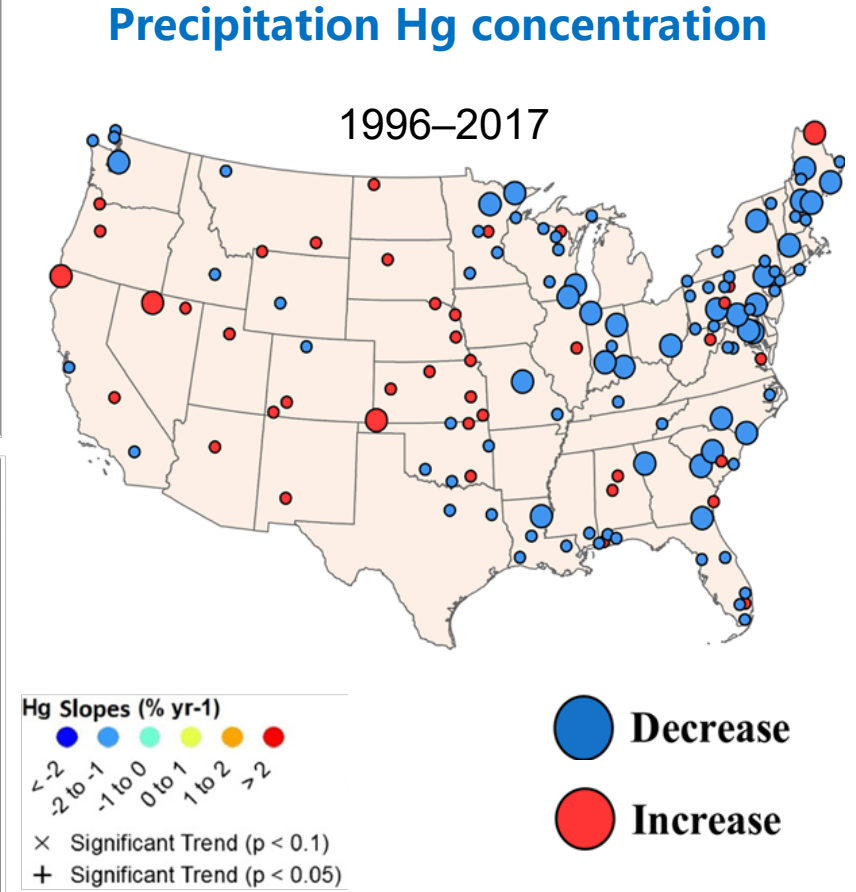
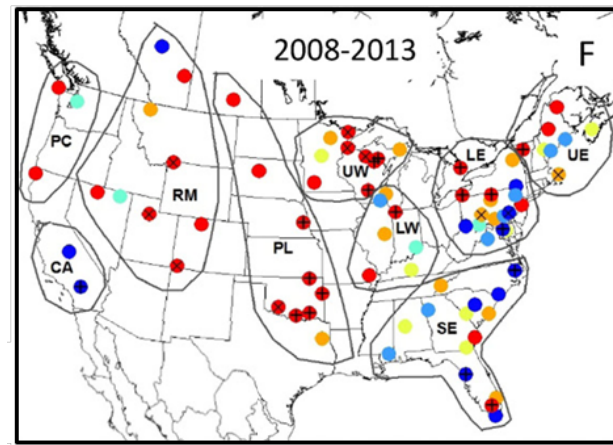
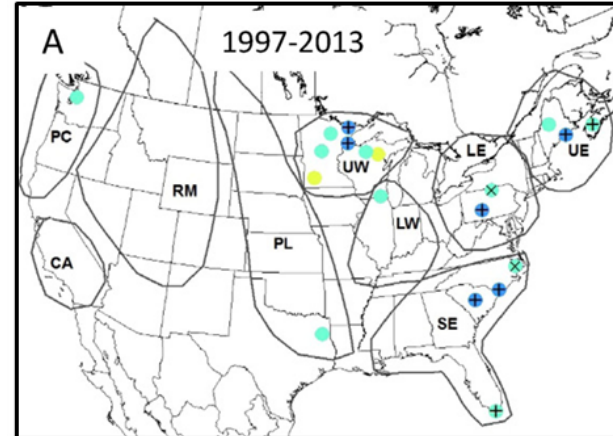
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- **Methodology**
 - The machine learning model (XGBoost)
 - The generalized additive model (GAM)
- **Impacts on Atmospheric Mercury Concentration**
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- **Take-Home Messages**

Long-term change of atmospheric Hg pollution in the US

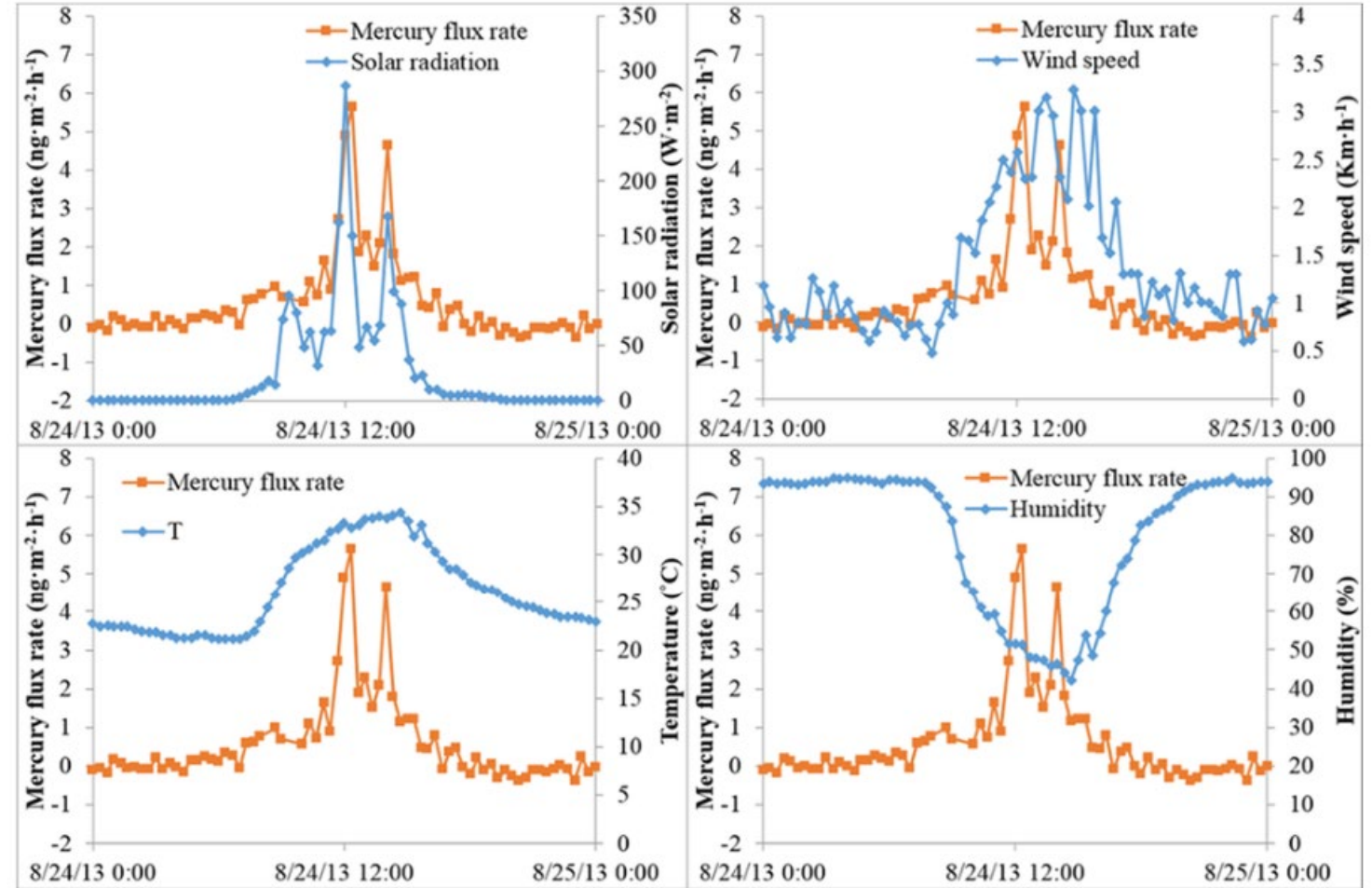
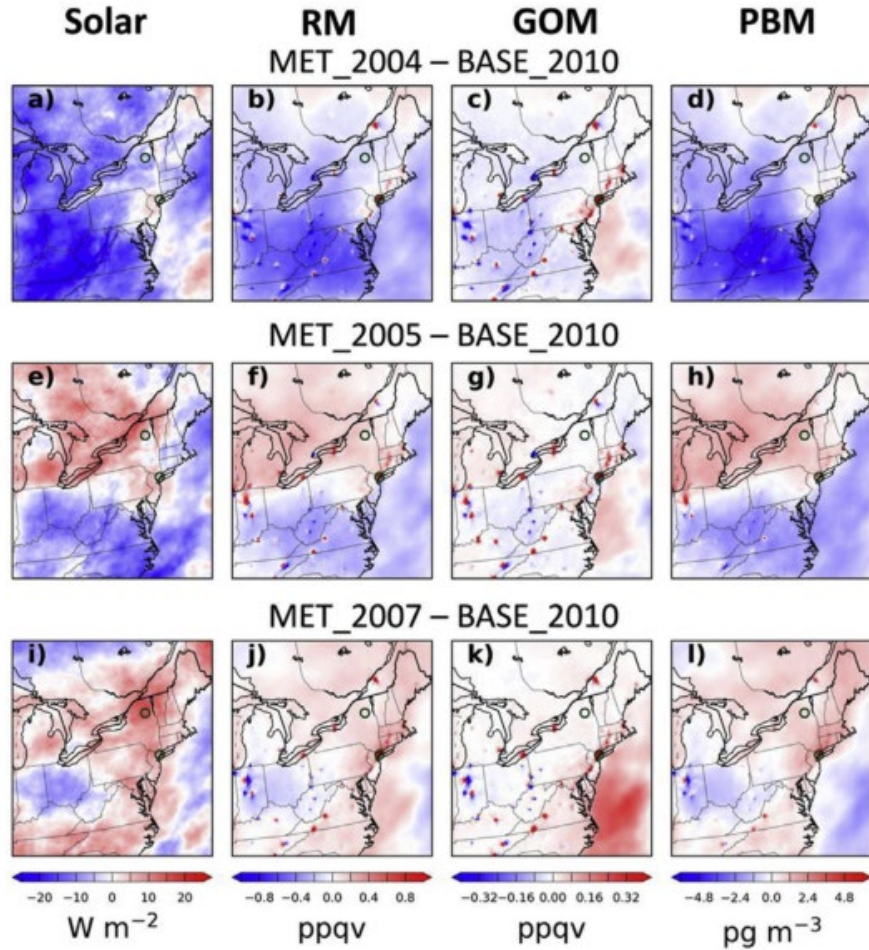


Long-term **decrease** in North America during 1995–2013



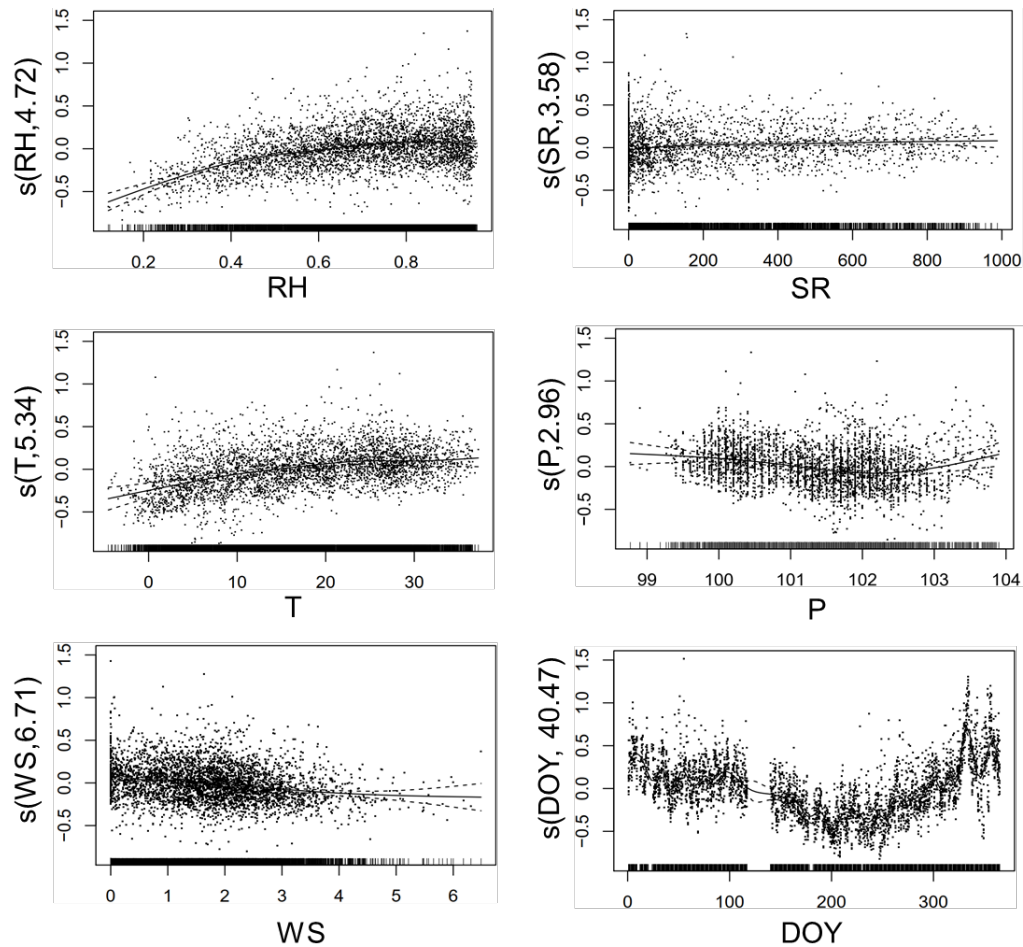
Overall **decreasing** trend in the **eastern US** during 1995–2017, but significant **increasing** trend in the **western US** after ~2008

Impacts of meteorology on atmospheric Hg pollution

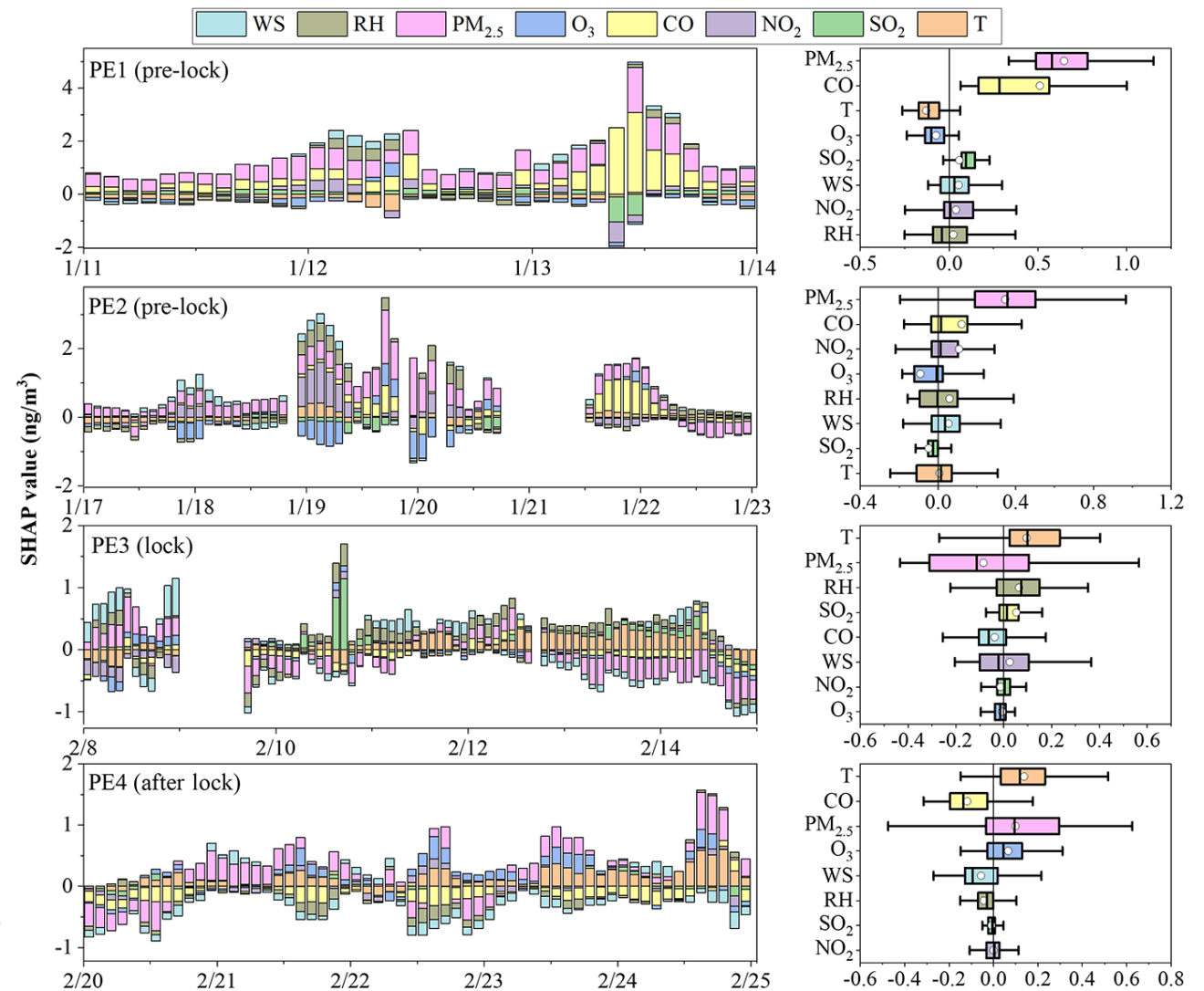


Solar radiation, wind speed, temperature and humidity are key to atmospheric Hg concentration and deposition

Quantification of anthropogenic and natural contributions



Advanced statistical and machine learning models have been used to quantify impacts of key factors



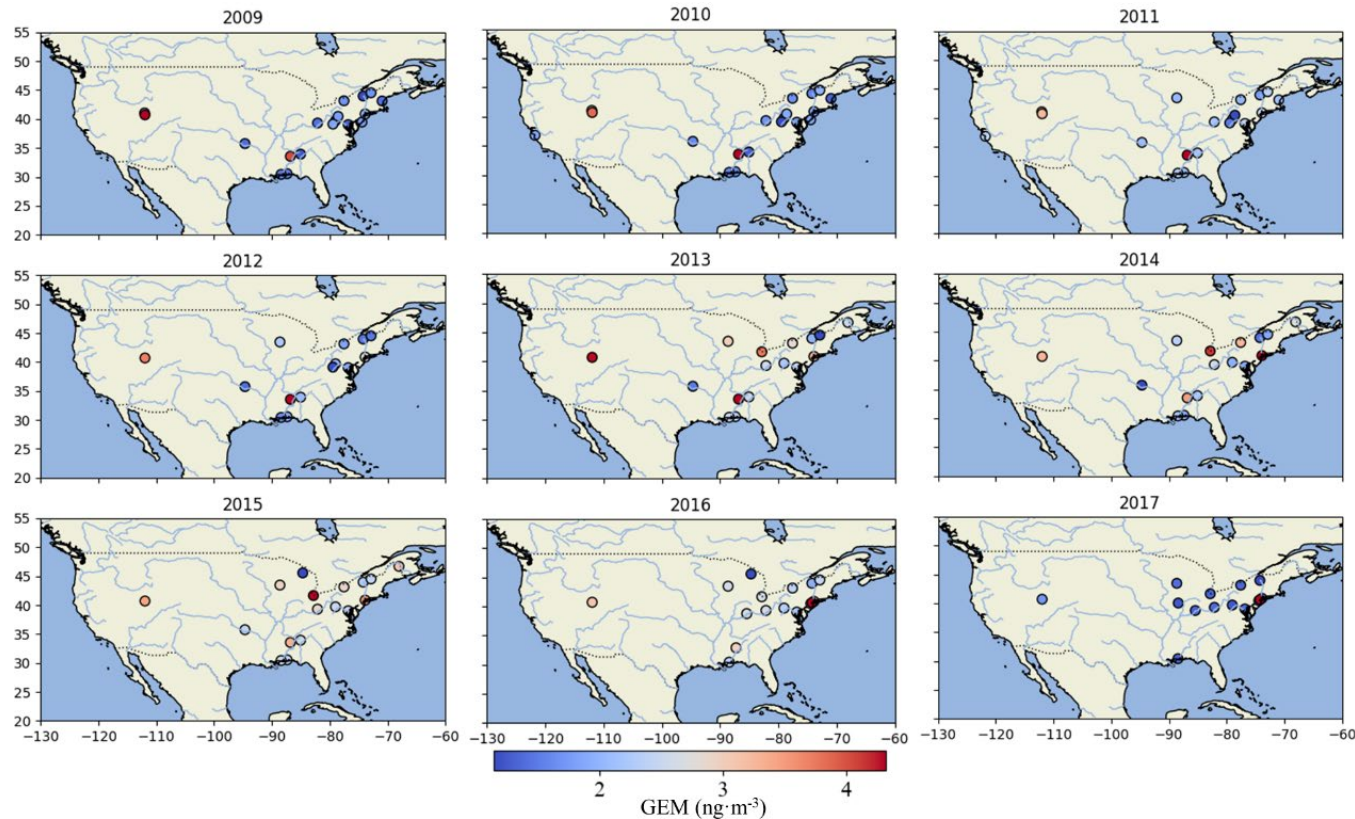
Scientific questions in this study

- How did long-term anthropogenic and natural perturbations change regional atmospheric Hg pollution patterns?
- How different are the changes of atmospheric Hg concentration and wet deposition flux in response to the perturbations?
- What will be the influence of global climate change in future on the regional atmospheric Hg pollution patterns?

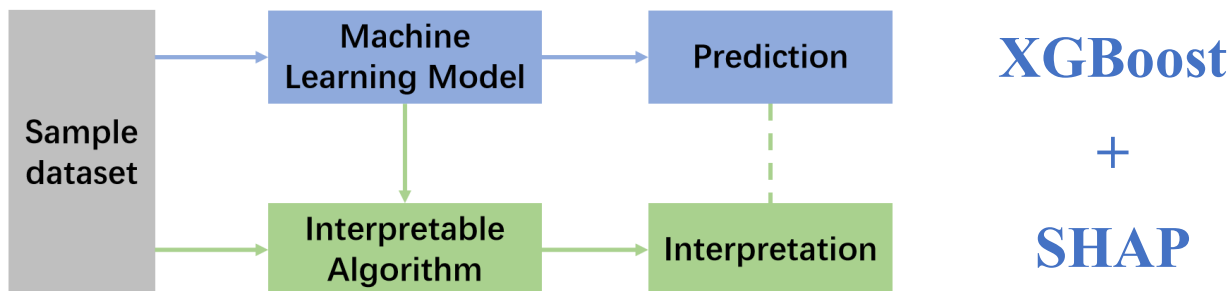
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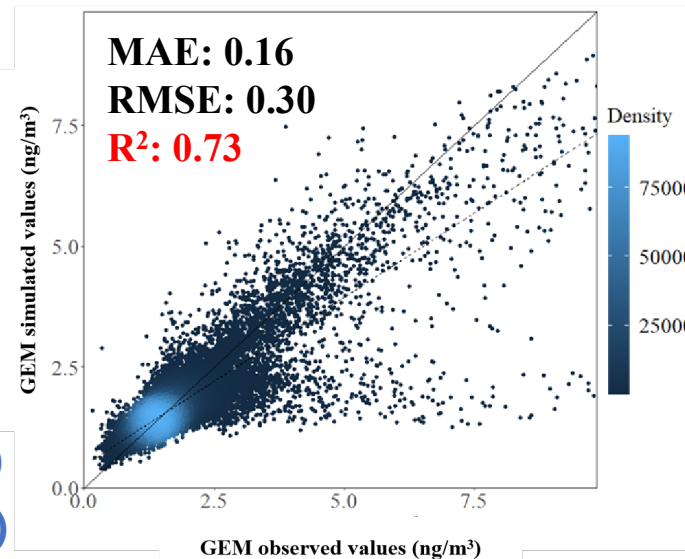
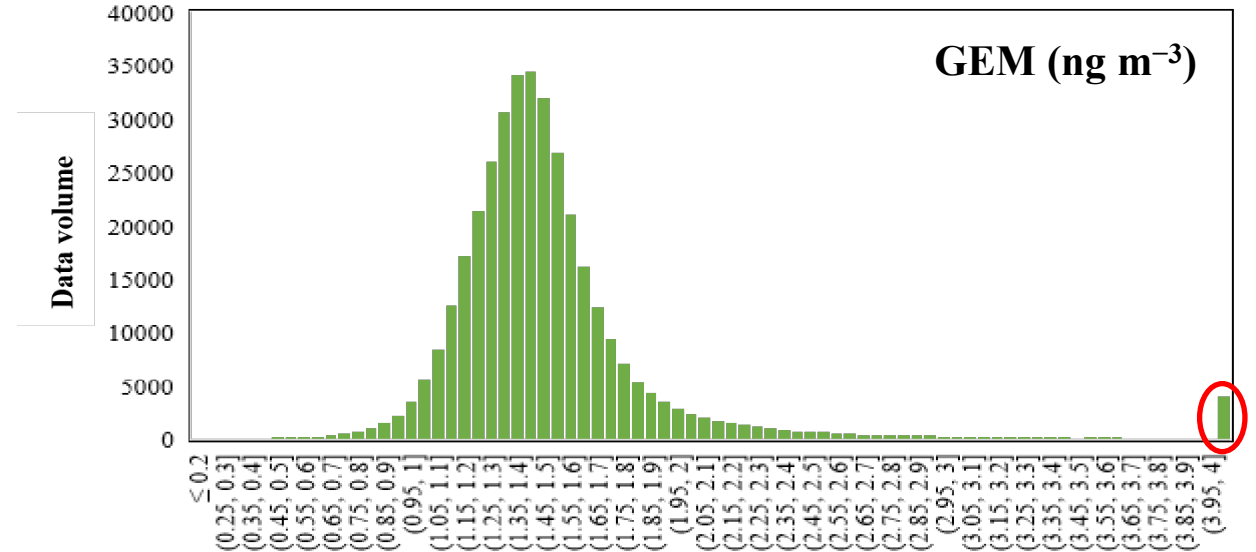
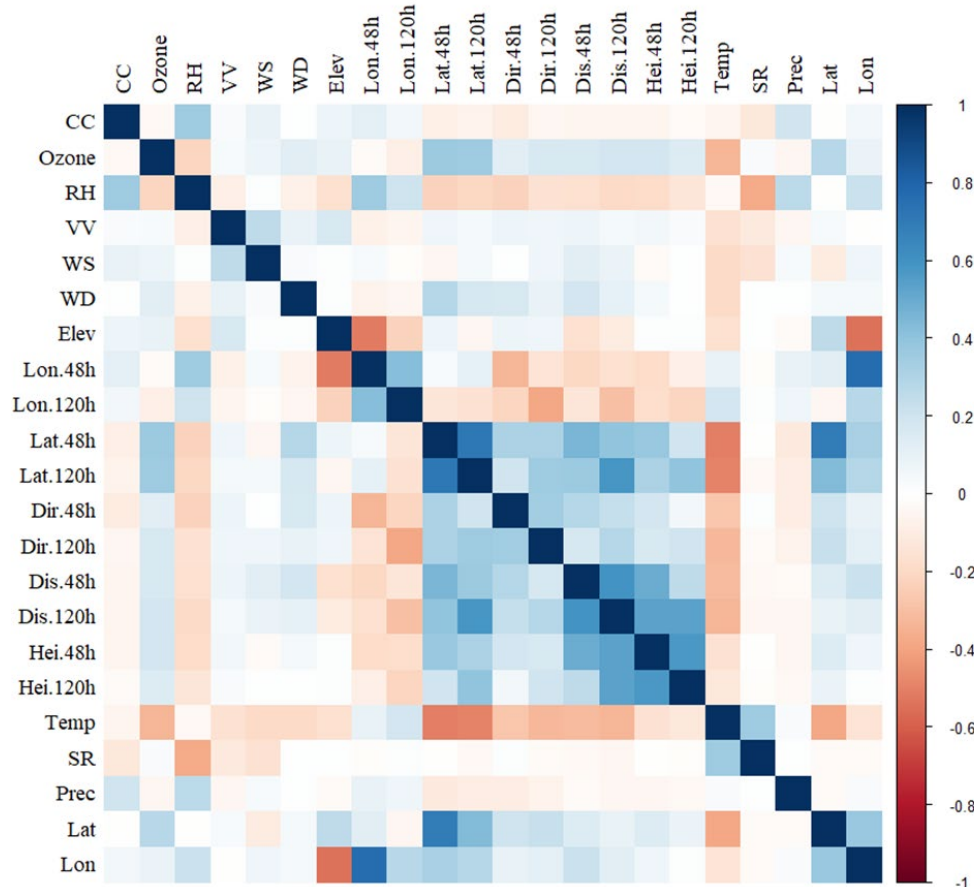
A machine learning model for atmospheric Hg concentration



| Database | Variables |
|--------------|--|
| AMNet | <ul style="list-style-type: none"> ✓ GEM (hourly data, $\text{ng}\cdot\text{m}^{-3}$) ✓ Elevation (Elev, m) ✓ Longitude (Lon, °) ✓ Latitude (Lat, °) |
| HYSPLIT | <ul style="list-style-type: none"> ✓ 48-h backward trajectory ✓ 120-h backward trajectory |
| ECMWF (ERA5) | <ul style="list-style-type: none"> ✓ Relative humidity (RH, %) ✓ Cloud cover (CC, %) ✓ Solar radiation (SR, $\text{J}\cdot\text{m}^{-2}$) ✓ Total column ozone (Ozone, $\text{kg}\cdot\text{m}^{-2}$) ✓ Wind speed (WS, $\text{m}\cdot\text{s}^{-1}$) ✓ Wind direction (WD, °) ✓ Temperature (Temp, K) ✓ Precipitation (Prec, mm) ✓ Vertical velocity (VV, $\text{Pa}\cdot\text{s}^{-1}$) |



XGBoost model configuration and validation



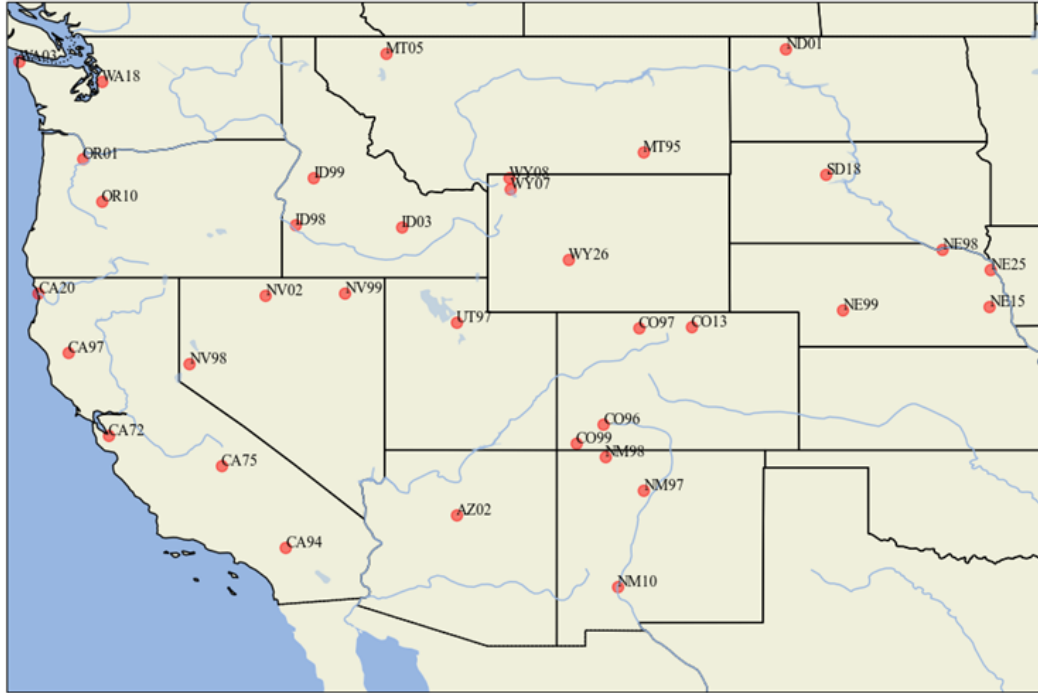
| No. | R ² | RMSE | MAE |
|-----|----------------|-------|-------|
| 1 | 0.724 | 0.295 | 0.157 |
| 2 | 0.715 | 0.304 | 0.158 |
| 3 | 0.736 | 0.295 | 0.157 |
| 4 | 0.734 | 0.287 | 0.157 |
| 5 | 0.738 | 0.294 | 0.156 |
| 6 | 0.739 | 0.296 | 0.158 |
| 7 | 0.731 | 0.301 | 0.159 |
| 8 | 0.722 | 0.304 | 0.159 |
| 9 | 0.733 | 0.299 | 0.157 |
| 10 | 0.734 | 0.288 | 0.157 |

- Limited correlations between any two predictors
- Outliers removed for the dependent variable (GEM)
- Good model performance (10-fold cross-validation)

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An generalized additive model for Hg wet deposition flux



Target region: Western US

Generalized Additive Model (GAM)

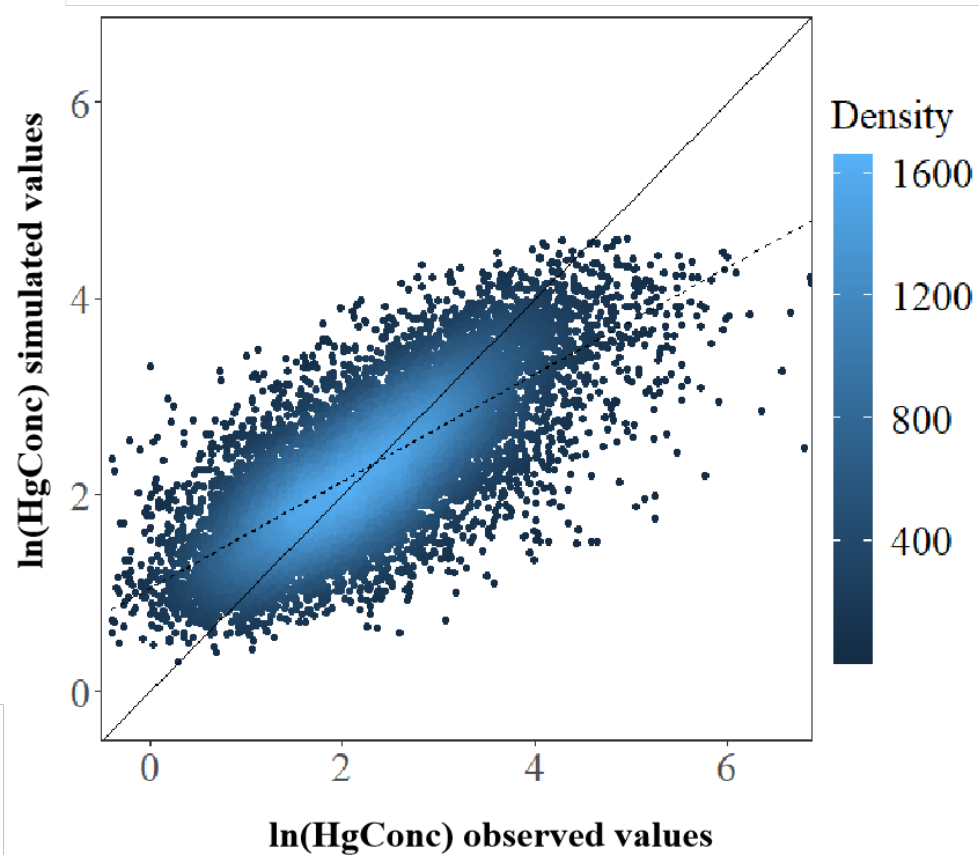
$$g(u) = a_0 + s_1(x_1) + s_2(x_2) + \dots + s_k(x_k)$$

- Observation data: Mercury Deposition Network (MDN)
- Historical meteorological data: European Centre for Medium-range Weather Forecast (ECMWF)
- Future meteorological data: Coupled Model Intercomparison Project Phase 6 (CMIP6)

| Database | Variables | |
|---------------|---|--|
| MDN | <ul style="list-style-type: none"> ✓ Precipitation Hg concentration (HgConc, weekly data, ng L⁻¹) | <ul style="list-style-type: none"> ✓ Precipitation (Prec, mm) ✓ Elevation (Elev, m) |
| ECMWF (ERA5) | <ul style="list-style-type: none"> ✓ Relative humidity (RH, %) ✓ Total cloud cover (TCC, %) ✓ Solar radiation (SR, W m⁻²) | <ul style="list-style-type: none"> ✓ Wind speed (WS, m s⁻¹) ✓ Temperature (Temp, K) |
| ECMWF (CMIP6) | <ul style="list-style-type: none"> ✓ Relative humidity (RH, %) ✓ Total cloud cover (TCC, %) ✓ Solar radiation (SR, W m⁻²) | <ul style="list-style-type: none"> ✓ Wind speed (WS, m s⁻¹) ✓ Temperature (Temp, K) ✓ Precipitation (Prec, mm) |

Performance of the generalized additive model

$$\ln(\text{HgConc}) \sim s(\text{Prec}) + s(\text{Temp}) + s(\text{TCC}) + s(\text{WS}) + s(\text{RH}) + s(\text{Elev}) + s(\text{SR})$$



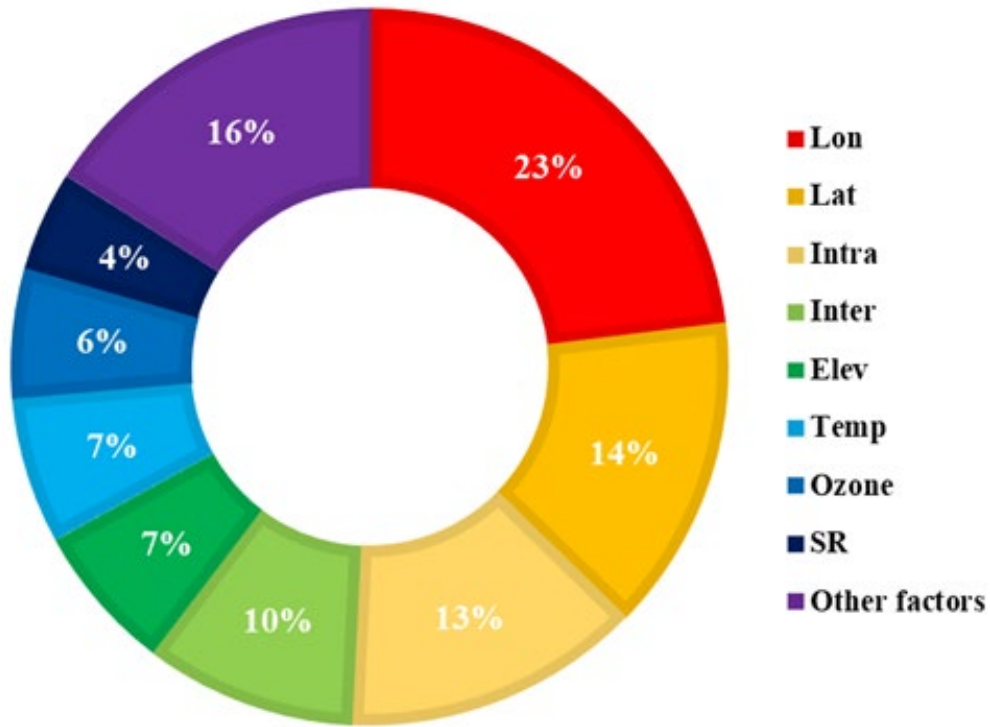
| No. | Random cross-validation | | Temporal cross-validation | | Spatial cross-validation | |
|-----|-------------------------|-------|---------------------------|-------|--------------------------|-------|
| | R ² | RMSE | R ² | RMSE | R ² | RMSE |
| 1 | 0.589 | 0.687 | 0.462 | 0.762 | 0.557 | 0.744 |
| 2 | 0.548 | 0.725 | 0.526 | 0.701 | 0.505 | 0.745 |
| 3 | 0.504 | 0.771 | 0.544 | 0.715 | 0.534 | 0.634 |
| 4 | 0.543 | 0.699 | 0.481 | 0.785 | 0.452 | 0.711 |
| 5 | 0.510 | 0.725 | 0.548 | 0.741 | 0.515 | 0.831 |
| 6 | 0.523 | 0.742 | 0.555 | 0.759 | 0.489 | 0.766 |
| 7 | 0.571 | 0.710 | 0.527 | 0.728 | 0.539 | 0.791 |
| 8 | 0.526 | 0.732 | 0.588 | 0.682 | 0.448 | 0.723 |
| 9 | 0.542 | 0.715 | 0.556 | 0.725 | 0.342 | 0.751 |
| 10 | 0.502 | 0.753 | 0.536 | 0.695 | 0.505 | 0.699 |

- The dependent variable was selected to be the **logarithm of Hg concentration in precipitation**
- Both **temporal and spatial 10-fold cross-validations** show **good model performance for GAM**

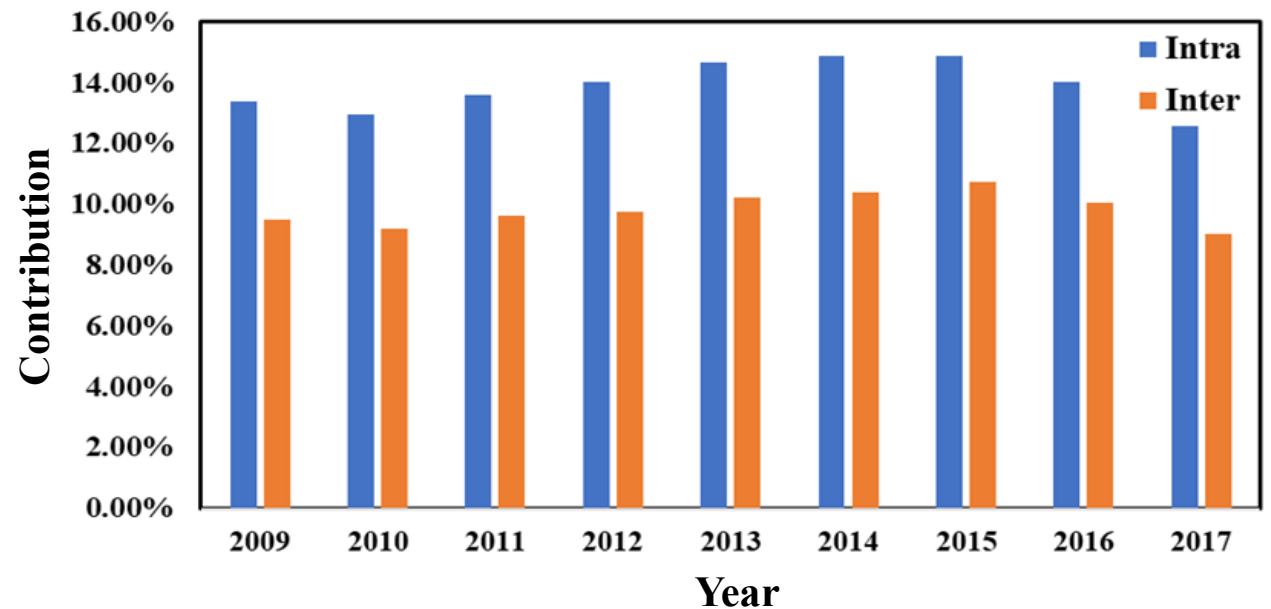
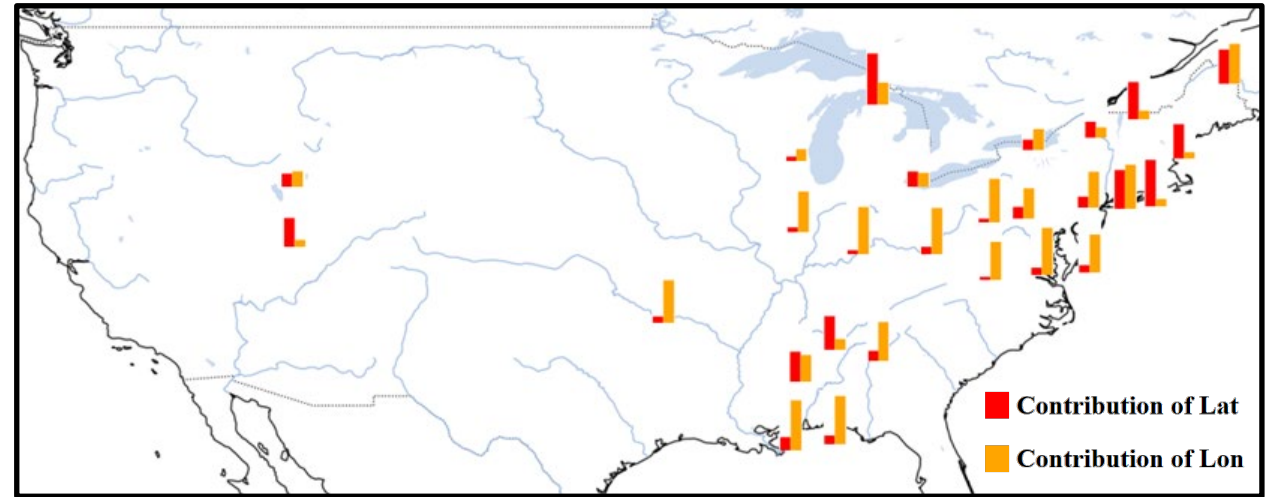
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Contributions of key drivers to GEM concentration variation

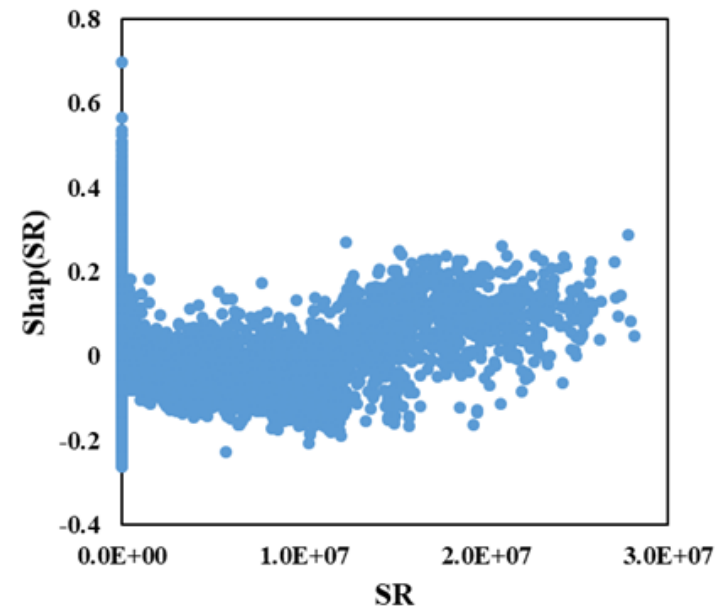
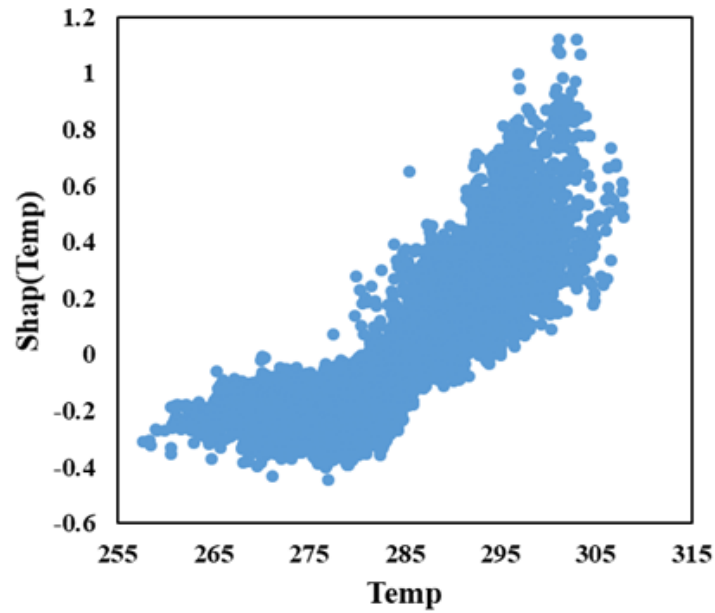


- **Geographic features, meteorological factors, and Hg transport** contributed **44%, 27%, and 23%** to GEM variation, respectively
- The contribution of **intra- and inter-regional Hg transport** to GEM variation experienced an **increase followed by a decrease**

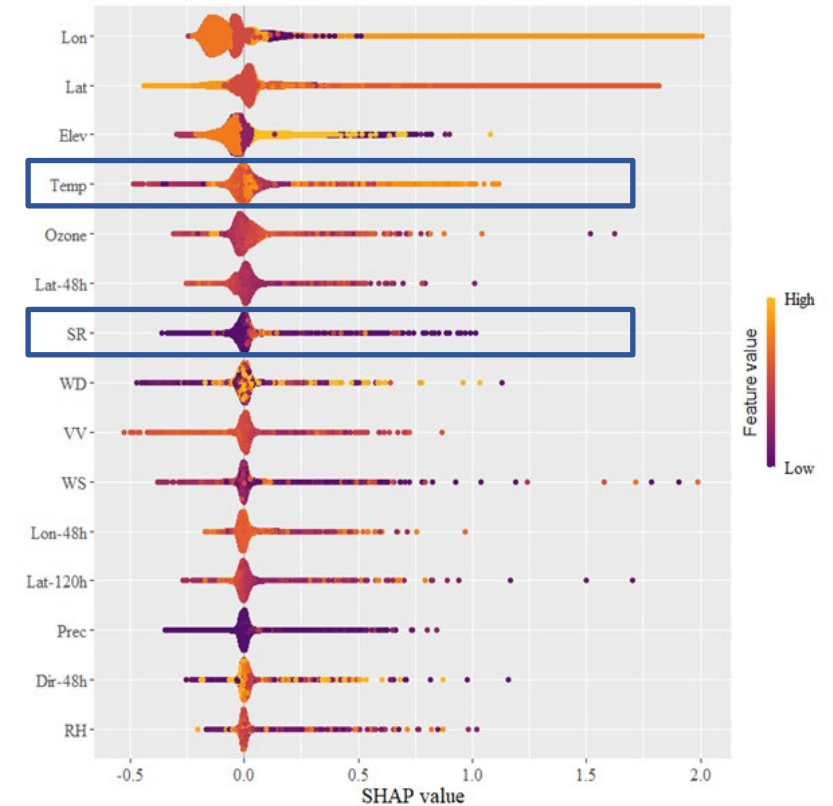
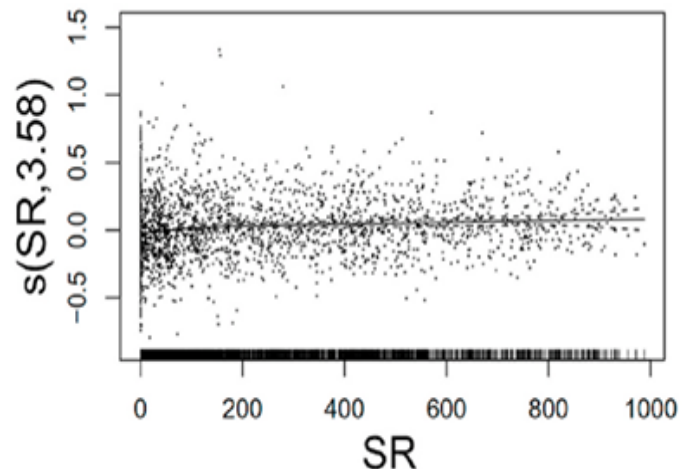
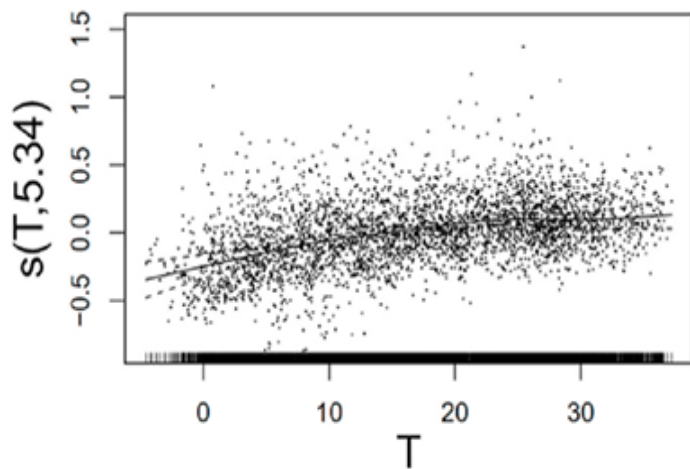


Impacts of meteorological factors on GEM concentration

Continental US



Eastern China

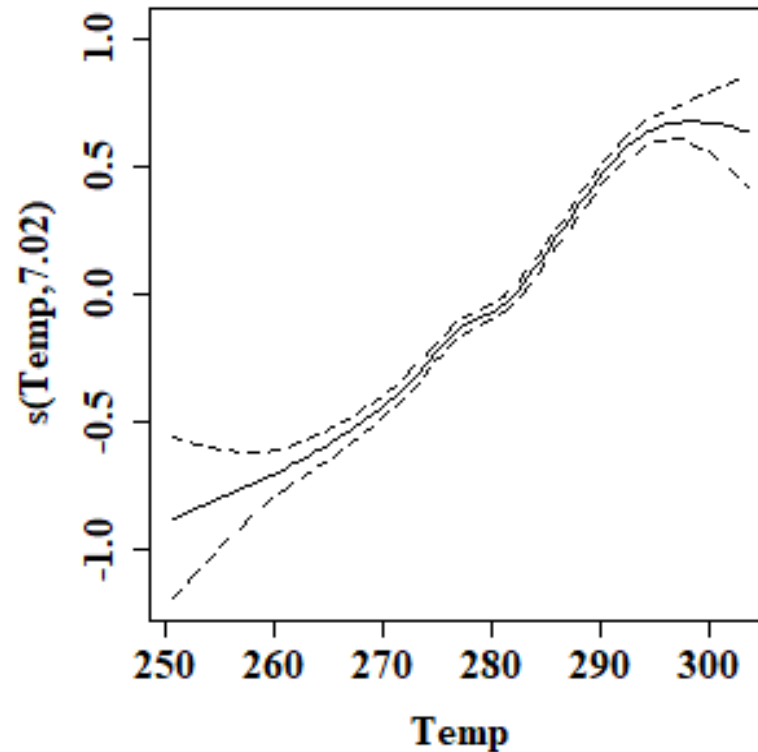
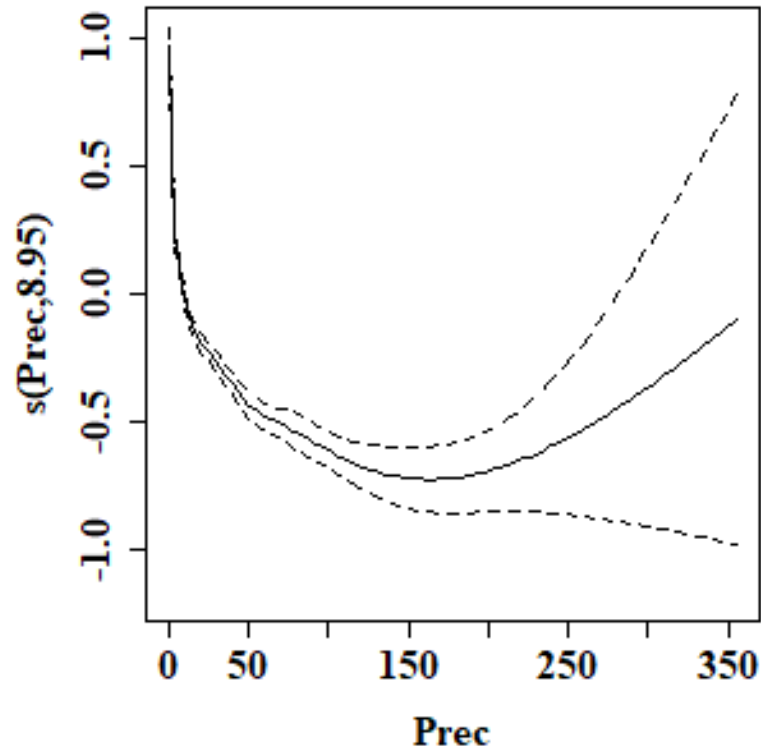


- Temperature and solar radiation are key to GEM concentration
- Natural and legacy Hg emissions are important via high temperature

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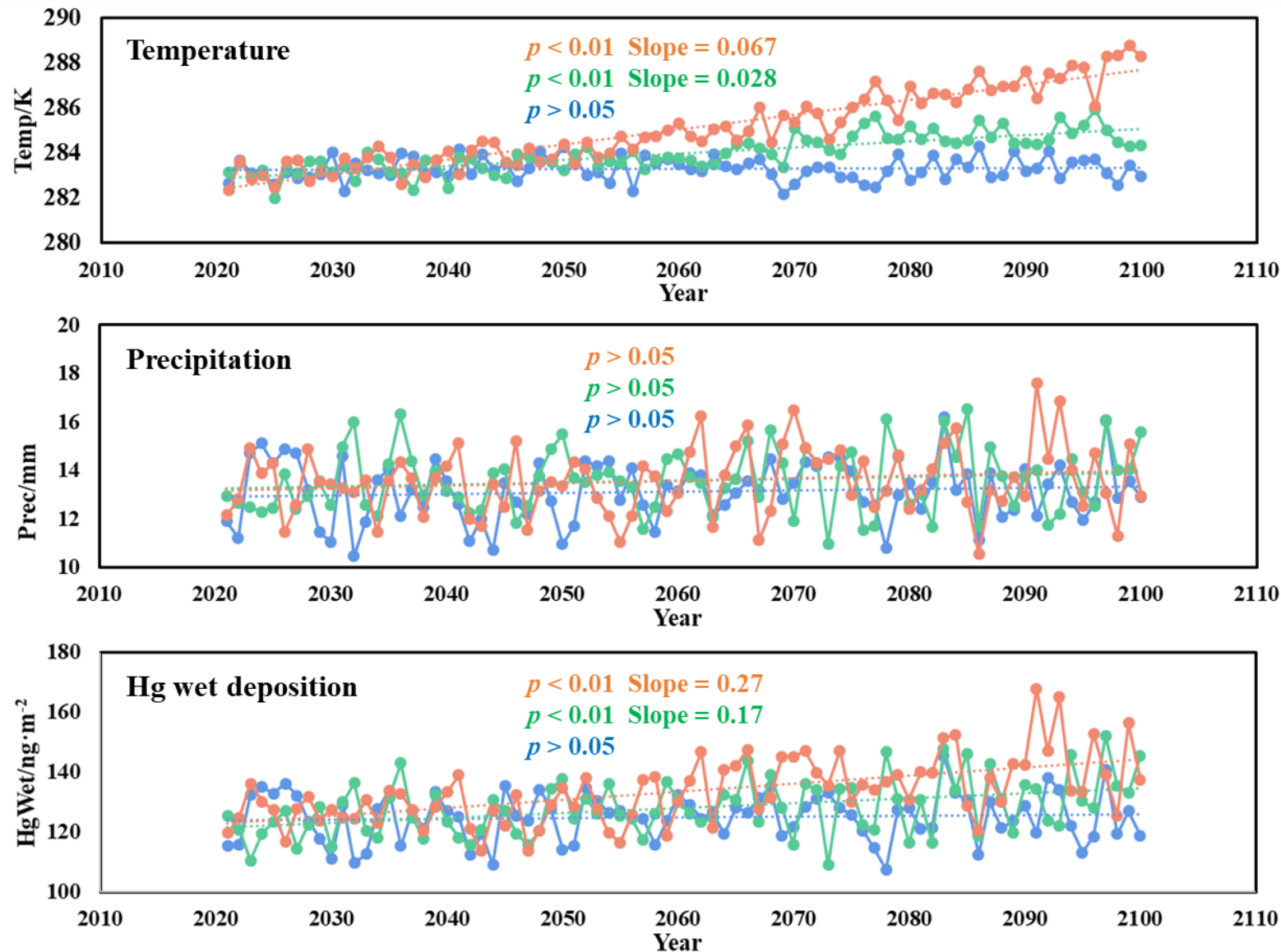
Impacts of meteorology on precipitation Hg concentration



| Variable | <i>F</i> value | Share | <i>p</i> value |
|----------|----------------|--------|-----------------------|
| Prec | 223.96 | 36.71% | $< 2 \times 10^{-16}$ |
| Temp | 123.58 | 20.26% | $< 2 \times 10^{-16}$ |
| SR | 97.12 | 15.92% | $< 2 \times 10^{-16}$ |
| TCC | 58.52 | 9.59% | $< 2 \times 10^{-16}$ |
| Elev | 43.62 | 7.15% | $< 2 \times 10^{-16}$ |
| RH | 33.56 | 5.50% | $< 2 \times 10^{-16}$ |
| WS | 29.70 | 4.87% | $< 2 \times 10^{-16}$ |

- **Precipitation** directly contributes to Hg wet deposition, while Hg concentration in precipitation **decreases dramatically** with increasing precipitation when it is low due to **the dilution effect**
- **Temperature** is **positively** correlated with precipitation Hg concentration, with a similar pattern as on GEM, but in a **milder** way at high level

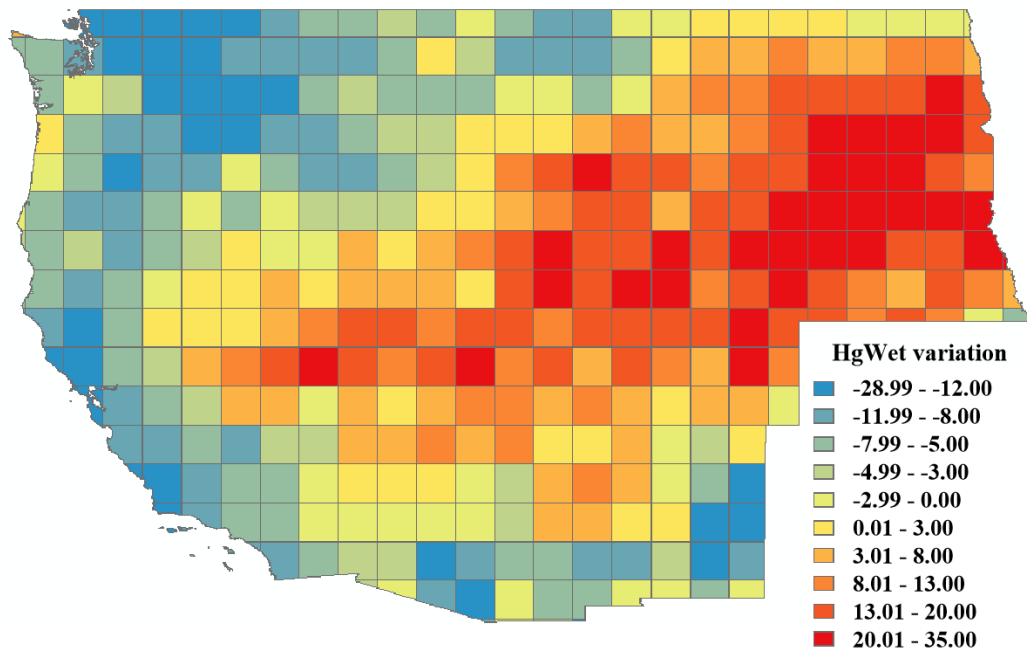
Trends of future meteorology and Hg wet deposition



- Hg wet deposition flux will **increase** with more significant **fluctuations** in **SSP2-4.5** or **SSP5-8.5** scenarios
- The **increase** is going to be driven by **increasing temperature**
- The **larger fluctuation** is going to be driven by **extreme precipitation**

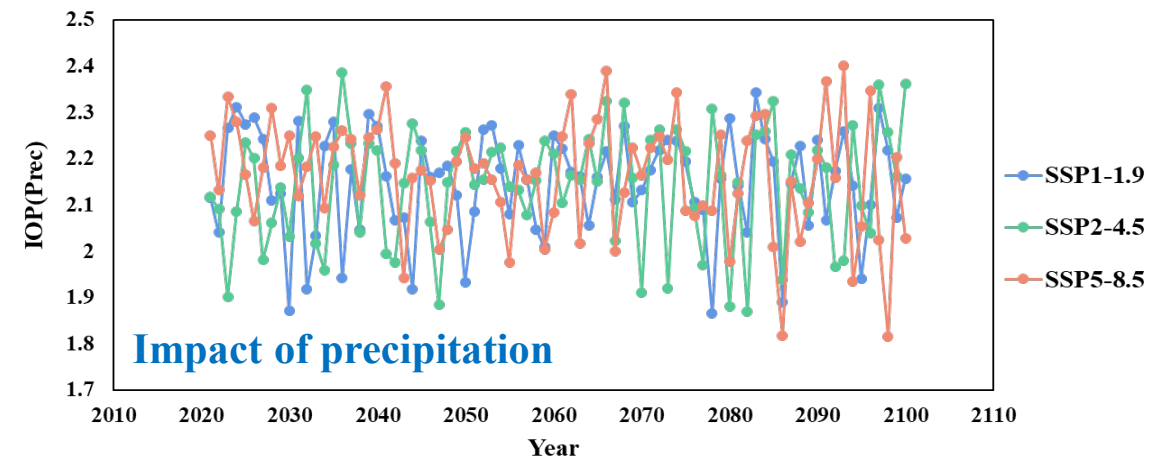
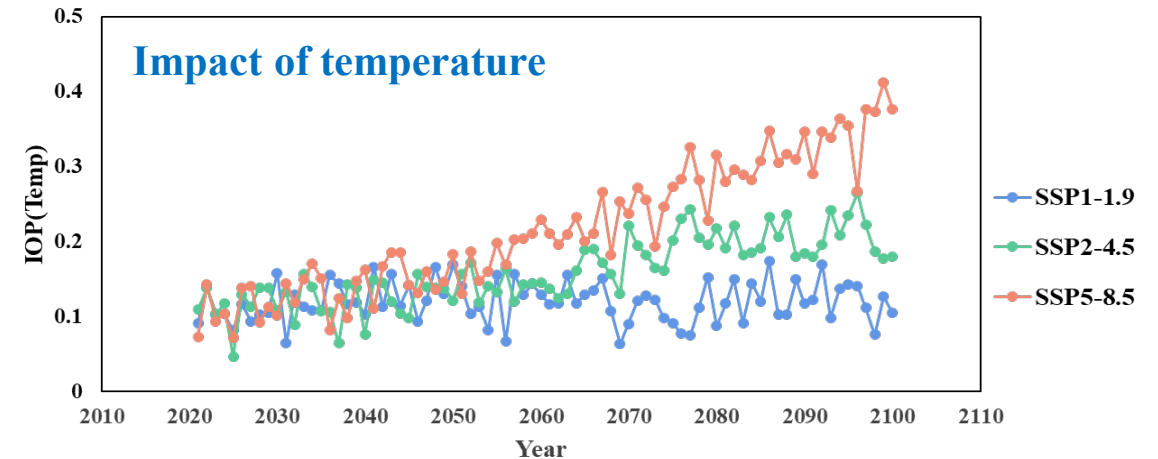
Impacts of future climate change on Hg wet deposition

Changes in Hg wet deposition in the western US from 2030 to 2060



- Hg wet deposition will **reduce** along the **west coast** of the **US** and **increase** significantly in **inland area**
- **Global warming** will **boost** Hg wet deposition flux, while **extreme precipitation** will **intensify variability**

Impacts of temperature and precipitation on Hg wet deposition flux in the western US (2020–2100)



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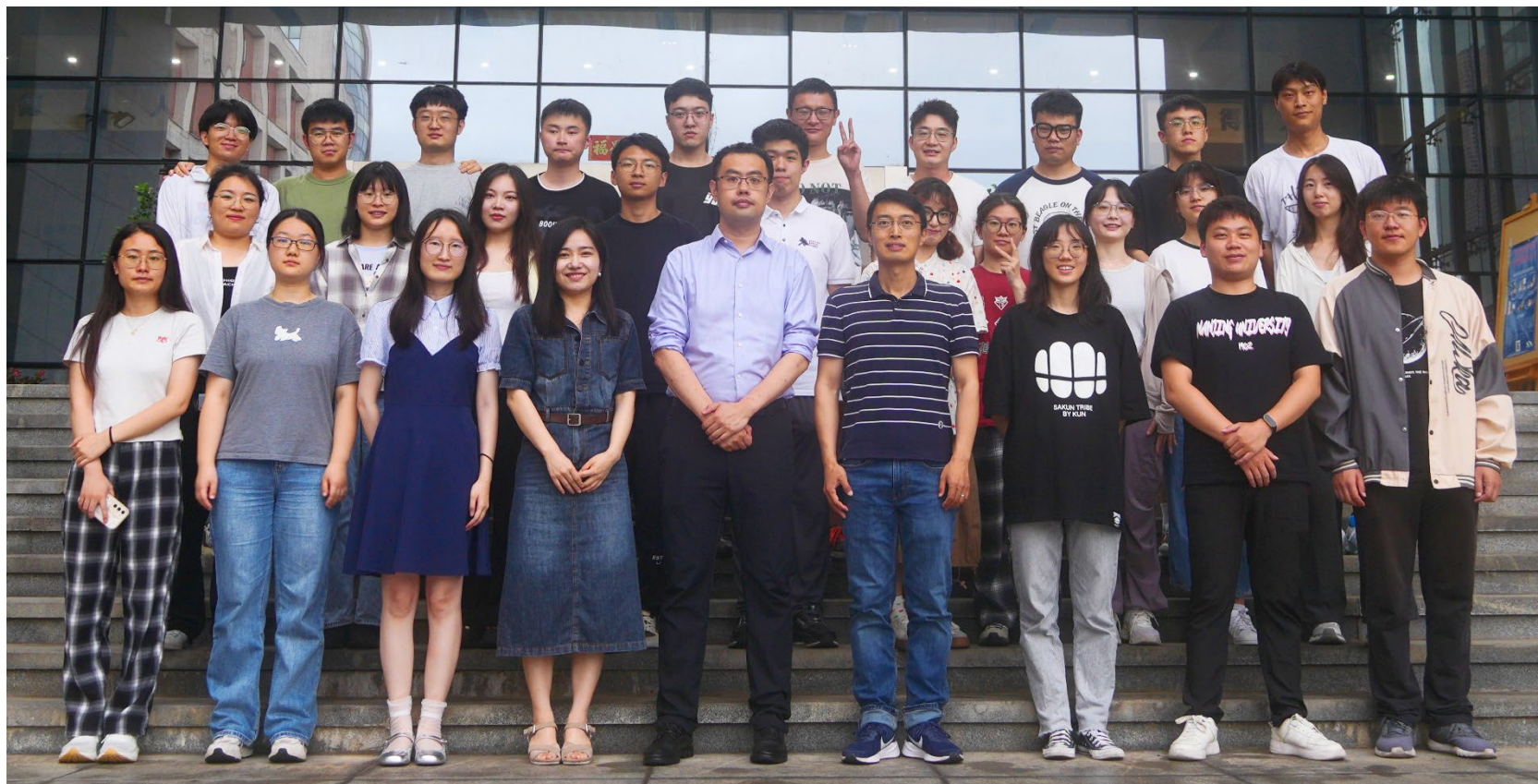
Take-home messages

- Advanced statistical and machine learning models are effective tools for identifying the key drivers for atmospheric Hg pollution.
- The declining of local anthropogenic emissions and intra- and inter-regional transport drives the decrease of GEM in the eastern US.
- Precipitation and temperature are key factors for Hg wet deposition which will be controlled by future extreme weather conditions.

The 16th International Conference on Mercury as a Global Pollutant

Oral Session: Advances in Statistical/Machine Learning and Process-Based Models

ICMGP 2024
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Thank you very much for your attention

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