Enhanced global estimation of fine particulate matter concentrations by combining deep learning with geophysical a priori information

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with contributions from

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HAQAST Meeting
Salt Lake City
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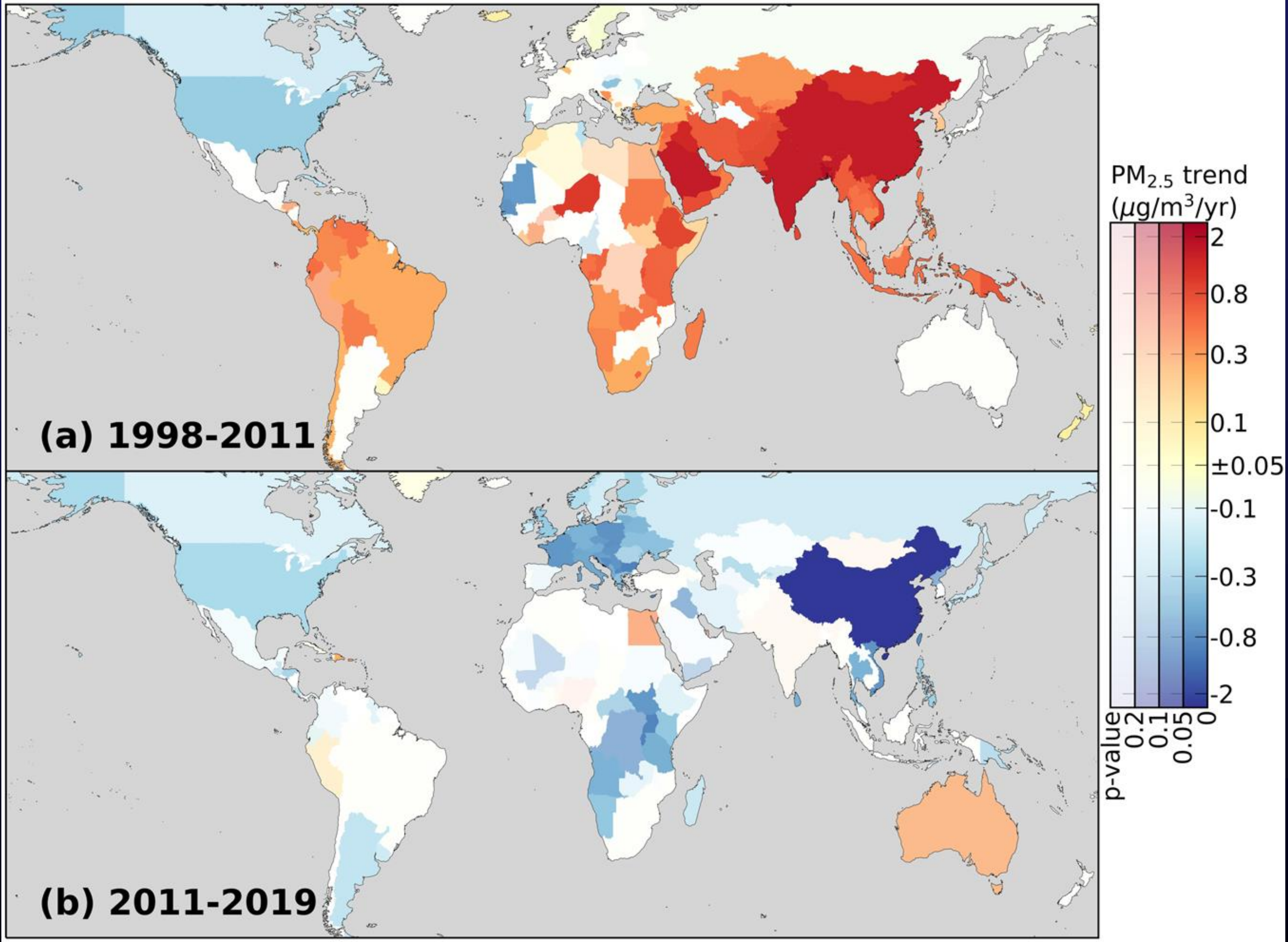
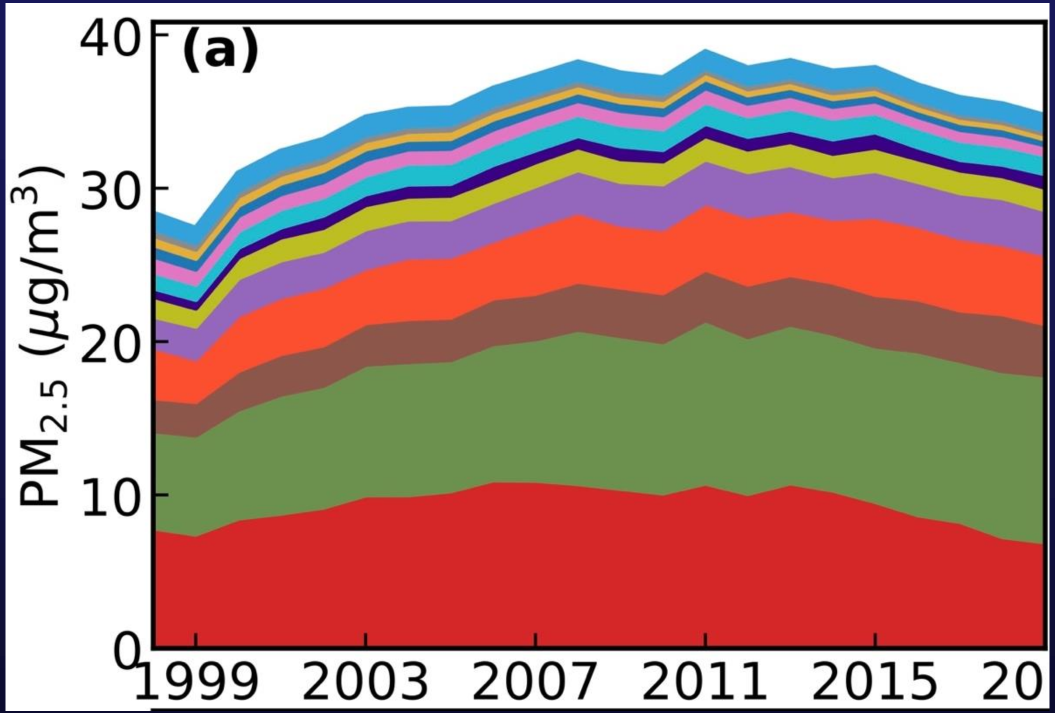
Reversal of Trends in Global Fine Particulate Matter Air Pollution

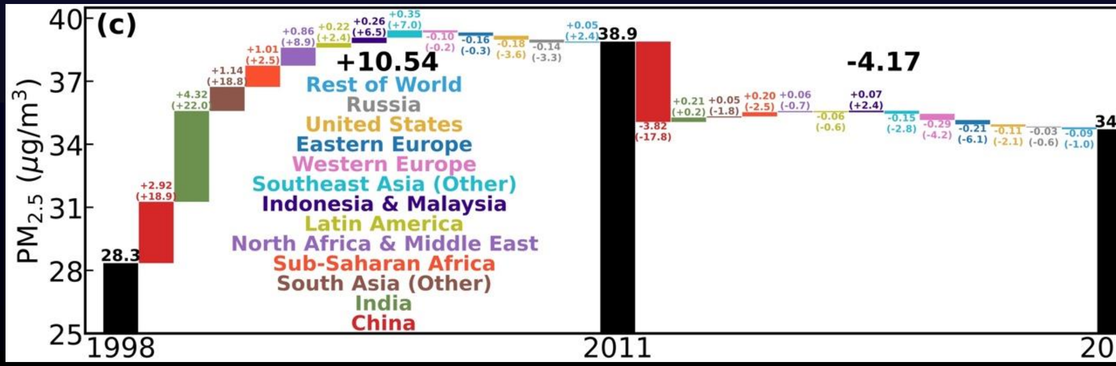
National Trends in Population-weighted $PM_{2.5}$



Evolution of Global $PM_{2.5}$ Exposure

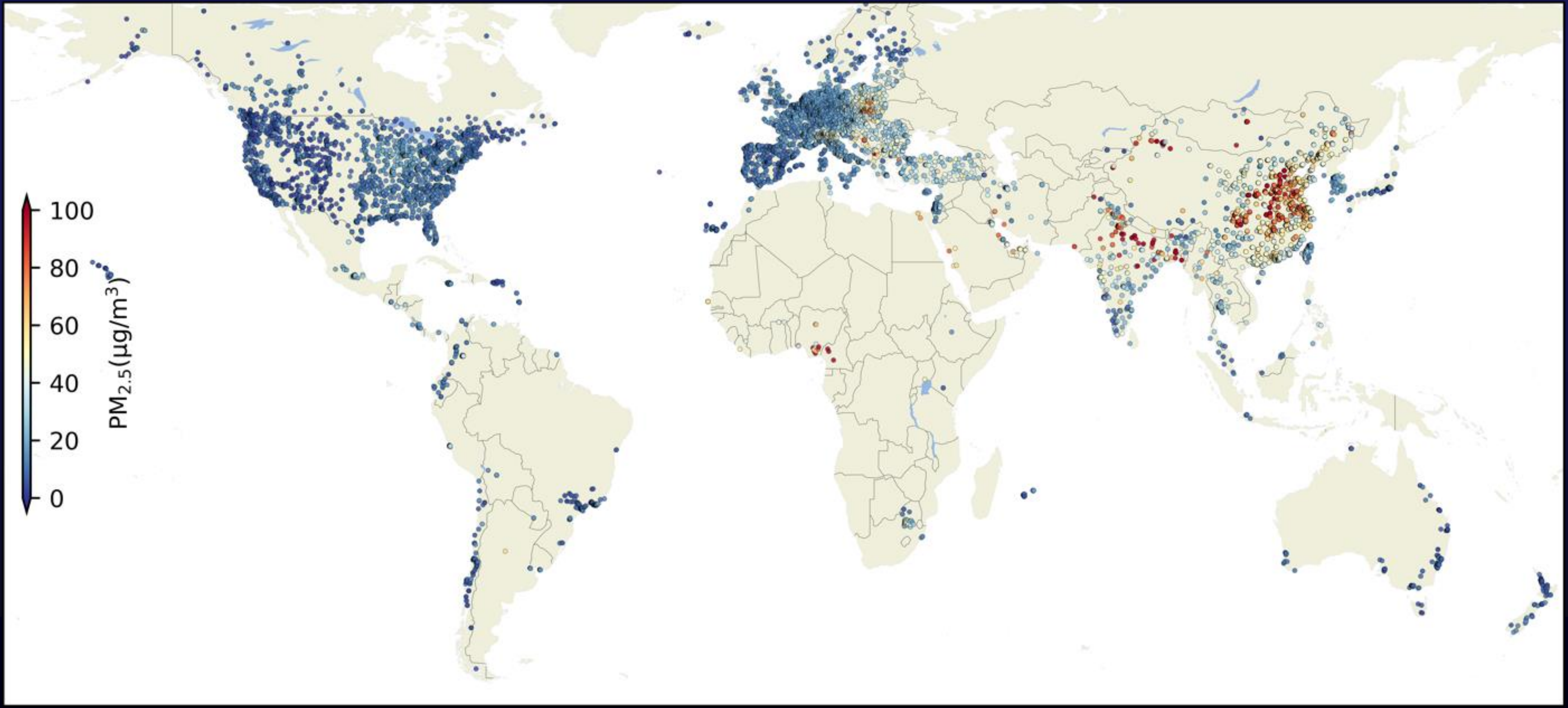


Regional contribution to population-weighted $PM_{2.5}$



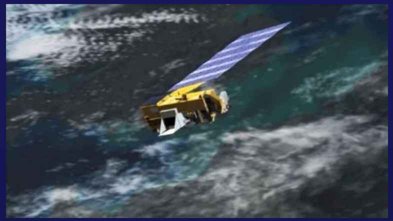
Li et al., Nat. Comm., 2023

Ground-based Measurements are Unevenly Distributed (and Autocorrelated)



Shen et al., submitted

Satellite-Based Estimates of $PM_{2.5}$



Aerosol Optical Depth (AOD) from multiple satellite instruments and algorithms constrained with AERONET

Geophysical Satellite-Based $PM_{2.5}$

Calculate coincident local solution to $PM_{2.5} = f(x,y,t,AOD)$

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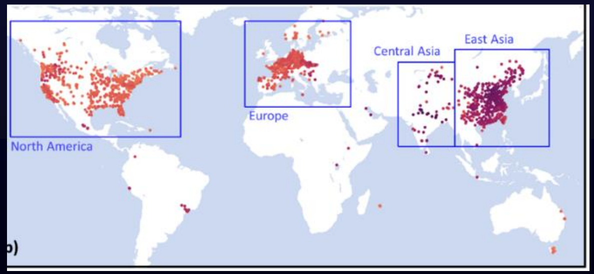
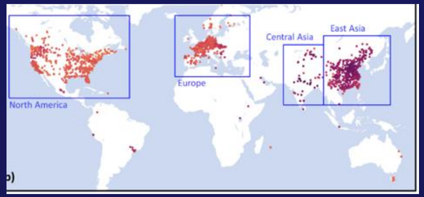
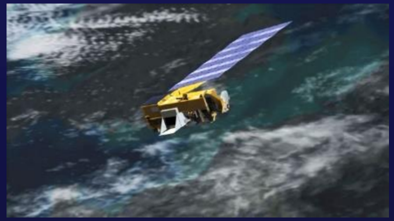
Hybrid Satellite-Based $PM_{2.5}$

Statistical fusion with ground-based monitors



Two Alternative Frameworks for Deep Learning





Deep learning

Direct $PM_{2.5}$ Estimates

Geophysical Satellite-Based $PM_{2.5}$

Geophysically-Based $PM_{2.5}$ Estimates

Aerosol Optical Depth (AOD) from multiple satellite instruments and algorithms constrained with AERONET

Calculate coincident local solution to $PM_{2.5} = f(x,y,t,AOD)$

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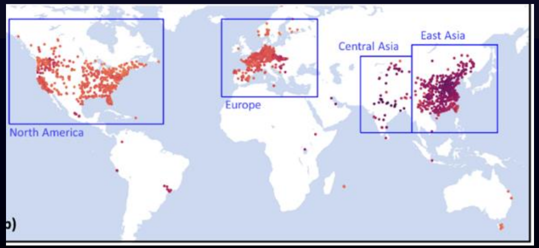
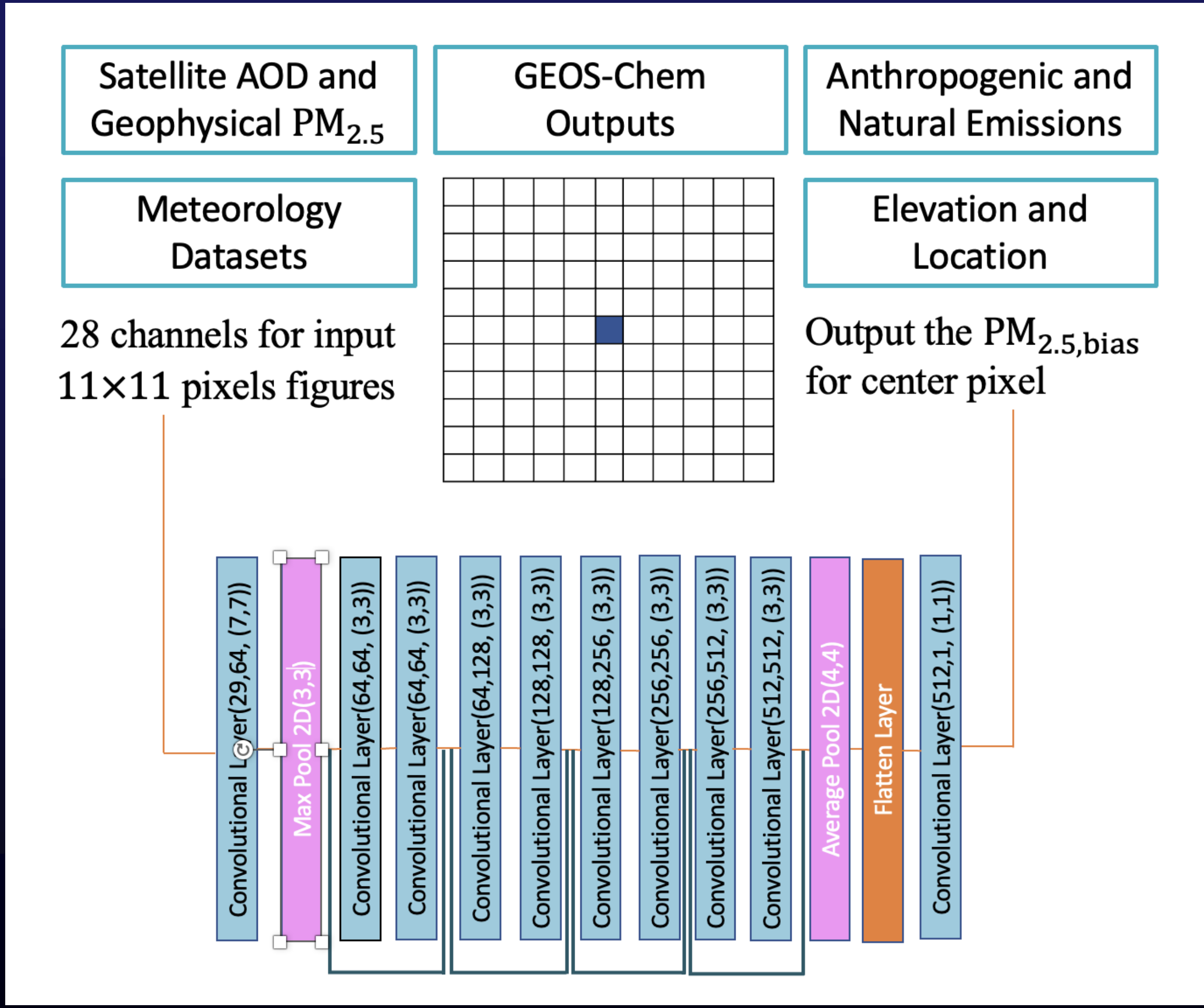
Deep learning

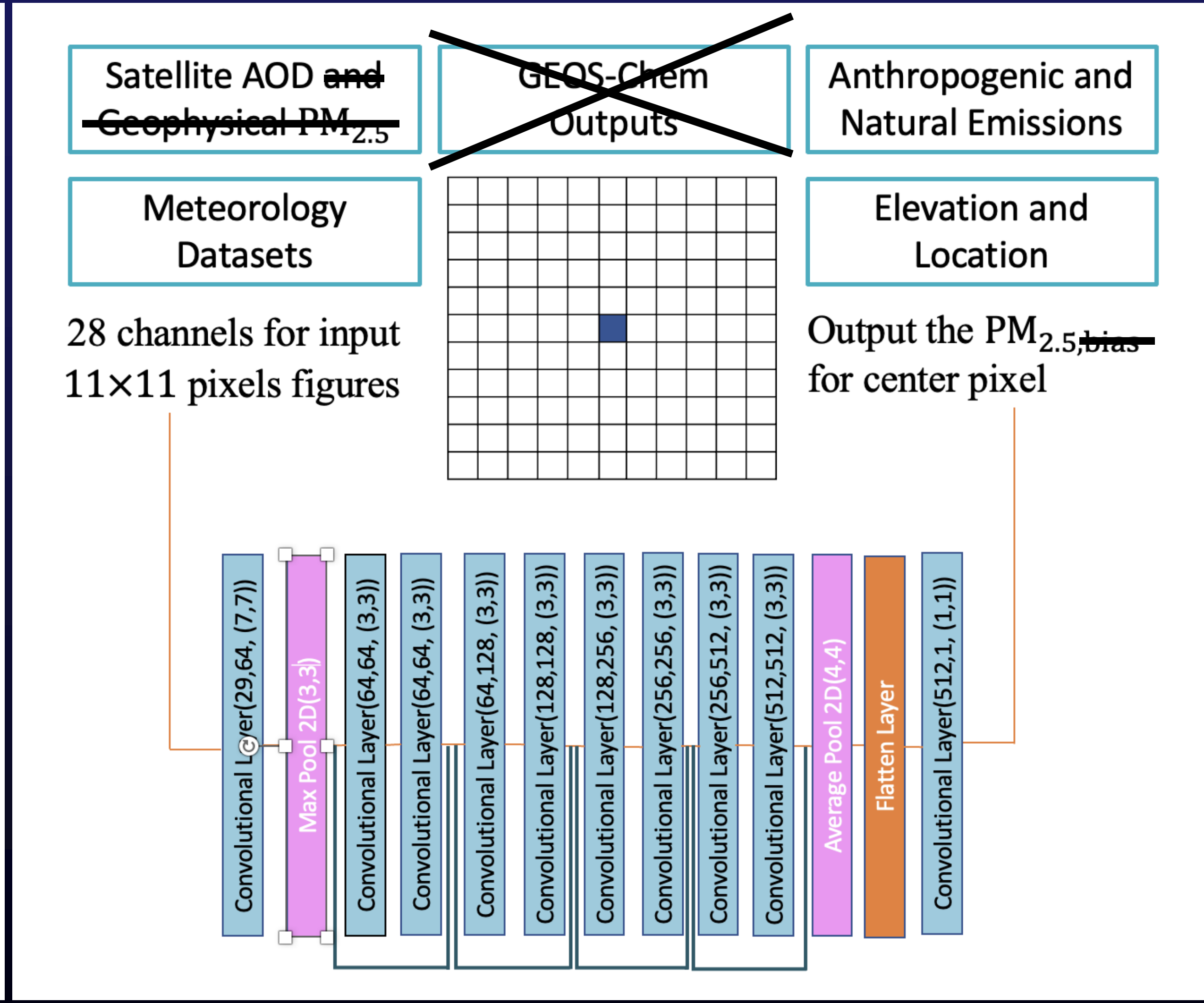


Two Alternative Deep Learning Frameworks

With Geophysical A Priori Information



Without Geophysical A Priori Information



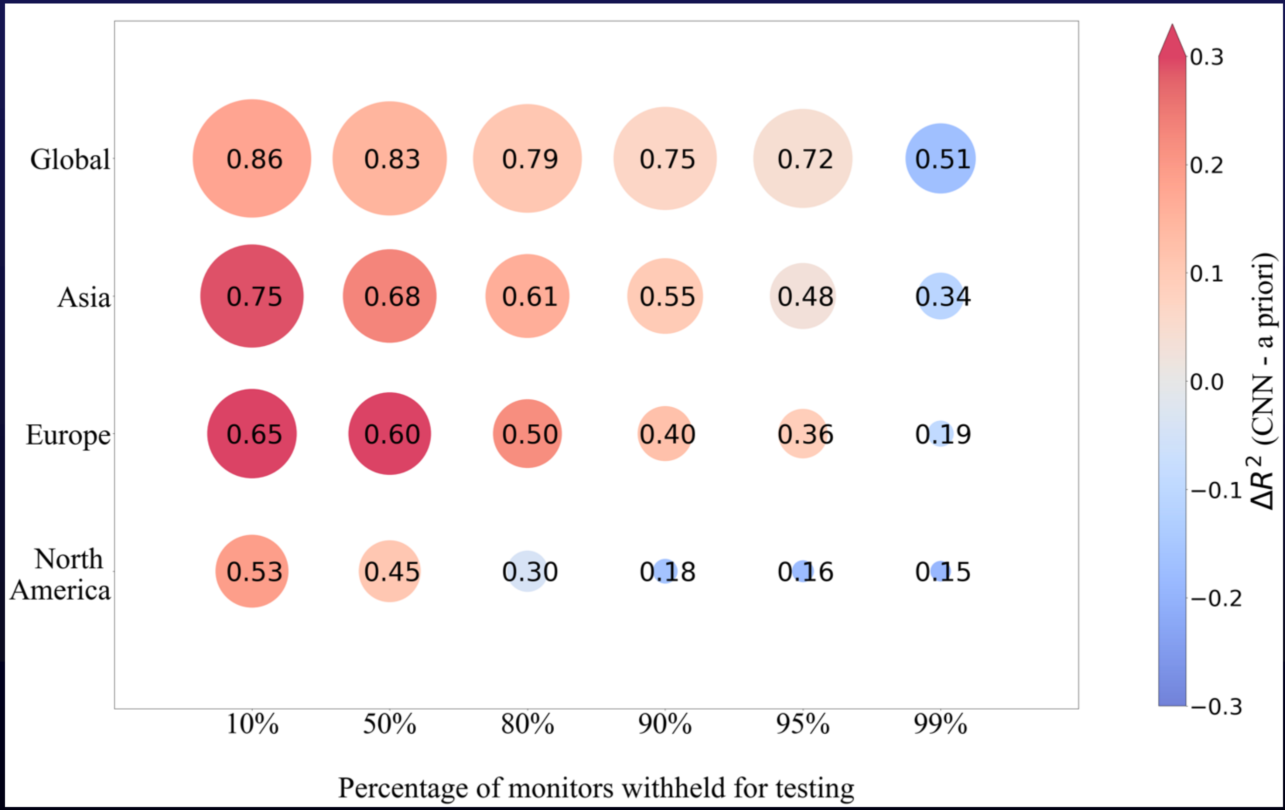
Shen et al., submitted

Geophysically-based Estimates Are More Robust to Sparse Monitoring

Results of n-fold Cross Validation with Varying Percent of Monitors withheld for Testing

Geophysically-based Including GEOS-Chem Output Data

Direct Approach Excluding GEOS-Chem Output Data

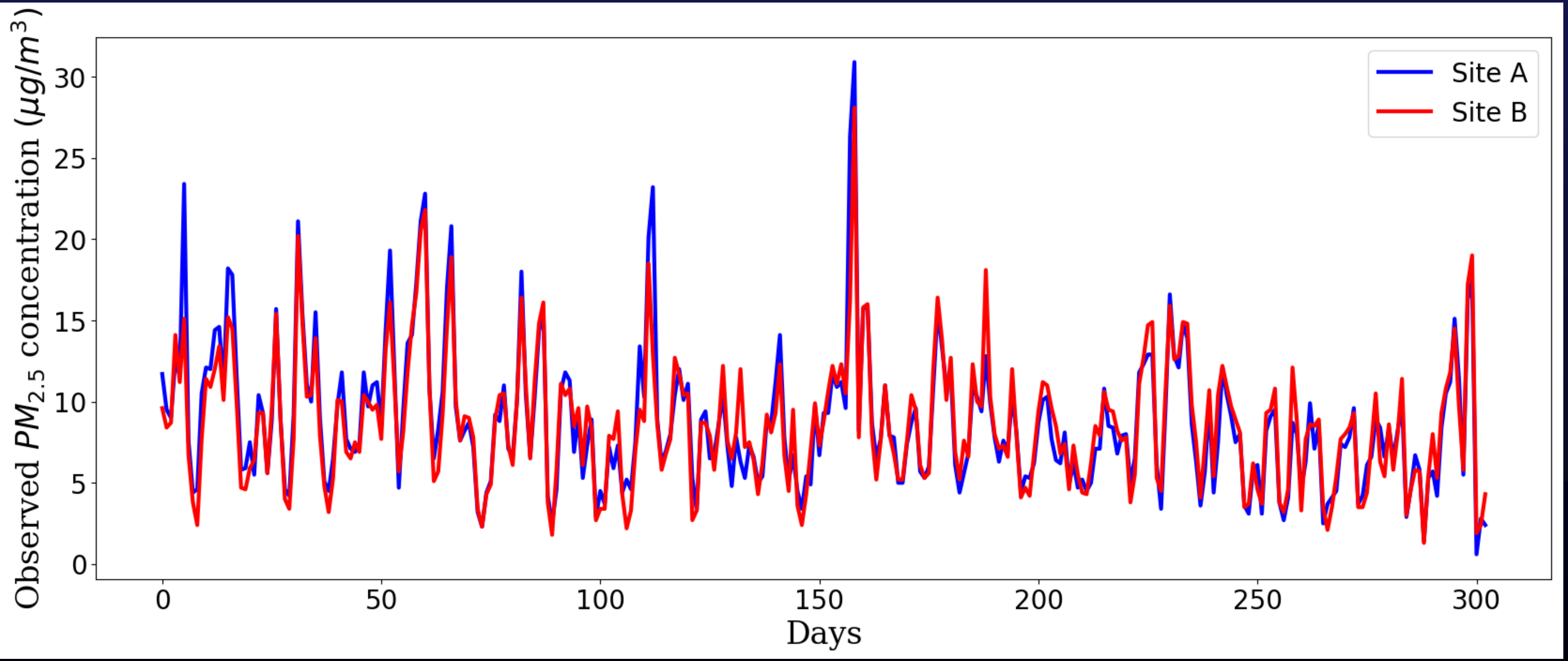


Shen et al., submitted

Nearby $PM_{2.5}$ Monitors Exhibit Autocorrelation

Withholding Adjacent Monitors in Traditional n-fold Cross Validation Overestimates True Model Performance

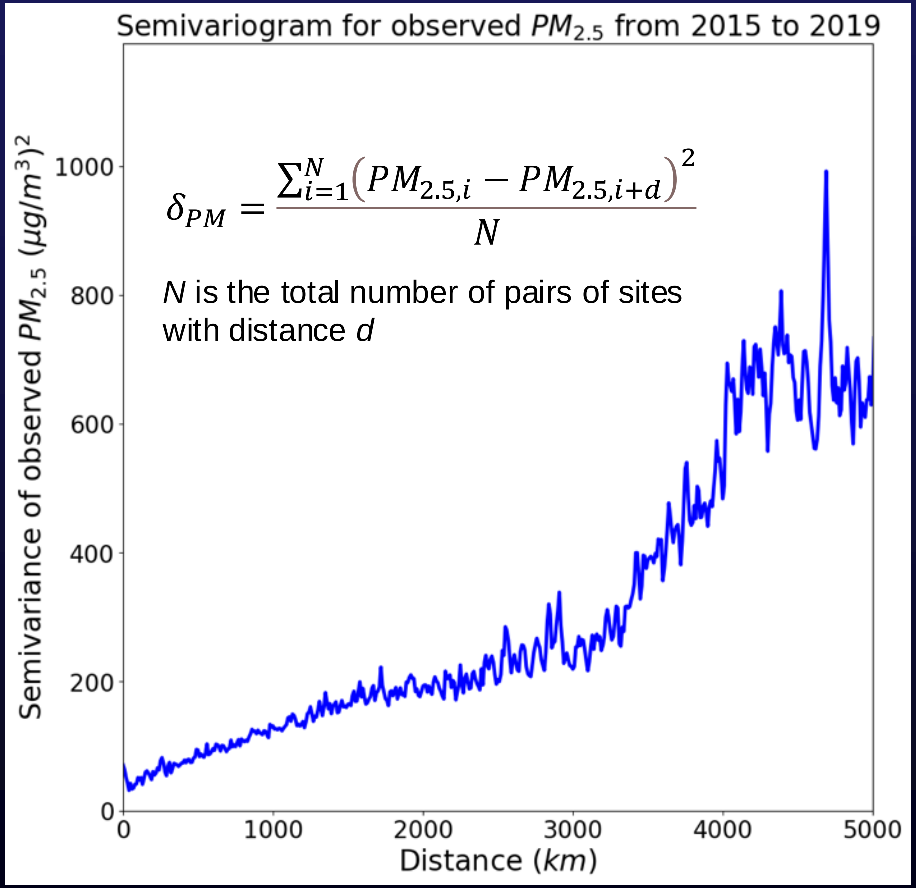
Timeseries of Two $PM_{2.5}$ Monitors 1km Apart



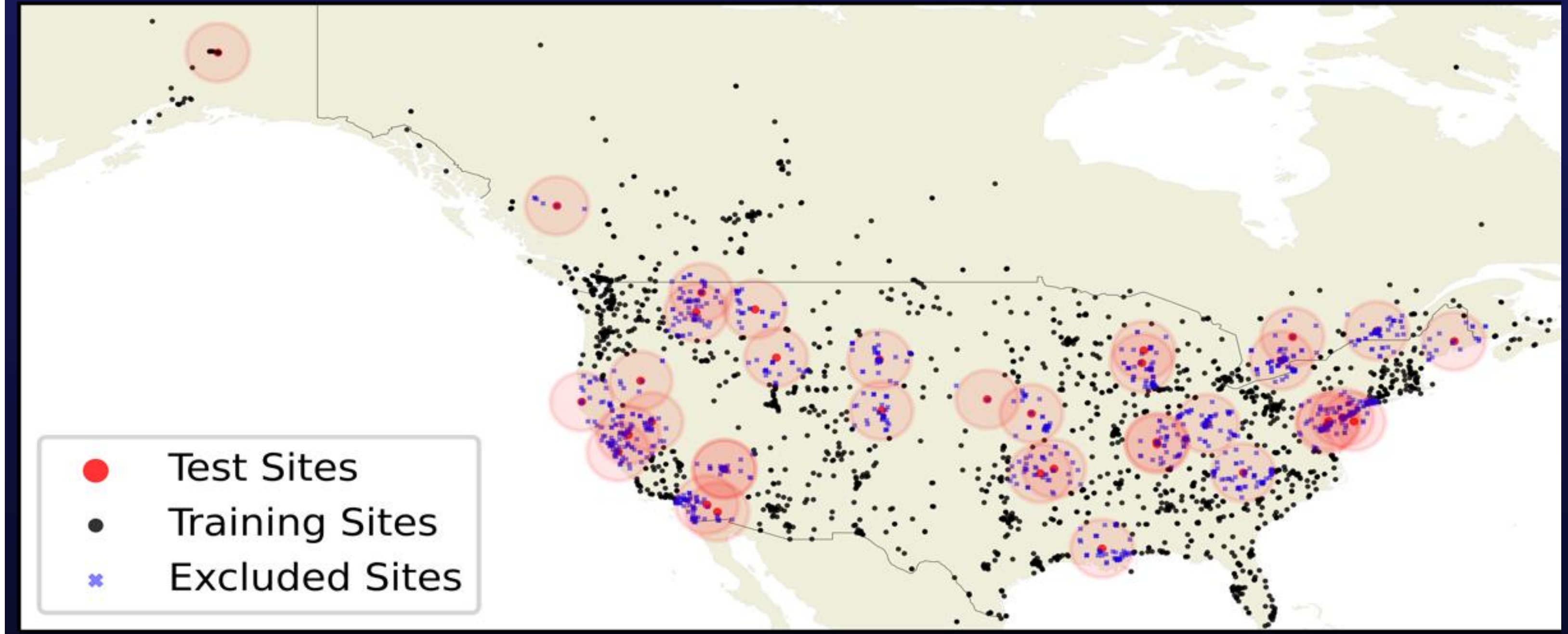
Siyuan Shen

Strategy to Address Spatial Autocorrelation: Buffer Leave-One-Out Cross Validation

Evidence of spatial autocorrelation in annual $PM_{2.5}$

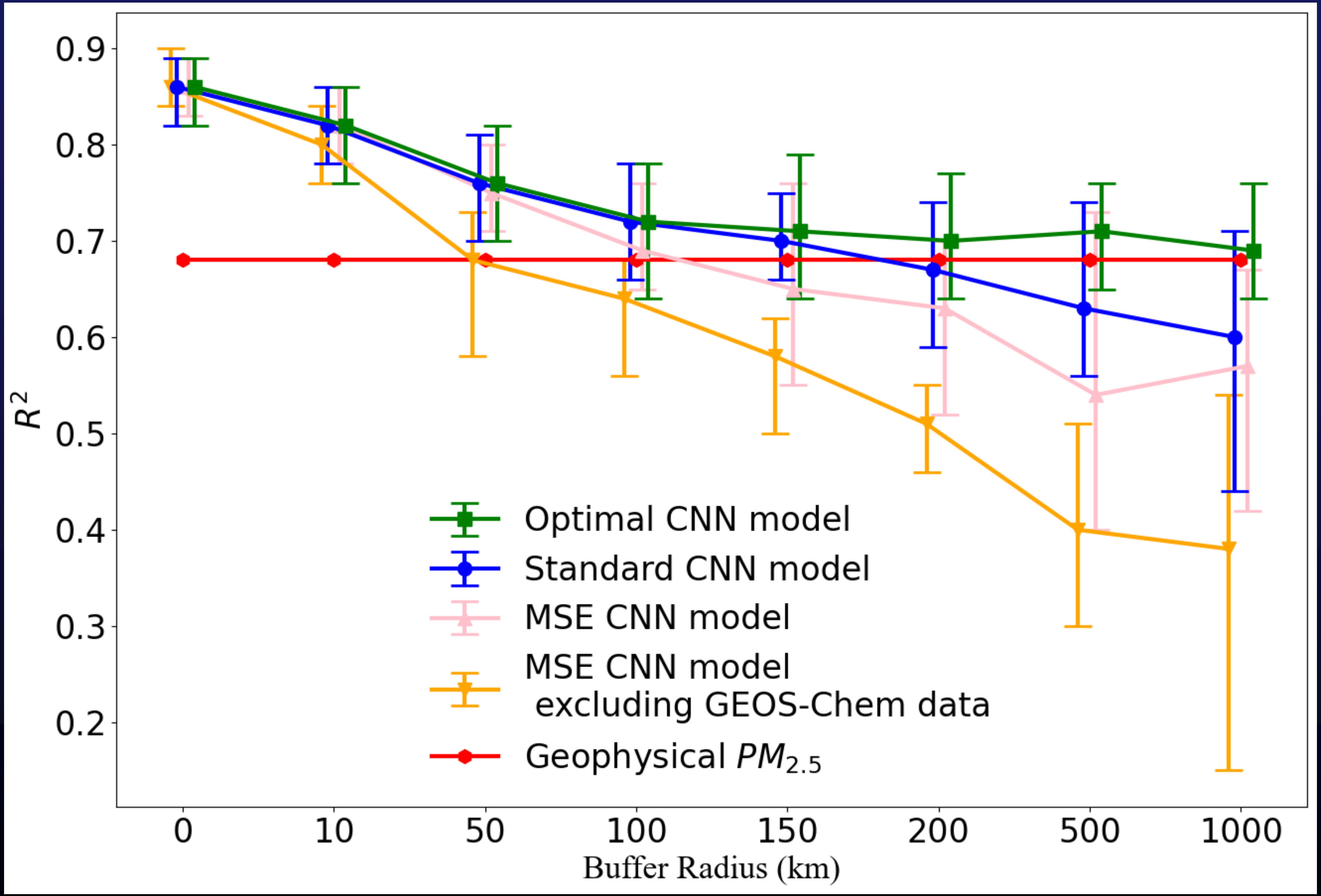


Exclude from training all sites within buffer surrounding test site



Shen et al., submitted

Geophysical Constraints Aid Prediction in Sparsely-Monitored Regions



Optimal model relaxes to geophysical $PM_{2.5}$ with increasing distance from monitor

Excluding geophysical constraints reduces performance away from monitors

Shen et al., in prep.

Conclusions

- Geophysical a priori information aids deep learning prediction for sparse monitoring
- Geophysical a priori information reduces susceptibility to overestimating model performance due to autocorrelation
- Reversal of trends in global burden of $PM_{2.5}$

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