

Evaluation of High-Spatial-Resolution Air Pollutant Concentration and AQI Estimates Across the U.S. by Fusing Low-Cost and Reference Monitor Observations with Chemical Transport Model Forecasts

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- Public and private sectors need high spatiotemporal air quality information in near-real time
- Demand is driven by:
 - Risks from extreme air quality events, such as wildfires, when pollution from smoke is great and spatial and temporal variability are high
 - Information that serves communities at local scales



Example application: U.S. Forest Service (USFS) / U.S. Environmental Protection Agency (EPA) fire and smoke map

- To meet the need for high spatiotemporal air quality information in near-real time, we aimed to develop estimates of current air quality for the U.S. that provide:
 - Complete national coverage (no spatial gaps)
 - High spatial resolution (1–5 km)
 - Hourly results that are available in near-real time
- Different methods for complete coverage include:
 - Use of Chemical Transport Model (CTM) forecasts
 - Use of satellite-derived surfaces
 - Fusion methods (spatial interpolation, machine learning, LUR, and others)

- Fusion methods for predicting air quality at a high-spatiotemporal resolution range from simple to complex and have been shown to vary in accuracy/precision
- Existing methods can be computationally intensive, and lack transparency for users and decision makers

Method/Product	Advantages	Limitations	
Residual kriging interpolation	Relatively simple covariance weighting approach	Computationally intensive for large domains	
Inverse distance weighted (IDW) interpolation	Simple, computationally efficient	Simplified pollutant decay	
Geographically weighted regression	Spatial calibration technique	Availability of local covariates	
Land use regression	Standard exposure covariate technique	Computationally intensive	
XGBoost regression	Sophisticated ML regression with important regressor	Computationally intensive	
Convolutional neural network	Deep learning technique	Computationally intensive	
Ensemble machine learning	State of art exposure models	Computationally intensive	

- We adapted the Schulte et al.*
 approach for the Los Angeles basin and scaled it to the entire U.S. domain at 1 x
 1 km spatial resolution
- We selected our approach based on four top priorities:
 - Demonstrated performance
 - Simplicity/transparency
 - Computational feasibility
 - Opportunities for future improvements



Methodology



Methodology

- Utilized subdomains (N=30) in order to generate national scale results at 1 km spatial resolution within 15 minutes
- Selection of subdomains considered:
 - Density of observations
 - Size of the domain
 - Spatial autocorrelation within the subdomain
 - Semivariogram fitting performance



Results



Category	Good	Moderate	Unhealthy for Sensitive Groups	Unhealthy	Very Unhealthy	Hazardous	Beyond Index
Color							
24-hour PM _{2.5} concentration (μg/m ³)	0-12	12.1–35. 4	35.5-55.4	55.5-150.4	150.5– 250.4	250.5–5 00.4	500.5+
AQI	0-50	51-100	101-150	151-200	201-300	301-500	501+







March 27, 2022, 16:00 UTC

PM2.5 Concentration (µg/m3)



Kriging of Residuals

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Kriging of Residuals



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- Stratified 10-fold cross validation at AirNow monitors
- Accuracy—Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE) — and precision (R-squared, F1-score classification) are computed
- Evaluating January 2022 and July 2021
- Understand model performance across regions and pollution episodes
- Compared to alternative methods

Potential Considerations

- Monitor spatial density
- Regionally variable spatial covariance
- Sensor measurement uncertainties relative to AirNow PM_{2.5} FEMs
- Urban/rural topographies
- Regional transport patterns



- During January 2022, the hourly, national scale result using the kriging of residuals methods at 1 km spatial resolution has an RMSE of 5.8 µg/m³
- Comparable with Schulte et. al. results for Southern California at 5 km resolution (5.94 µg/m³)
- AQI category is correctly predicted 85% of the time



- Lower RMSE in urban areas with greater density of monitors
- RMSE and other regression metrics are influenced by CTM model biases
- RMSE can also vary at small spatial scales in areas of more dense monitoring:
 - Local influences from low-cost sensors
 - Different reference grade instrumentation



Kriging of residuals method better predicts hourly reference-grade observations than traditional methods that use inverse distance weighting (IDW) of observations

Method	LSQ Regression Equation	R ²	Sample size
Kriging of Residuals	Y=2.96 + 0.605X	0.48	601451
IDW of Observations	Y = 4.32 + 0.54X	0.36	601451
Chemical Transport Mod	Y=4.82 + 0.409X	0.16	601451



- Kriging of residuals results in a lower RMSE (5.8 μg/m³) than IDW of observations (7.2 μg/m³) or CTM (9.1 μg/m³)
- RMSE peaks during morning and evening



Summary

- Developed a national-scale hourly product at 1-km spatial resolution that can be used operationally in near-real time
- Accuracy for PM_{2.5} across diverse U.S. geographical regions comparable to the 6 µg/m³ RMSE reported for Los Angeles Basin (Schulte et al., 2020)
- Kriging of residuals method better predicts AirNow PM_{2.5} observations than IDW of AirNow or NAQFC alone
- Ongoing improvements are being made, with additional covariates and data sources
- Please also visit our poster on our hourly forecasting work