Applying Satellite-derived $PM_{2.5}$ Data to Policy-relevant Air Quality Metrics

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Introduction

In the United States, fine particulate matter ($PM_{2.5}$) contributes to roughly 48,000 deaths (State of the Global Air, 2020). In addition to premature mortality, exposure to $PM_{2.5}$ can lead to respiratory, cardiovascular, and other diseases. The U.S. Environmental Protection Agency (EPA) monitors $PM_{2.5}$ through its monitoring network.

The American Lung Association State of the Air Report

The American Lung Association (ALA) publishes an annual State of the Air report that acts as an air quality "report card". The report uses EPA $PM_{2.5}$ design values (DV) calculated from ground monitor data. The DV is the annual mean $PM_{2.5}$ concentration from a monitor, averaged over three consecutive years (e.g., 2013, 2014, and 2015 data is used to calculate the 2015 DV period). This report puts air pollution into everyday language by assigning passing (DV ≤ 12.0 µg/m³) or failing (DV ≥ 12.1 µg/m³) grades to counties and ranks them from dirtiest to cleanest.

Still, nearly 80% of counties lack air quality monitors (Holloway et al., 2021), leaving residents of those counties unaware of the air they breathe. Satellite-derived estimates of $PM_{2.5}$ can complement the ground monitor-based approach used by the ALA to provide $PM_{2.5}$ concentration estimates across the U.S.

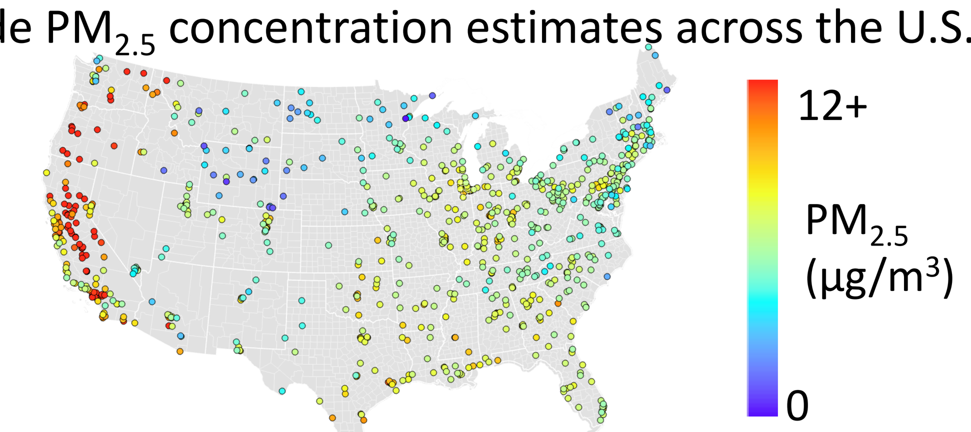

Figure 1: *EPA $PM_{2.5}$ monitors and their 2020 annual concentration*

Satellite-derived Datasets

Dataset	Temporal Coverage	Spatial Resolution	Remote Sensing AOD Retrieval Method*			Models/ Machine Learning Algorithms	Ground-Based Data	References
			MODIS	MISR	Sea-WiFS			
Global/ Regional Estimates (V5.GL.02) (WashU GL)	1998-2020	0.01° x 0.01°, Entire U.S.	Deep Blue, Dark Target, MAIAC	MISR	Dark Blue	GEOS-Chem, GWR	EPA, other	van Donkelaar et al., 2021
North American Regional Estimates (V4.NA.03) (WashU NA)	2000-2018	0.01° x 0.01°, CONUS	Deep Blue, Dark Target, MAIAC	MISR	Dark Blue	GEOS-Chem, GWR	EPA, other	Hammer et al., 2020; van Donkelaar et al., 2019
$PM_{2.5}$ Concentrations for the CONUS (SEDAC)	2000-2016	1km x 1km, CONUS	MAIAC			Neural Network, Random Forest, Gradient Boosting	EPA, other	Di et al., 2019

Table 1*: A condensed list of the publicly available datasets we collected to reflect the ones we used in our analysis. highlighting some of the features.*

Results

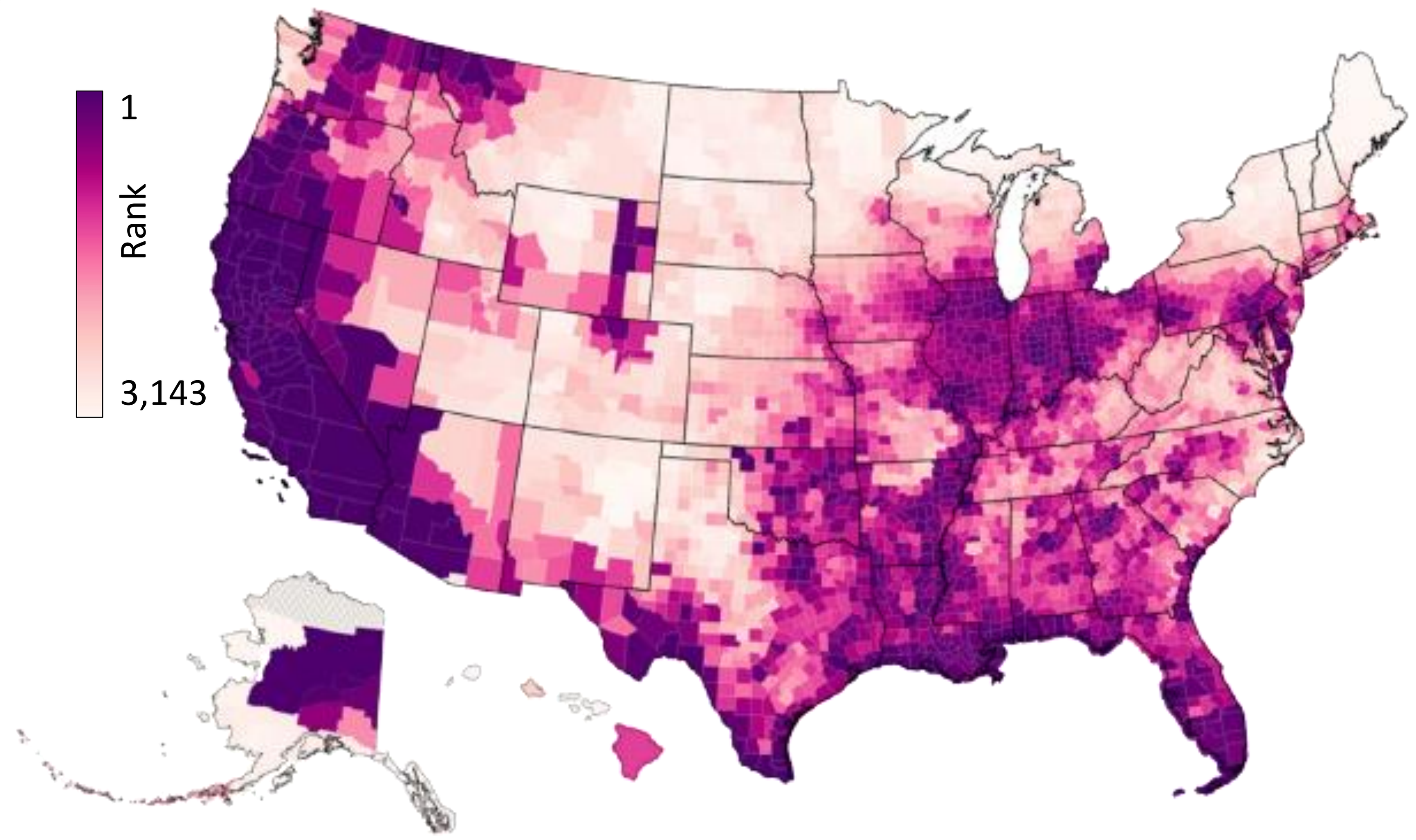

Figure 2: *Counties ranked from dirtiest to cleanest based on the WashU GL 2018-2020 $PM_{2.5}$ DVE.*

Maximum Method

Assigning a county's DVE with its maximum 1km x 1km grid value showed the greatest correlation between the EPA DVs and the satellite-derived DVEs as well as their ranks. This suggests that monitors are placed in more polluted areas of the country.

Based on our analysis of annual average $PM_{2.5}$ we found:

- The satellite data detected high levels (≥12.1 µg/m³) of $PM_{2.5}$ in counties with no monitors
- There was both agreement and disagreement between monitor data and satellite data
- The satellite-derived $PM_{2.5}$ data products had varying concentration levels

Conclusion

- Publicly available data-fusion products can provide estimates of near surface $PM_{2.5}$ providing air quality information away from monitors
- We were able to calculate passing and failing metrics for all U.S. counties using all three methods
- Using the maximum grid per county showed good agreement with the $PM_{2.5}$ analysis approach used by the American Lung Association for annual average $PM_{2.5}$
- Alternate approaches could be appropriate for analyzing gridded data for comparison to monitor data depending on the goal of the analysis

Methods

We allocated the 2013-2020 gridded satellite-derived $PM_{2.5}$ datasets to U.S. counties using three statistical methods.

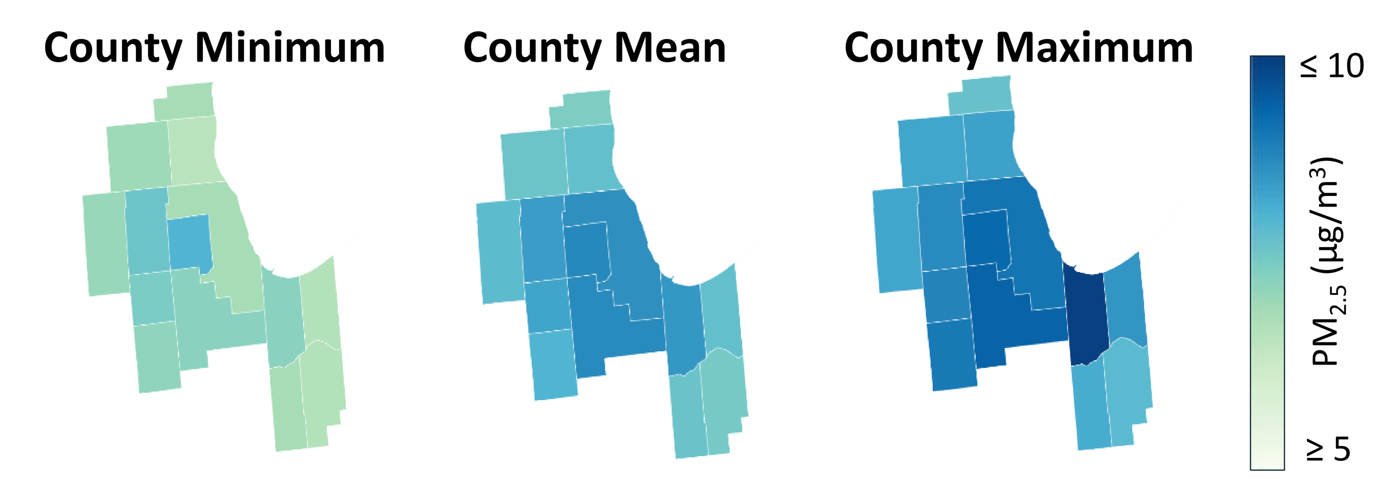

Figure 2: *The 2018-2020 DVE over the Chicago Metropolitan area calculated from all three methods*

- **Minimum**: assigning the minimum pixel value within a county as the county concentration
- **Mean**: assigning the average of all the gridded pixel values within a county as the county concentration
- **Maximum**: assigning the maximum pixel value within a county as the county concentration

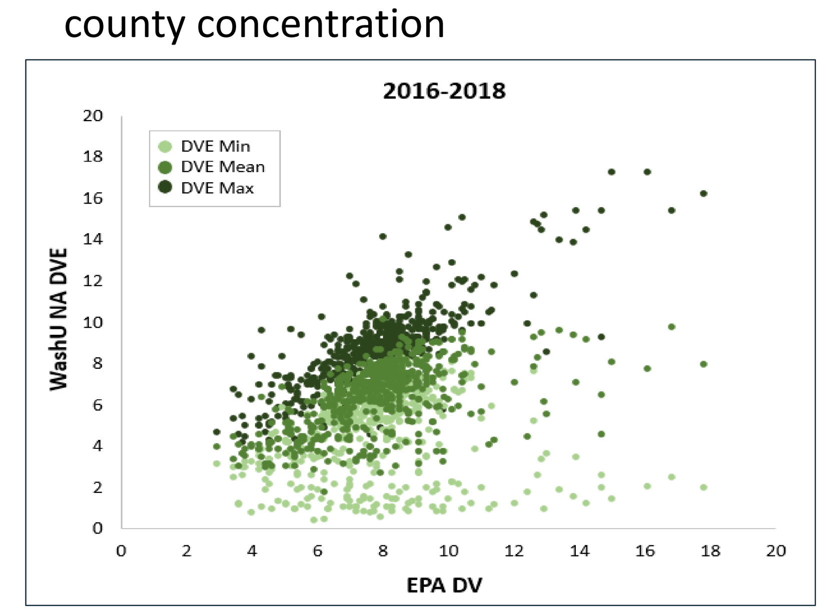

Figure 3*: A scatter plot of the 2016-2018 EPA DVs (µg/m³) vs. the WashU NA DVEs (µg/m³) using all three methods .*

Following the methodology from the ALA State of the Air Report, we calculated annual average $PM_{2.5}$ design value equivalents (DVEs) and assigned grades and rankings to each county.

We used correlations to compare our results to the ALA report.

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