GeoHealth

RESEARCH ARTICLE

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Special Section:
Dust and dust storms: From physical processes to human health, safety, and welfare

Key Points:

- Accuracy of dust metrics from public data products (National Weather Service storms, Copernicus Atmosphere Monitoring Service (CAMS), Modern-Era Retrospective analysis for Research and Applications—Version 2, and CMAQ-EQUATES) were compared to a "gold standard" data set
- Maximum dust aerosol (0.9–20 μm) mixing ratio metric from CAMS had the strongest association with the "gold standard" dust event variable
- Aerosol mixing ratios from CAMS may be a more useful dust metric for epidemiologic studies than commonly used dust characterization methods

Supporting Information:

Supporting Information may be found in the online version of this article.

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Evaluating Data Product Exposure Metrics for Use in Epidemiologic Studies of Dust Storms

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Abstract Dust storms are increasing in frequency and correlate with adverse health outcomes but remain understudied in the United States (U.S.), partially due to the limited spatio-temporal coverage, resolution, and accuracy of current data sets. In this work, dust-related metrics from four public areal data products were compared to a monitor-based "gold standard" dust data set. The data products included the National Weather Service (NWS) storm event database, the Modern-Era Retrospective analysis for Research and Applications—Version 2, the EPA's Air QUAlity TimE Series (EQUATES) Project using the Community Multiscale Air Quality Modeling System (CMAQ), and the Copernicus Atmosphere Monitoring Service global reanalysis product. California, Nevada, Utah, and Arizona, which account for most dust storms reported in the U.S., were examined. Dichotomous and continuous metrics based on reported dust storms, particulate matter concentrations (PM_{10} and $PM_{2.5}$), and aerosol-type variables were extracted or derived from the data products. Associations between these metrics and a validated dust storm detection method utilizing Interagency Monitoring of Protected Visual Environments monitors were estimated via quasi-binomial regression. In general, metrics from CAMS yielded the strongest associations with the "gold standard," followed by the NWS storm database metric. Dust aerosol (0.9–20 μm) mixing ratio, vertically integrated mass of dust aerosol (9–20 μm), and dust aerosol optical depth at 550 nm from CAMS generated the highest standardized odds ratios among all metrics. Future work will apply machine-learning methods to the best-performing metrics to create a public dust storm database suitable for long-term epidemiologic studies.

Plain Language Summary Health studies of dust storms are limited by the kinds of dust data that are available over large areas and long periods of time. Our study compares four publicly available data products to determine which is most suitable for large-scale population studies of dust storms in the southwestern U.S. Using dust-related variables from these products, the study evaluated relationships with a previously validated "gold standard" data set that identifies dust storms only on certain days and at certain locations. The study found that the dust-related variables from the Copernicus Atmosphere Monitoring Service (CAMS) product had the strongest associations with the "gold standard," followed by the National Weather Service storm events database, a long-term model run from one of the Environmental Protection Agency's air quality models (CMAQ—EQUATES), and one of the National Aeronautics and Space Administration's data sets (MERRA-2). Specifically, variables from CAMS that were based on daily maximum values of dust particles in the air performed the best. Future work will apply complex computer-based methods to the best-performing exposure metrics to create a public dust storm database suitable for use in long-term population health studies.

1. Introduction

Dust storm incidence has increased over the last several decades within the United States (U.S.), especially in the southwestern region due to baseline climate aridity and increasing prevalence of drought (Pu & Ginoux, 2017; Tong et al., 2017; Wehner et al., 2017). While the International Panel on Climate Change predicts that anthropogenic climate change will continue to exacerbate these underlying conditions, few population-level epidemiologic studies have been conducted in the U.S. on dust storms (Herrera-Molina et al., 2021; Mirzabaev et al., 2019). A

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key limitation for dust storm research is the dearth of data sources available at the scale and coverage necessary for long-term population health assessments (Crooks et al., 2016; Rublee et al., 2020; Tobías & Stafoggia, 2020).

While there is notable inconsistency in the terminology around airborne dust, dust events, and/or dust storms, this paper will use the term "dust event" throughout except in reference to events recorded as "dust storms" in the National Weather Service (NWS) Storm Events Database or when discussing dust storms in general.

The U.S. Environmental Protection Agency (EPA) recognizes windblown dust as an important factor affecting air quality and other atmospheric events (U.S. Environmental Protection Agency, 2022). Dust from dust storms consists of heterogeneous mixtures of particulate matter (PM) less than or equal to 2.5 μm in diameter ($PM_{2.5}$) the coarse fraction of particulate matter ($PM_{10\text{-}2.5}$), and larger particles, of heterogeneous composition (Rublee et al., 2020). $PM_{2.5}$ in particular is known to have relatively high penetrance into the deeper organ and tissue systems causing adverse health outcomes (U.S. Environmental Protection Agency (EPA), 2019), and recent work has focused on the dust contribution to this size fraction (Ardon-Dryer & Kelley, 2022; Dagsson-Waldhauserova et al., 2016). In addition to their local impact, dust events can lift large amounts of dust high into the atmosphere that can then travel over inter-continental distances (Zhang et al., 2016).

Epidemiologic studies performed in the United States, southern Europe, east Asia, the Middle East, and Australia have found adverse short-term health outcomes pertaining to dust event exposure, including cardiovascular and respiratory outcomes and bacterial- and fungal-related infectious disease, as well as accidental and non-accidental premature mortality (Achakulwisut et al., 2018; Al-Taiar & Thalib, 2014; Crooks et al., 2016; Schweitzer et al., 2018; Tobias et al., 2019; Tong et al., 2017). Several previous epidemiologic studies of dust storms in the U.S. have relied on data from the U.S. NWS Storm Event database (Crooks et al., 2016; Rublee et al., 2020), which collects event information based on visual reporting from trained spotters, law enforcement, and members of the public. The Storm Event database has advantages for use in health studies, including ostensibly complete spatial and temporal coverage going back to the 1990s. However, it has limitations with respect to accuracy, spatial resolution (limited to the Weather Forecast Zone (WFZ), roughly county-sized areal units), and consistency with regard to reporting, which have prompted questions about its utility (Ardon-Dryer et al., 2023; Tong et al., 2022).

To be most useful in population health studies, a dust event data set needs to encompass a complete, long-term time-series (a decade or longer) at daily resolution or better, have complete spatial coverage across the dustiest regions of the U.S., have relatively high spatial resolution, and should accurately reflect the dust content of the air near ground level. Several other data products produce dust-related variables that represent potential candidates for use in dust event epidemiology research in the U.S. These products include the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) product (Gelaro et al., 2017), the Community Multiscale Air Quality (CMAQ)—EPA's Air QUAlity TimE Series Project (EQUATES) product (Appel et al., 2021), and the Copernicus Atmosphere Monitoring Service (CAMS) Global Reanalysis (EAC4) product (Inness et al., 2019). These publicly available products have been used in a variety of atmospheric science applications, and they offer better spatial resolution and consistency than NWS, though to our knowledge they have not been used in dust-related epidemiology research in the U.S. Each of these data products contains dust-relevant output variables and provides complete coverage over most of North America for over a decade at daily temporal resolution.

The aim of this study was to compare daily dust-related metrics derived from the NWS Storm Event database, the MERRA-2 product, the CMAQ –EQUATES product, and the CAMS EAC4 product to a "gold-standard" dust event data set developed using the Interagency Monitoring of Protected Visual Environments (IMPROVE) monitors located in U.S. National Parks and Wilderness Areas (Tong et al., 2017). While the present study does not highlight a specific adverse health outcome, a metric or set of metrics that strongly associate with the "gold standard" could be used to produce spatially- and temporally complete dust event predictions across a broad geographical region and long time span, aligned with the needs of future long-term population epidemiologic studies.

2. Methods

2.1. Data

Dust -related air pollution exposure metrics were collected across four southwestern states in the U.S. with high dust activity (Arizona, California, Nevada, and Utah) from four publicly available areal data sets (NWS, MERRA-2, CMAQ, CAMS). These were compared against a validated empirical dust event data set based on the IMPROVE network. Only data covering IMPROVE sites on days when the IMPROVE monitors reported concentrations (generally every third day between 3rd January 2003 and 29th June 2016) were included in the comparison. In order to create a common set of unique exposure days across all data products for comparison, 20 days were excluded within the date range across all data products when no data existed for any one of the data products out of a total 4,927 days. Data used in these analyses are available on the Open Science Framework: https://doi.org/10.17605/OSF.IO/TF94G.

2.1.1. Interagency Monitoring of PROtected Visual Environments (IMPROVE)

The IMPROVE monitors are operated jointly across several U.S. federal agencies to assess visibility and PM pollution in U.S. National Parks and Wilderness Areas, measuring 24-hr $PM_{2.5}$ total mass, $PM_{2.5}$ speciated mass, and PM_{10} mass. Previous work from Tong et al. (2017) identified dust events using an algorithm that combined IMPROVE PM size fraction concentrations, IMPROVE $PM_{2.5}$ species concentrations, and ratios among them, which was trained on known dust events identified from satellite imagery (Tong et al., 2017). In particular, five factors aided in dust event identification: high concentrations of PM_{10} and $PM_{2.5}$, low ratios of $PM_{2.5}$ to PM_{10}, high concentrations of certain elements found in the earth's crust (Si, Ca, K, Fe, and Ti), low concentrations of elements from anthropogenic components (As, Zn, Cu, Pb, sulfate, nitrate, organic carbon, and elemental carbon), and low concentrations of pollution elements from anthropogenic sources (Cu, Zn, Pb, and K).

While the IMPROVE network is limited in spatial coverage and temporal completeness, the fact that dust events have previously been identified and validated (Tong et al., 2017) with IMPROVE data allows us to use the IMPROVE-based dust product as the "gold standard" dust product against which the four areal data products below were compared. Specifically, the IMPROVE-derived data set will include dust storms previously detected during the study period.

2.1.2. United States National Weather Service (NWS) Storm Events Database

NWS data includes storm events collected and reported since the 1950s and has included "Dust Storm" as a specific event category since 1993 (U.S. National Weather Service (NWS), 2022). The location information is limited to the WFZ in which the storm was observed. WFZs are roughly county-sized geographies, though their boundaries do not, in general, correspond to county boundaries, especially in the western U.S. The database includes the start and end dates for each dust storm, though we used only the start date since the overwhelming majority of identified dust storms lasted less than 1 day (Crooks et al., 2016). While the spatial and temporal domains of the database cover our study region for the duration of the study period, inconsistencies may exist in the accuracy and reliability of results due to the nature of storm event reporting between or within WFZs. Although the NWS dust storm reports are not routinely confirmed or quality-assured, they have a history of usage in epidemiologic literature owing to their accessibility and the lack of higher-quality alternatives appropriate for long-term population studies (Comrie, 2021; Crooks et al., 2016; Jones, 2020; Rublee et al., 2020).

2.1.3. Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2)

MERRA-2 is an atmospheric reanalysis data product developed by the U.S. National Aeronautics and Space Administration with global coverage since 1980. Dust aerosol-related variables are produced via the Goddard Chemistry, Aerosol, Radiation, and Transport (GOCART) model integrated into the Goddard Earth Observing System Model, Version 5 modeling system, which incorporates meteorological and bias-corrected aerosol optical depth (AOD) data from satellites and ground monitors. GOCART produces estimates for surface mass concentrations of dust, including total dust and dust $PM_{2.5}$, as well as other aerosol components (sea salt, black carbon, organic carbon, and sulfate). MERRA-2 has a spatial resolution of $0.5° \times 0.625°$. We examined the following variables pertaining to airborne dust: column mass density, extinction aerosol optical thickness (AOT), surface mass concentration, and surface wind speed. To be consistent with other data products in this work and with most of the air pollution epidemiology literature, we averaged the 3-hr MERRA-2 output over 24-hr periods.

2.1.4. Community Multiscale Air Quality (CMAQ)—EPA's Air QUAlity TimE Series Project (EQUATES)

CMAQ is an atmospheric chemical transport model developed for regulatory purposes. CMAQ produces estimates of atmospheric concentrations for pollutants such as PM_{10}, $PM_{2.5}$ and their species, as well as gaseous pollutants like ozone (Inness et al., 2019). For EQUATES, EPA modelers ran CMAQ with consistent settings over the years 2002 through 2017, covering the conterminous U.S. at 12 km horizontal grid spacing. EQUATES utilized the Weather Research and Forecasting model version 4.1.1 for simulating weather conditions and CMAQ model version 5.3.2 for air quality modeling. EQUATES does not assimilate empirical concentration data from ground monitors or remote sensing instruments, nor does it report dust-specific variables. However, it does report variables that overlap with dust, including PM_{10}, $PM_{2.5}$, $PM_{2.5}$ species, and coarse PM (PM_{10}–$PM_{2.5}$), which we examined.

2.1.5. Copernicus Atmosphere Monitoring Service (CAMS) Global Reanalysis (EAC4)

The CAMS global reanalysis of atmospheric composition utilizes 4D-Var assimilation of the Integrated Forecast System by the European Centre for Medium-Range Weather Forecasts across a 12-hr window to combine model data with observations across the world and create an estimate of the state of the atmosphere. The current version spans the years 2003 through 2021 using $0.75° \times 0.75°$ horizontal resolution with a temporal resolution of 3-hr increments. The following variables were utilized from the CAMS data set: PM_{10} and $PM_{2.5}$ (from which coarse PM was derived), dust aerosol mixing ratio, vertically integrated masses of dust aerosol, and dust AOD. Daily mean and maximum values in each grid cell were derived from the 3-hr values and calculated over the same sampling days as the IMPROVE sites.

2.2. Dust Event Classification

Airborne dust events are naturally extreme events, so continuous metrics based on continuous concentration or AOT values may not effectively capture dust events as distinct meteorological phenomena. Therefore, for each of the areal data products, dichotomous metrics were created from the continuous variables using threshold cutoff values at the 95th, 98th, and 99th percentiles and the percentile at the furthest distance from the diagonal on the Receiver Operator Characteristic (ROC) curve with respect to the IMPROVE dust events, across the entire study domain. ROC curves were fitted using the pROC package (Robin et al., 2011) in R version 4.2.0 (R Core Team, 2022). In addition to the creation of dichotomous exposure metrics, metrics based on log transforms of the continuous variables were also created. Thus, the full set of dust metrics included the original continuous variables as well as their log-transformed and dichotomized variants. Overall, variables were selected from each data set if they were relevant for general aerosol detection (e.g., $PM_{2.5}$, PM_{10}, etc.) or if they contained “dust” as a keyword within the variable title or description (e.g., vertically integrated masses of dust aerosol). PM_{10} and $PM_{2.5}$, in this instance, represent proxies for dust rather than calculated or measured dust content.

2.3. Alignment With IMPROVE Sites

Spatial and temporal intersections between the IMPROVE data and the areal data products (MERRA-2, NWS storm events database, CAMS, and CMAQ) were performed using the sf (Pebesma, 2018) and stars (Pebesma & Bivan, 2023) packages in R. Specifically, WFZs from NWS and grid cells from the other three data products of interest were spatially merged with IMPROVE monitor site locations, such that only WFZs and grid cells containing IMPROVE sites were used. Furthermore, only those IMPROVE sites in the four southwestern states of Arizona, California, Nevada, and Utah, and only those days where the IMPROVE network and all four areal data products reported data were kept for analysis. In particular, days were excluded when the IMPROVE data monitors did not report data as well as days when any one of the areal data products had missing data, which accounted for a total of 20 days. In this case, the 20 missing days originated from the MERRA-2 data set and likely reflected an absence of recording while undergoing system updates, calibrations, or other necessary downtimes.

2.4. Statistical Analysis

2.4.1. Descriptive Analysis

Summary measures were calculated across each continuous metric for the data products of interest, including minimum, maximum, mean, standard deviation, median, and 25th and 75th interquartile values.

2.4.2. Statistical Models

To estimate and compare the associations between the various dust metrics and the IMPROVE “gold standard” IMPROVE dust event data, bivariate measures of association (log odds ratios) between each metric and

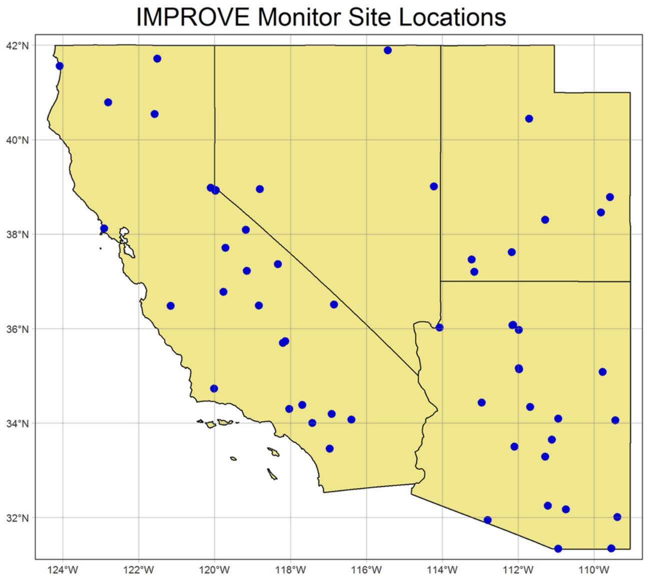

Figure 1. A map of the study area, including the US states of Arizona, California, Nevada, and Utah, along with the IMPROVE monitor site locations.

the IMPROVE dust event were estimated using quasi-binomial regression implemented in the gnm package in R (Turner & Firth, 2022). Graphic representations were created using ggplot2 (Wickham, 2016) in R. Within the date range for the data (January 2003–June 2016), all months were included whether a dust storm was detected or not.

All models treated the dust event indicator variable from the IMPROVE data as the outcome. Crude models included only the specific dust metric as a predictor, while adjusted models also included a separate intercept for each combination of year, month and IMPROVE site. The adjusted models thus accounted for space- and time-varying factors that could influence the odds of an IMPROVE dust event but that were not captured in the dust metrics. The adjusted models can generate predictions at all days in our time domain but only at the IMPROVE sites, while the crude models, by not adjusting for differences between sites, could in principle make predictions across the entire spatio-temporal domain. We thus present crude models for their generalizability and adjusted models to evaluate the impact of spatial and temporal confounding. Future work will explore dust event predictive models.

Because of differences in units and variability among the continuous metrics, to facilitate comparisons between the continuous metrics' measures of association, each metric's estimated log OR and confidence interval was scaled by the metric's inter-quartile range.

3. Results

3.1. Descriptive Analysis

A total of 68,422 site-days (combinations of site locations across days within the study) were used in the analysis, covering 4,907 unique days. These numbers exclude the 20 days that had missing information for the MERRA-2 data product, thus leaving 99.59% of the days with IMPROVE data available for analysis. Of the 4,907 days, there were 82 days with dust events identified by IMPROVE monitors and 4,825 days without dust events. The NWS data included a day with two reported dust events that overlapped with an IMPROVE storm; thus, this site-day was duplicated for the NWS analysis, yielding 83 storms for the NWS analysis. All data products included 50 unique IMPROVE monitoring site locations within the ground monitoring network. Figure 1 displays a map of the four states included in the study, as well as the IMPROVE monitor site locations across each state. Site code information is provided by state in Supporting Information S1 under item 1 Table S1. Additional maps provided in Supporting Information S1 document detail the continuous and dichotomized variables across all data products over the study domain (S3).

Table 1 presents the descriptive statistics for the candidate dust exposure variables, stratified by data source (CAMS, CMAQ, and MERRA-2). The NWS dust storm indicator was not included in the table since the variable is dichotomous and would not display meaningful values for the included statistics. Notably, several of the metrics have extremely wide ranges, where the minimum (min) value is at or close to zero and the maximum (max) value is orders of magnitude larger than the median. Many of the variables also have high standard deviations and heterogeneity between the mean and median values, suggestive of right skew. Expanded descriptions are provided in Supporting Information S1 under Item 2 Table S2 along with each data source documentation URL.

3.2. Crude Models With Dichotomous Metrics

Among the crude models with dichotomous predictors (Figure 2), the NWS dust storm indicator had the strongest association with IMPROVE dust events, with a log OR of 3.57 (95% CI: 2.40, 4.75; $p = 2.63 \times 10^{-9}$). The NWS indicator was followed closely by two CAMS metrics: the maximum and mean dust aerosol (0.9–20 μm) mixing ratios greater than or equal to the 99th percentile, with log odds ratios of 3.55 (95% CI: 3.04, 4.05; $p = 1.44 \times 10^{-43}$) and 3.48 (95% CI: 2.97, 3.99; $p = 1.08 \times 10^{-40}$), respectively. While the log odds ratios from CAMS were slightly attenuated compared to NWS, their standard errors were ~50% smaller, yielding more

Table 1
Descriptive Statistics for Dust Exposure Metrics

Source	Metric	Units	Min	Max	Mean	Median	SD	25th	75th
CAMS	aermr04_max	kg/kg	0.0	14.0	0.6	0.2	1.1	0.0	0.8
CAMS	aermr04_mean	kg/kg	0.0	6.6	0.4	0.1	0.6	0.0	0.4
CAMS	aermr05_max	kg/kg	0.0	34.2	1.3	0.3	2.3	0.1	1.6
CAMS	aermr05_mean	kg/kg	0.0	15.8	0.7	0.2	1.3	0.0	0.8
CAMS	aermr06_max	kg/kg	0.0	125.9	3.2	0.3	7.1	0.0	2.9
CAMS	aermr06_mean	kg/kg	0.0	82.3	1.4	0.1	3.3	0.0	1.1
CAMS	aermssdul_max	μg/m^2	0.0	188,171.0	7,216.4	1,353.6	13,978.7	262.0	7,324.9
CAMS	aermssdul_mean	μg/m^2	0.0	115,364.9	4,243.5	785.3	8,197.3	150.1	4,179.6
CAMS	aermssdum_max	μg/m^2	3.9	51,464.3	2,941.0	1,098.5	4,470.7	300.7	3,582.1
CAMS	aermssdum_mean	μg/m^2	2.2	42,900.4	1,994.5	674.1	3,289.9	184.6	2,244.2
CAMS	duaod550_max	~	0.00	0.13	0.01	0.00	0.01	0.00	0.01
CAMS	duaod550_mean	~	0.00	0.11	0.01	0.00	0.01	0.00	0.01
CAMS	pm10_max	μg/m^3	0.1	5,038.0	32.3	21.9	90.1	14.5	32.8
CAMS	pm10_mean	μg/m^3	0.0	2,495.3	18.6	13.6	41.9	8.6	20.5
CAMS	pm2p5_max	μg/m^3	0.0	3,649.3	22.8	15.3	65.4	10.0	23.0
CAMS	pm2p5_mean	μg/m^3	0.0	1,812.8	13.0	9.4	30.4	6.0	14.2
CAMS	PMcoarse_max	μg/m^3	0.0	1,388.7	9.7	6.7	24.8	4.4	10.0
CAMS	PMcoarse_mean	μg/m^3	0.0	682.5	5.6	4.1	11.5	2.6	6.2
CMAQ	NH4_PM25_ratio	~	0.0	0.2	0.1	0.1	0.0	0.0	0.1
CMAQ	OC_PM25_ratio	~	0.0	0.6	0.2	0.2	0.1	0.2	0.3
CMAQ	PM10_AVG	μg/m^3	0.0	975.0	7.6	6.1	6.8	3.9	9.6
CMAQ	PM10_PM25_ratio	~	1.1	9.6	2.0	1.8	0.7	1.6	2.1
CMAQ	PM25_AVG	μg/m^3	0.0	878.7	4.0	3.3	4.7	2.0	4.9
CMAQ	PM25_EC_AVG	μg/m^3	0.0	35.0	0.2	0.1	0.4	0.0	0.1
CMAQ	PM25_NH4_AVG	μg/m^3	0.0	6.2	0.2	0.2	0.2	0.1	0.3
CMAQ	PM25_NO3_AVG	μg/m^3	0.0	19.7	0.2	0.1	0.6	0.1	0.2
CMAQ	PM25_OC_AVG	μg/m^3	0.0	522.6	0.9	0.7	2.3	0.4	1.1
CMAQ	PM25_other	μg/m^3	0.0	317.9	1.8	1.4	1.9	0.8	2.2
CMAQ	PM25_SO4_AVG	μg/m^3	0.0	4.9	0.7	0.6	0.4	0.4	0.9
CMAQ	PM25other_PM25_ratio	~	0.1	0.8	0.4	0.4	0.1	0.4	0.5
CMAQ	PMcoarse	μg/m^3	0.0	96.3	3.6	2.7	3.1	1.7	4.5
MERRA-2	DUCMASS_ug	μg/m^2	780.6	553,655.4	31,527.8	22,744.5	27,403.2	12,058.7	43,273.3
MERRA-2	DUCMASS25_ug	μg/m^2	367.7	144,132.4	10,305.7	7,400.1	8,570.4	4,147.9	14,330.6
MERRA-2	DUEXTT25	~	0	0.19	0.01	0.01	0.01	0.01	0.02
MERRA-2	DUEXTTAU	~	0	0.34	0.02	0.02	0.02	0.01	0.03
MERRA-2	DUSCAT25	~	0	0.18	0.01	0.01	0.01	0.01	0.02
MERRA-2	DUSCATAU	~	0	0.32	0.02	0.02	0.02	0.01	0.03
MERRA-2	DUSMASS_ug	μg/m^3	0.0	205.2	10.4	7.4	10.7	4.1	12.9
MERRA-2	DUSMASS25_ug	μg/m^3	0.0	45.6	2.7	2.0	2.4	1.2	3.4
MERRA-2	SPEEDMAX	m/s	1.3	24.7	5.4	5.0	2.0	4.0	6.5

Note. Min, minimum; Max, maximum; SD, standard deviation; 25th, 25th percentile; 75th, 75th percentile. A more detailed description of each variable is provided in Supporting Information S1 under item 2.

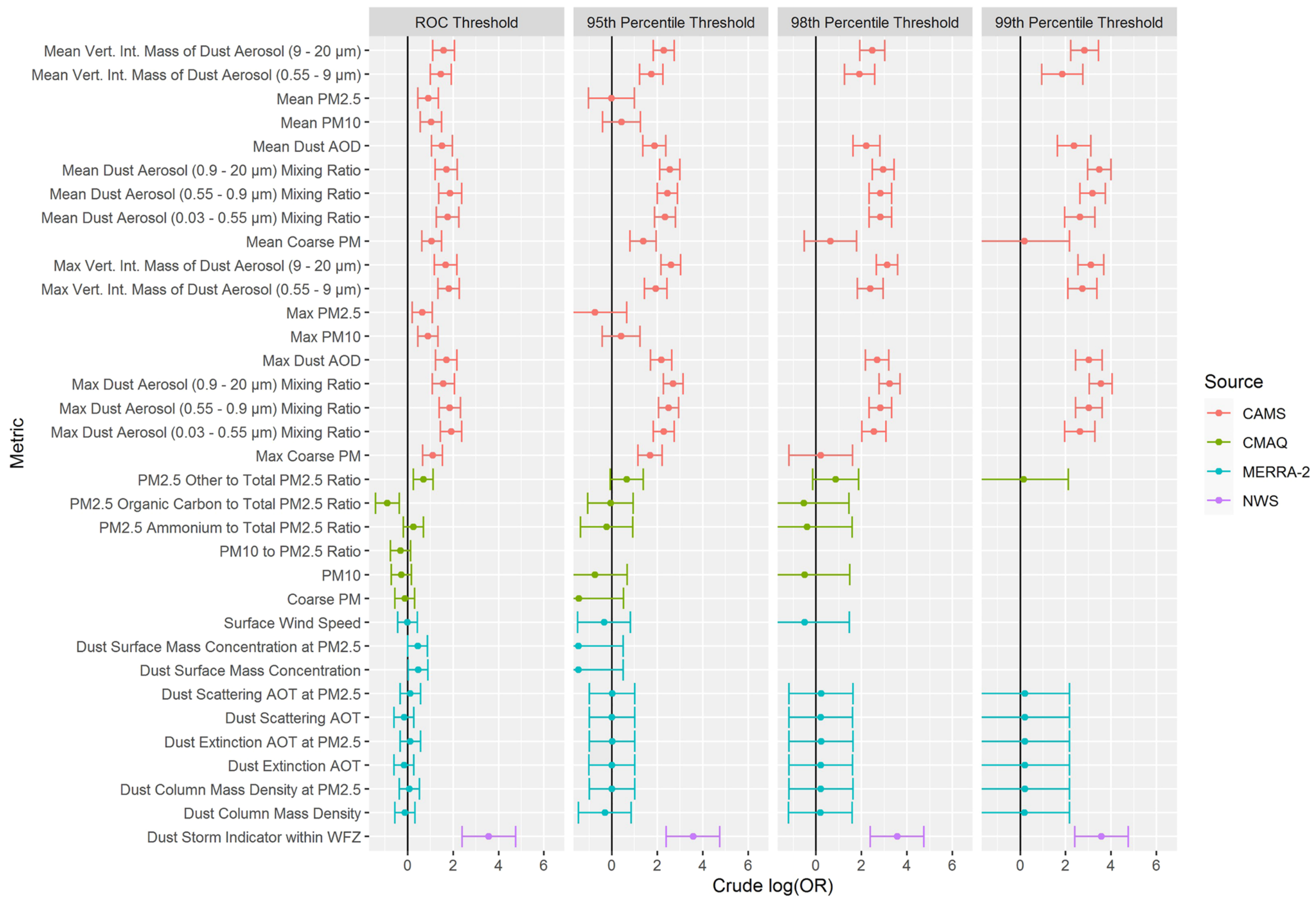

Figure 2. **Crude log odds ratios for dichotomous dust exposure metrics and IMPROVE dust events**. Dust exposure metrics are listed in the rows and dichotomization thresholds (ROC, and 95th, 98th, and 99th percentile thresholds) in the columns for visual comparison, where the log OR are estimated with respect to the IMPROVE-detected dust event outcome. The log OR estimate for the NWS dust storm variable (which is innately dichotomous) is displayed under all thresholds to facilitate comparison. A missing log OR indicates that a particular quasi-binomial logistic regression model failed to converge. 95% confidence intervals are displayed for each log OR. Here, the null value is zero, and a positive association means that a particular exposure metric was positively associated with the IMPROVE-based dust event indicator outcome.

precise estimates and smaller *p*-values. Among the CAMS metrics, stronger associations tended to be observed at the more extreme dichotomization thresholds (98th and 99th percentile). CAMS metrics and the NWS dust storm indicator tended to out-perform MERRA-2 and CMAQ metrics.

3.3. Crude Models With Continuous Metrics

Among the crude models with continuous dust event predictors (Figure 3), the log transformed maximum dust aerosol (0.55–0.9 μm) mixing ratio from CAMS had the strongest association, with an IQR-standardized log OR of 2.30 (95% CI: 1.57, 3.03; $p = 7.11 \times 10^{-10}$). Following that metric, the log transformed maximum dust aerosol (0.9–20 μm) mixing ratio and the log transformed maximum dust aerosol (0.03–0.55 μm) mixing ratio from CAMS yielded IQR-standardized log odds ratios of 2.28 (95% CI: 1.62, 2.95; $p = 1.52 \times 10^{-11}$) and 2.16 (95% CI: 1.49, 2.83; $p = 2.43 \times 10^{-10}$), respectively. Among CAMS metrics, the daily maximum metrics tended to have stronger associations than the daily mean metrics relative to the IMPROVE-detected dust event outcome. CAMS metrics tended to out-perform MERRA-2 and CMAQ metrics.

3.4. Adjusted Models With Dichotomous Metrics

Among the dichotomous metrics (Figure 4), the maximum dust aerosol (0.9–20 μm) mixing ratio from CAMS greater than or equal to the 99th percentile yielded the strongest association, with a log OR of 5.30 (95% CI: 5.11,

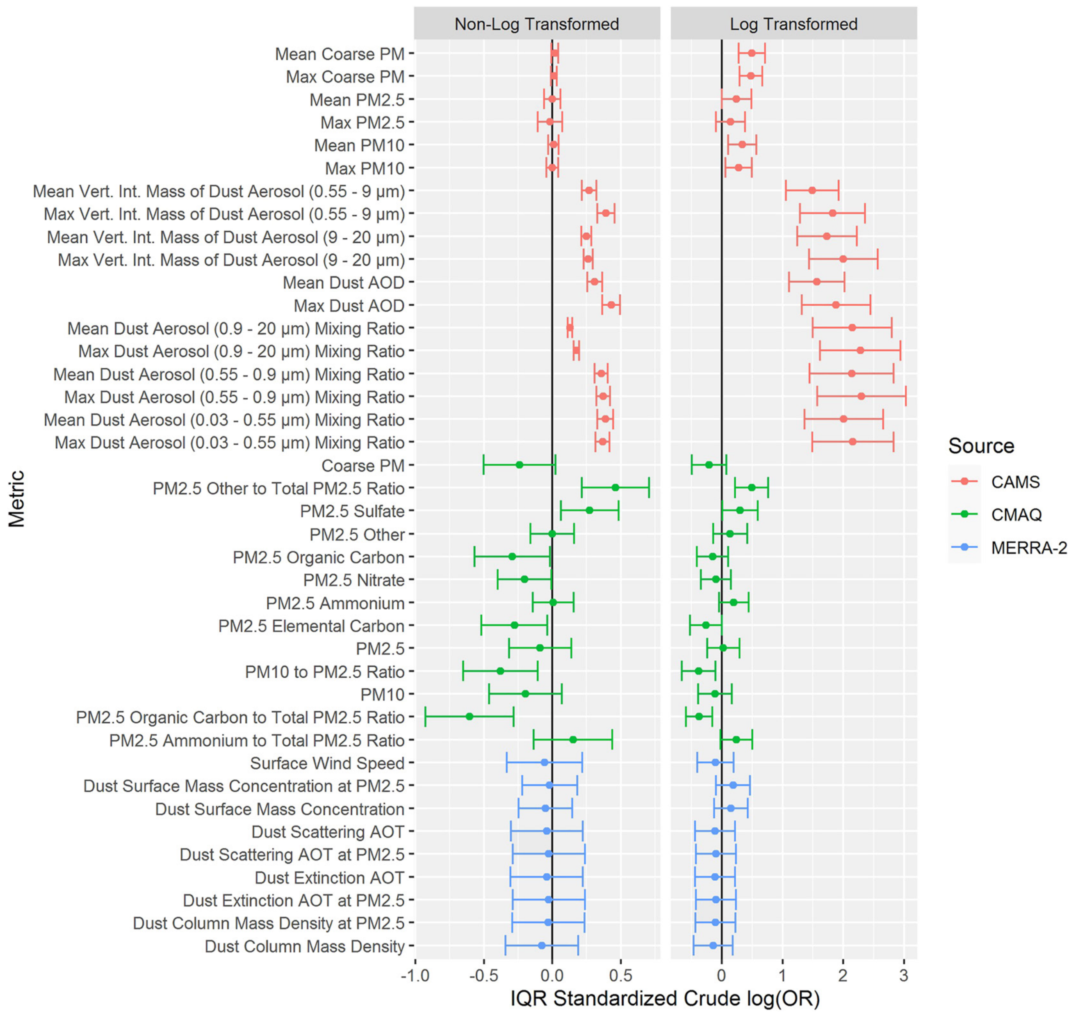

Figure 3. Inter-quartile range standardized crude log odds ratios for continuous dust exposure metrics and IMPROVE dust events. Dust exposure metrics are listed in the rows. The left column presents log OR from models using un-transformed variables, while the right column presents log OR from models using log-transformed variables. The log OR include 95% confidence intervals and represent the quasi-binomial logistic regression model with the IMPROVE-derived dust event indicator as the outcome, where zero represents the null value.

5.50; $p = 0.0000$). This metric was followed by CAMS maximum dust AOD (550 nm) and maximum dust aerosol (0.9–20 μm) mixing ratio greater than or equal to the 98th percentile, with log odds ratios of 4.41 (95% CI: 4.24, 4.57; $p = 0.0000$) and 4.31 (95% CI: 4.18, 4.44; $p = 0.0000$), respectively. Among the CAMS metrics, stronger associations tended to be observed at the more extreme dichotomization thresholds (98th and 99th percentile). CAMS metrics and the NWS dust storm indicator tended to out-perform MERRA-2 and CMAQ metrics.

3.5. Adjusted Models With Continuous Metrics

For the adjusted continuous predictors (Figure 5), the log transformed maximum dust aerosol (0.9–20 μm) mixing ratio from CAMS had the strongest association with an IQR-standardized log OR of 3.62 (95% CI: 3.49, 3.76; $p = 0.0000$). This metric was followed by the log transformed mean dust aerosol (0.9–20 μm) mixing ratio and the log transformed maximum vertically integrated mass of dust aerosol (9–20 μm) from CAMS, with IQR-standardized log odds ratios of 3.34 (95% CI: 3.21, 3.47; $p = 0.0000$) and 3.11 (95% CI: 3.00, 3.22; $p = 0.0000$), respectively. Among CAMS metrics, the daily maximum metrics tended to have stronger associations than the daily mean metrics relative to the IMPROVE-detected dust event outcome. CAMS metrics tended to out-perform MERRA-2 and CMAQ metrics.

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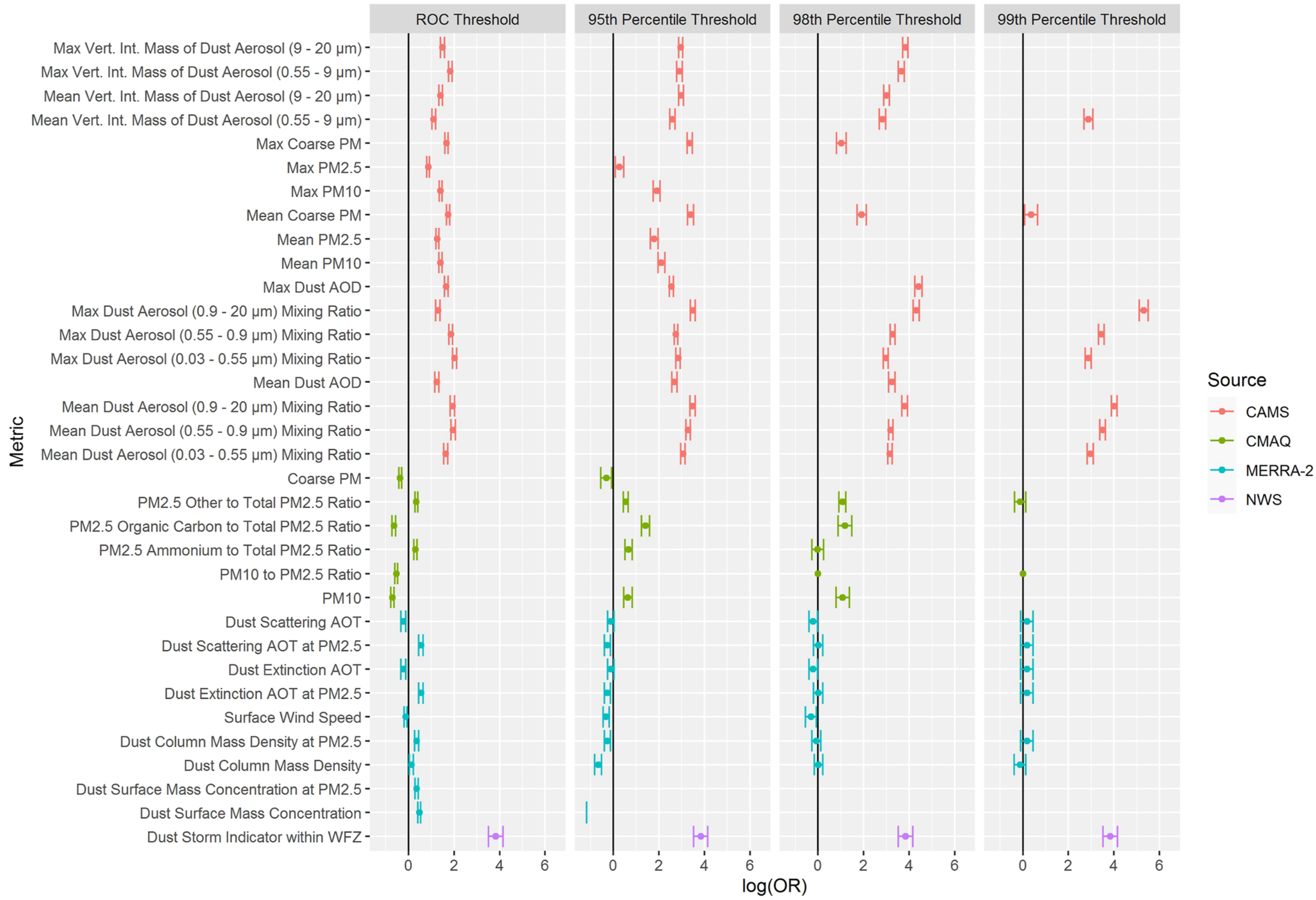

Figure 4. Adjusted log odds ratios for dichotomous dust exposure metrics and IMPROVE dust events. Dust exposure metrics are listed in the rows and dichotomization thresholds (ROC, and 95th, 98th, and 99th percentile thresholds) in the columns for visual comparison, where the log OR are estimated with respect to the IMPROVE-detected dust event outcome. Models controlled for all combinations of year, month, and IMPROVE site location. The log OR estimate for the NWS dust storm variable (which is innately dichotomous) is displayed under all thresholds to facilitate comparison. Missing log OR indicate models that failed to converge. Zero represents the null value between the exposure metric and the IMPROVE-derived dust event outcome in a quasi-binomial logistic regression model. 95% confidence intervals are included with each log OR.

4. Discussion

4.1. Summary

Among the four data products, certain CAMS metrics yielded the largest associations relative to the IMPROVE dust event indicator, followed by NWS, CMAQ, and MERRA-2. Among the CAMS metrics, those based on the maximum dust aerosol mixing ratio between 0.9 and 20 μm yielded the strongest associations. In general, the CAMS metrics derived from daily maximum values performed slightly better than metrics derived from daily means, which can be useful in situations with extreme exposure types (U.S. Environmental Protection Agency (EPA), 2011).

Furthermore, adjusted associations, which included an intercept term in the model for each combination of location (site) and time (year-month), tended to be stronger and more precise than crude associations. For instance, the crude log transformed maximum dust aerosol (0.9–20 μm) mixing ratio from CAMS had a log OR of 2.28 compared to the adjusted log OR of 3.62, suggesting that controlling for site location and time made the exposure metric better at predicting when a dust event had occurred. Along the same line, the crude 95% confidence interval was 1.62–2.95 (difference of 1.33) versus the adjusted 95% confidence interval from 3.49 to 3.76 (difference of 0.27), so accounting for site location and year-month increased the precision, as well. This could suggest that the adjusted models capture more of the heterogeneity in the estimated concentrations for the exposure metrics that occur across time and space and aligns with previous work (Crooks et al., 2016; Yu et al., 2012).

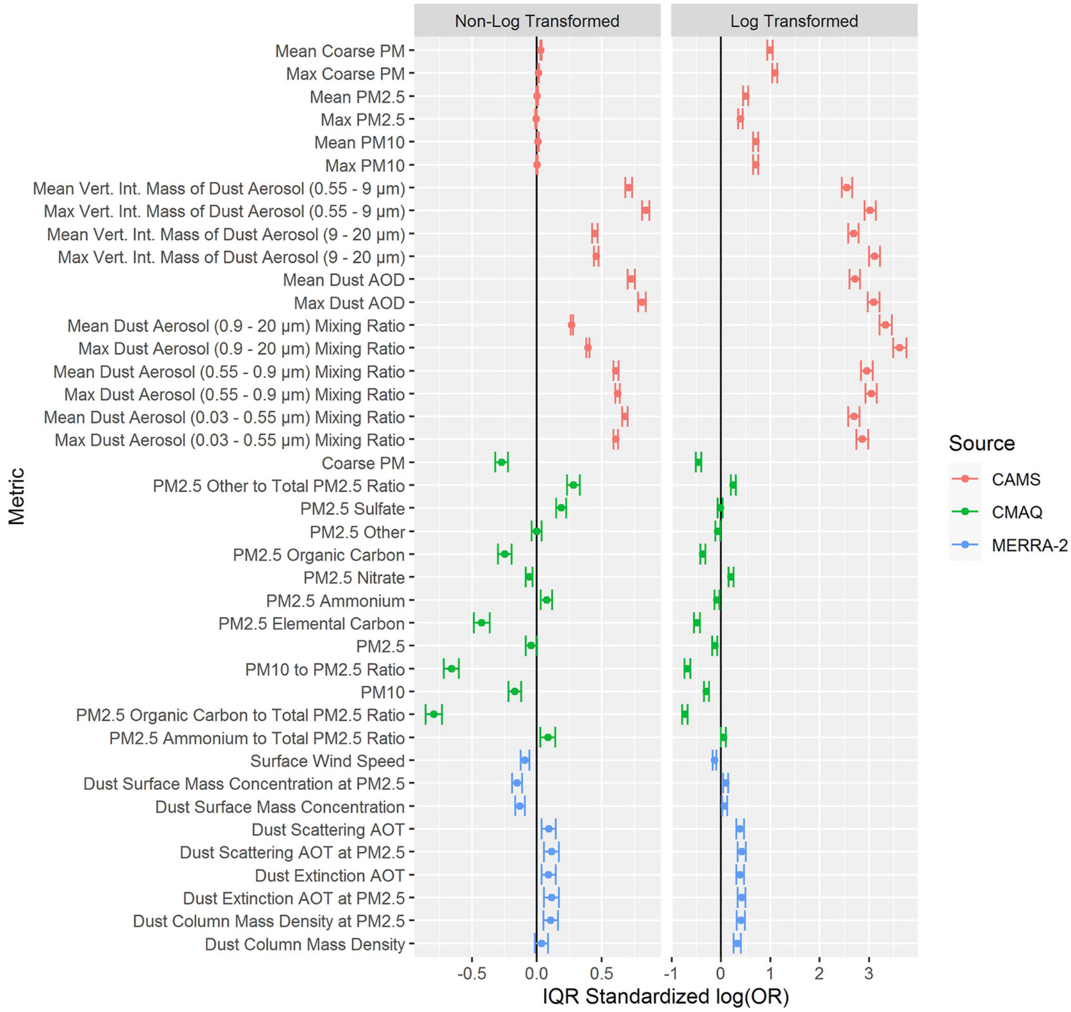

Figure 5. Adjusted inter-quartile range standardized log odds ratios for continuous dust exposure metrics and IMPROVE dust events. Dust exposure metrics are listed in the rows. The left column presents log ORs from models using un-transformed variables, while the right column presents log ORs from models using log-transformed variables. Models controlled for all combinations of year, month, and IMPROVE site location. The log OR include 95% confidence intervals and represent the quasi-binomial logistic regression model with the IMPROVE-derived dust event indicator as the outcome, where zero represents the null value.

However, among the dichotomous metrics from all products, the NWS dust storm indicator had the strongest crude associations, though, with relatively wide confidence intervals compared to the best dichotomous CAMS metrics. Specifically, the NWS indicator had a log OR of 3.57 with a 95% confidence interval of 2.40–4.75 (width of 2.35) compared to the maximum dust aerosol (0.9–20 μm) mixing ratio greater than or equal to the 99th percentile, with a log OR of 3.55 and a 95% confidence interval from 3.04 to 4.05 (width of 1.01). Thus, the ability to predict a dust event was slightly higher with the NWS indicator but it also had a confidence interval over twice as wide as that of the CAMS dust aerosol mixing ratio, implying less precision. The results of the NWS dust storm indicator might suggest that the NWS storm events database is still sensitive to detecting dust events, even with the inconsistencies in reporting and temporal and spatial coverage (Tong et al., 2023).

For all of the dichotomous exposure metrics, the higher percentile thresholds performed somewhat better than lower thresholds, which may relate to the extreme and relatively acute nature of dust events in general and those validated in the IMPROVE data set in particular (Shi et al., 2020).

Curiously, surface wind speed did not perform well at any of the percentile thresholds, despite previous work indicating it as an important factor in airborne dust events (Csavina et al., 2014). This could imply that wind speed is necessary but not sufficient on its own to accurately identify dust events. That is, a particular location could have high wind speed but if the top layer of soil is not dry enough, then it might not produce a dust storm (Csavina et al., 2014; Liu et al., 2004). In brief, Liu et al. (2004) found that wind speed was positively correlated with dust storm frequency, but negatively correlated with seasonal precipitation, soil moisture, and land vegetation in northern China. Csavina et al. (2014) noted that PM_{10} dust concentrations among dust events in Arizona, USA and Chihuahua, Mexico had the highest correlations when both wind speed (high) and relative humidity (low) were considered. The coarse PM exposure metric also seemed to not perform well from the CMAQ or CAMS data sets, which was noted in previous work (Raman et al., 2014; Rublee et al., 2020; Tong et al., 2012). Since the coarse PM was calculated as the arithmetic difference between the average PM_{10} and $PM_{2.5}$ concentrations, it is possible that other sources of coarse mass are contained within the estimate and decreasing the sensitivity of the metric in this instance. Another important factor examined in previous work includes a positive correlation between dust storms and temperature as well as periodic climate changes, such as the El Nino-Southern Oscillation, which brings changes in temperature and precipitation (Labban & Butt, 2021). Taken together, it may be important to consider combinations of climatic variables in addition to the metrics examined in the present study for the identification and prediction of dust events.

Out of the four areal data products, CAMS was unique in that it integrated ground-based observations with satellite-based observations along with recursive calibration for meteorological observations, which might have led to better performance and may suggest that combinations of these data types provide higher capacities for dust event detection compared to either data type alone (Lei et al., 2016). While the daily maximum variables tended to out-perform the daily mean variables, the differences between them were modest. Since dust events generally possess extreme aerosol concentrations for relatively acute periods of time, it follows that the maximum values might identify dust events more accurately than mean values (Ardon-Dryer & Kelley, 2022; Kelley & Ardon-Dryer, 2021).

4.2. Limitations

The present study had several imitations. First, the IMPROVE dust event data extended only through June 2016, precluding inclusion of more recent dust events. Second, within the study period, roughly 2/3 of days were dropped due to the observations schedule of the IMPROVE monitors, while other days were dropped due to gaps in the areal data product data, thus reducing power. Third, all of the areal data products had relatively low spatial resolution by the standards of modern air pollution epidemiology studies, with the highest resolution product (CMAQ-EQUATES) having a 12 km grid cell width, potentially reducing sensitivity. For instance, previous work in exposure epidemiology and dust modeling found that 2.5×2.5 km grid cells down to 1 km grid cells offered advantages over larger grid cells for estimating fine PM (Baxter et al., 2013; Kim et al., 2017; Kumar et al., 2013). Still, the data products utilized in the present study had other features (spatial and temporal completeness, daily temporal resolution, and long time-series) making them potential candidates for future epidemiologic work.

The results from this study agree with previous work highlighting limitations in the NWS storm event database, such as misclassification of dust storms, the reliance on multiple sources of input without verification, and the potential inconsistencies in the reports (Ardon-Dryer et al., 2023). The storm event database, however, remains an important tool for identifying weather-related events, including dust storms, though caution should be used when applying the data set to answer epidemiologic questions pertaining to airborne dust exposure and health.

4.3. Conclusion and Future Directions

The CAMS data set represents a reanalysis of meteorologic, aerosol, and emissions data. Based on the adjusted model results, useful in the identification of dust events on days where data collection for IMPROVE monitors did not occur, the maximum dust aerosol (0.9–20 μm) mixing ratio from CAMS variables was mostly strongly associated with the "gold standard" dust event variable derived from IMPROVE monitor observations. Similarly, for the crude models, the results suggested that the most extreme threshold (99th percentile) can serve as a possible dust event metric in future studies.

Thus, the results suggest that CAMS aerosol extreme values—high dichotomization thresholds, often using daily maximum values rather than daily average values—are most strongly associated with dust events. This may stem from the fact that airborne dust events represent extreme but transient confluences of high wind and dust aerosols, and thus averaged variables may be less sensitive to the presence of dust events.

Subsequent studies should explore why the CAMS exposure metrics seemed to outperform metrics from MERRA-2 and CMAQ, including how tuning model parameters may improve or worsen the capability to detect dust events. Our future work will utilize those CAMS dust exposure metrics with stronger crude associations to build a machine learning predictive model for dust events. This model will yield spatially- and temporally complete dust event predictions over the full domain for use in large-scale population health studies, and could help to address the dearth of epidemiologic studies pertaining to dust exposure in the U.S. for acute and long-term adverse health outcomes.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data from the NWS Storm Events Database (U.S. National Weather Service (NWS), 2022), MERRA-2 (Gelaro et al., 2017), CMAQ-EQUATES (Appel et al., 2021), and CAMS global reanalysis (Inness et al., 2019) were utilized in the creation of this manuscript. The statistical analyses were conducted in R version 4.2.0 (R Core Team, 2022) using the gnm (Turner & Firth, 2022) and the figures were created with ggplot2 (Wickham, 2016). Spatial operations were performed with the sf (Pebesma, 2018) and stars (Pebesma & Bivan, 2023) packages. Data is available through the Open Science Framework: https://doi.org/10.17605/OSF.IO/TF94G. The project is titled "Dust storm characterization 2021_2023." Specifically, the RData files are located within the "Dust Storm Exposure Metric Data 2021_2023" folder.

Data Citation: Hohsfield (2023), https://doi.org/10.17605/OSF.IO/TF94G.

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