Air Pollution and Meteorology as Risk Factors for COVID-19 Death in a Cohort from Southern California

ONLINE DATA SUPPLEMENT

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I. Kaiser Permanente Southern California Cohort and Health Data

KPSC Cohort Health Data Ascertainment

We defined COVID-19 hospitalizations as those occurring within 21 days of a COVID-19 diagnosis or positive test. Hospitalizations lasting fewer than 24 hours were excluded and transfers from non-KP hospitals to KP hospitals were consolidated into a single hospitalization. Data sources include internal data sources, including KPSC hospital, clinic and emergency department data, and the California state death master files and Social Security Administration Death Master files. Data are cleaned and scored for accuracy using a proprietary algorithm.

Elixhauser Disease Categories Employed

Five broad comorbidity categories were created to identify co-morbidities that may increase a person's risk of a severe COVID-19 outcomes.^{1,2} We use Elixhauser disease categories to create COVID-19 relevant disease categories. The Elixhauser comorbidity index aggregates diagnoses into 23 disease categories. The Elixhauser comboridity index sums the number of disease categories that a patient was diagnosed with to measure the burden of multiple morbidities. It was originally developed to predict mortality among hospitalized patients by aggregating the following Elixhauser co-morbidity categories: "Cardiovascular diseases" includes Elixhauser's Congestive Heart Failure, Cardiac Arrhythmia, Valvular Disease, Pulmonary Circulation Disorders, and Peripheral Vascular Disorders**;** "Pulmonary disease" including Elixhauser's Chronic Pulmonary Disease**; "**Hypertension " including Elixhauser's Hypertension uncomplicated and complicated;" "Diabetes" including Elixhauser comorbidities Diabetes with and without chronic complications; and the remainder of

the Elixhauser comorbidities were grouped into a residual category named "other". We further combined the four specific categories into a count of COVID-19 relevant disease categories that would allow us to stratify our analysis by chronic-disease burden.

II. Chemical Transport Model

Simulations for the year 2016 were carried out across California using the source-oriented UC Davis-California Institute of Technology (UCD-CIT) regional air quality model. The UCD/CIT airshed model is a reactive 3-D CTM that predicts the evolution of gas and particle phase pollutants in the atmosphere in the presence of emissions, transport, deposition, chemical reaction, and phase change as represented by Eq. (1)

Equation 1

$$
\frac{\partial c_i}{\partial t} + \nabla \cdot uC_i = \nabla K \nabla C_i + E_i - S_i + R_i^{gas}(C) + R_i^{part}(C) + R_i^{phase}(C)
$$

where C_i is the concentration of gas or particle phase species *i* at a particular location as a function of time *t*, *u* is the wind vector, *K* is the turbulent eddy diffusivity, E_i is the emissions rate, S_i is the loss rate, R_i^{gas} is the change in concentration due to gas-phase reactions, R_f^{part} is the change in concentration due to particle-phase reactions and *R*^{*phase*} is the change in concentration due to phase change.³ Loss rates include both dry and wet deposition. Phase change for inorganic species occurs using a kinetic treatment for gas-particle conversion ⁴ driven towards the point of thermodynamic equilibrium. ⁵ Phase change for organic species is also treated as a kinetic process with vapor pressures of semi-volatile organics calculated using the 2-product model.⁶

The basic capabilities of the UCD/CIT model are similar to the CMAQ model maintained by the U.S. EPA, but the UCD/CIT model has several source apportionment features and more particle size resolution, which makes it attractive for the current project. The UCD/CIT model explicitly tracks the mass and the number concentration of particles in 15 discrete size bins spanning the range from 10 nm through 10 µm, with tracer species used to quantify source contributions to the primary particle mass in each bin. A moving sectional bin approach is used 7 so that particle number and mass can be explicitly conserved with particle diameter acting as the dependent variable.

The emissions of particle source tracers are empirically set to be 1% of the total mass of primary particles emitted from each source category, so they do not significantly change the particle radius and the dry deposition rates. For a given source, the simulated concentration of artificial tracer directly correlates with the amount of PM mass emitted from that source in that size bin. The corresponding number concentration attributed to that source can be calculated using Eq. (2)

Equation 2

$$
num_i = \frac{trace_i \times 100}{\frac{\pi}{6} p p^3 \rho}
$$
 (eq Equation 2)

where *tracer_i* represents the artificial tracer mass in size bin *i*, *Dp* is the core particle diameter, and ρ is the core particle density. Core particle properties are calculated by removing any condensed species to better represent the properties of the particles when they were emitted. More details describing the source apportionment technique in UCD/CIT model are provided in previous studies.⁸⁻¹²

A total of 50 particle-phase chemical species are included in each size bin. Gas-phase concentrations of oxides of nitrogen (NOx), volatile organic compounds (VOCs), oxidants, ozone, and semi-volatile reaction products were predicted using the SAPRC-11 chemical mechanism.¹³ Phase change for inorganic species occurs using a kinetic treatment for gas-particle conversion ⁴ driven towards the point of thermodynamic equilibrium.⁵ Phase change for organic species is also treated as a kinetic process with vapor pressures of semi-volatile organics calculated using the 2-product model. 6

UCD/CIT model calculations were carried out using three nested model domains with 24 km, 4 km, and 1 km horizontal spatial resolution over the study domain. Sixteen telescoping levels were used in the vertical dimension with a thickness of 30 m at ground level and 1000 m at the top height of 5 km.

Meteorological Model

Hourly meteorology inputs to drive the regional chemical transport model at 24-km, 4-km, and 1-km resolution in the year 2016 were simulated using the Weather Research and Forecasting (WRF) v3.4 model (www.wrf-model.org). WRF model vertical resolution was 31 vertical layers from the ground level to the top pressure of 100 hPa. Initial and boundary conditions for meteorological simulations were be taken from North American Regional Reanalysis (NARR), which has a spatial resolution of 32 km and a temporal resolution of 3 h. The Yonsei University (YSU) boundary layer vertical diffusion scheme ¹⁴ and Pleim-Xiu land surface scheme ¹⁵ were adopted in this study. Four-dimensional data assimilation was applied to anchor the model predictions to observed meteorological patterns.

Emission Inventories

The year 2016 area source and point source emission inventories used in the current study were provided by the California Air Resources Board with several modifications. Because fugitive dust emissions were replaced by an online dust model ¹⁶ based on the wind speed, and soil moisture predicted by the WRF model. This change corrects the positive bias in dust emissions and PM_{2.5} mass noted by Hu et al.^{17,18} A major point source of unpaved road dust at MAGTFTC/MCAGCC Twentynine Palms military facility in San Bernardino County was converted to an area sources over a 9 km2 region around the base. Food cooking emissions in GAI 6069 (Victorville in San Bernardino County) were reduced by a factor of three so that the per capita emissions from food cooking activities were similar to those in Los Angeles County.

Area source emissions inventories provided by CARB had spatial resolution of 4-km. Area source emissions with spatial resolution of 1-km were created for major sources using spatial surrogates processed with the "Spatial Allocator" software maintained by U.S. EPA. *Table 1* summarizes all surrogates used to downscale 4km ARB area emissions to 1km, accounting for 80% of the statewide area source emissions.

Surrogate	Description	Data Source
302	Industrial-related/industrial employment	
441	Total population	
587	Off-road construction equipment	see details in reference paper: DOI 10.1016/j.atmosenv.2020.117665
588	On-road construction equipment	
621	Service & Commercial employment	
651	Single-family housing	
720	Farm road VMT	
190	Forestland	
530	Residential Gas Heating	
660	Unpaved road	California Air Resource Board (CARB) provided
100	All airports	
140	Commercial airports	
382	Military airports	
610	Secondary paved road	Tiger/Line shapefile, $S1400 + S1630 + S1640$
480	Primary Road	Tiger/Line shapefile, $S1100 + S1200$
570	Residential heating - wood	California Air Resource Board (CARB) shapefile
560	Restaurants	Food service market dataset from ESRI (NACIS 7225)

Table 1. Spatial surrogates used to downscale 4km ARB area emissions to 1km.

Mobile Source Emissions

Three spatial surrogates were created to downscale mobile emissions to 1 km resolution, including gasoline mobile, diesel mobile, and tire/brake wear. Explicit traffic counts collected by the U.S. Highway Performance Monitoring System (HPMS) were used to distribute the majority of the tailpipe emissions to highways and other principal arterial roads. MacDonald et al. 19 showed that ~70% of gasoline and ~80% of diesel vehicle fuel consumption in California occurs on roads with traffic count information. Emissions on these roads can be represented by VMT (i.e., traffic count x road length). The remaining \sim 30% of gasoline and \sim 20% of diesel vehicle activity can use road length as a spatial surrogate. This approximate treatment for the residual portion of the tailpipe emissions was done separately for urban and rural areas to ensure rural emissions were not overestimated.²⁰ 90% of the unmonitored gasoline and diesel activity occurs in urban areas, with the balance in rural areas. The final mobile gasoline and diesel surrogates were calculated using the equations:

Gasoline mobile surrogate = $70\% \times (AADT \times road \ length)_{normalized} +$

 $30\% \times (road length without traffic counts)_{normalized}$

Diesel mobile surrogate = $80\% \times (Truck$ AADT \times road length)_{normalized} +

 20% × (truck road length without traffic counts)_{normalized}

(Truck) Road length without traffic counts = $90\% \times$ urban road length + $10\% \times$ rural road length

Tire and brake wear emissions were estimated as a fixed fraction of tailpipe emissions for all engine types. The 2016 CARB emissions inventories 21 specify that gasoline/diesel emissions account for 86% / 14% of total mobile emissions. Thus, the tire and brake wear spatial surrogate was calculated using the equation:

> Tire & brake wear surrogate $= 86\% \times (Diesel\ mobile\ surrogate)_{normalized}$ $+ 14\% \times (Gasoline mobile surrogate)_{normalized}$

Data sources used for traffic surrogates are listed in Table 2.

Table 2: Data sources used for traffic surrogates

Description	Data Source
Gasoline vehicle traffic count – Average Annual Daily	https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm, accessed August
Traffic (AADT)	2020
Diesel vehicle traffic count – Truck AADT (with three or	Caltrans
more axles)	
Road shapefiles	https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-
	file.html, accessed August 2020
Truck road network can defined in the Freight Analysis	https://ops.fhwa.dot.gov/freight/freight_analysis/faf/, accessed August 2020).
Framework	

Soil NOx

Candidate soil NOx emissions were included in the calculations based on a biogeochemical model combined with fertilizer application rates.²² Soil NOx emissions varied by month of the year based on the effects of temperature on the biogeochemical cycle. Sensitivity studies carried out across years between 2000 – 2015 indicate the inclusion of soil NOx emissions improves the accuracy of model predictions for gas phase ozone and particulate nitrate. 23

Biogenic Emissions

Biogenic emissions were generated using the Model of Emissions of Gases and Aerosols from Nature (MEGANv2.1) based on the meteorological fields generated using the WRF model. The gridded geo-referenced emission factors and land cover variables required for MEGAN calculations were created using the MEGANv2.1 pre-processor tool and the ESRI_GRID leaf area index and plant functional type files available at the Community Data Portal. 24

Wildfires

Daily values of wildfire emissions were generated using the Global Fire Emissions Database (GFED).²⁵ Wildfire emissions were assigned the same particle size and composition distribution as routine biomass combustion. Typical wildfire plumes rise to 6-10 km in the atmosphere depending on the intensity of the fire and the local meteorological conditions.²⁶ Wildfire plumes were injected at the top of the model domain at a height of approximately 5 km in the current simulations.

Wildfire emissions were represented using the Global Fire Emissions Database (GFED).²⁷ GFED uses satellite images of burned areas combined with vegetation maps to estimate smoke released each day during wildfires. Spatial resolution of GFED emissions inventories are 0.25 degrees. Smoke from these fires impacted cities throughout central California as plumes were trapped within the Central Valley. Wildfire emissions were assigned particle size and composition profiles based on measurements during biomass burning experiments.²⁸

III. Bias Correction

Predicted monthly-averaged PM2.5 concentrations were compared to measured PM2.5 concentrations at all available monitoring sites across the study domains for the entire duration of the study years 2016. Summary statistics were calculated to characterize CTM performance, including the correlation coefficient (R), mean fractional error (MFE), mean fractional bias (MFB), mean error (ME), mean bias (MB), and root mean square error. Because PM2.5 predictions were moderately correlated with measured concentrations (R>0.5 at more than half the monitoring sites) but the predicted concentrations exceeded measured concentrations by a factor of approximately 50% (average MFB=0.549). This over-prediction is likely caused by an under-prediction of vertical mixing and dilution associated with the combination of updates to the WRF model v3.4 and the incorporation of non-local transport terms into the aerosol advection / diffusion algorithms.

The bias in CTM predictions at each monitoring location was combined with the CTM predicted concentrations of primary particles emitted from nine different source categories and the concentrations secondary nitrate and sulfate particulate matter to form a time-series that was analyzed using multi-linear regression (MLR) based on equation 3. An intercept was not considered in the regression equation under the assumption that any constant bias introduced by abnormally high boundary conditions or under-predicted wind speeds would manifest as over-predictions in the indicated particle metrics. An intercept (i.e. constant bias) would have the potential for overlap or "double counting" in the regression model formulation.

Equation 3

Bias = a_1 *Tracer1 + a_2 *Tracer2 +…+ a_9 *Tracer9 + a_{10} *Nitrate + a_{11} *Sulfate + a_{12} *Ammonium (eq Equation 3)

Here ai represents regression coefficients and Traceri represents the concentrations of primary particles emitted from: 1. On-road gasoline vehicles, 2. Offroad gasoline vehicles, 3. On-road diesel vehicles, 4. Offroad diesel vehicles, 5. Biomass combustion, 6. Food cooking, 7. Aircraft, 8. Natural gas combustion, and 9. All other sources. The time series from all 40 sites in the study domain were combined into a single dataset with 452 data points to support the twelve independent variables in the regression analysis. Multiple regression models were explored, with non-zero coefficients eventually selected for Tracer2, Tracer3, Tracer5, Tracer6, Tracer9, and inorganic ions. A single set of regression coefficients was able to explain the bias with an $R^2=0.82$ and a regression slope of 0.92.

The MLR bias equation (eq 3) was applied at each CTM grid cell to predict the bias in CTM concentrations. The baseline CTM concentrations were then adjusted using the equation

Equation 4 $C^{bias_corr} = C^{baseline} * (1-bias/C^{baseline})$ (eq Equation 4)

The corrected PM2.5 mass concentrations had a mean fraction bias of 0.181, significantly improving the accuracy of the exposure fields. Figure 1 illustrates the distribution of R and MFB values across the 40 monitoring sites in the study domain.

Figure 1: Summary of performance statistics for PM2.5 mass after bias correction. Ideal values are R=1 and $MFB=0.$

Bias corrections were only applied to primary PM components emitted directly to the atmosphere in the particle phase. Concentrations of secondary PM components predicted by the CTM were not adjusted because the measurements at the limited number of speciation sites suggested that secondary components were not overpredicted to the same extent as total mass. Bias corrections also were not applied to gas-phase species such as O3 and NO2 because these species are formed from chemical reactions in the atmosphere that have a non-linear

dependence on atmospheric mixing in which increasing concentrations of some species such as NO can decrease concentrations of other species such as $O₃$. The spatial pattern of the gas-phase concentrations should be approximately correct in the current analysis, but future studies should correct the mixing in the meteorological fields and repeat the CTM calculations to remove bias in all species.

IV. Chemical Transport Model Results

Figure 2 shows the location of PM_{2.5} monitoring locations in the core of the study domain. Figure 3-Figure 6 show the time series of predicted PM2.5 mass concentrations and measured concentrations across the counties within the study domain. Model predictions have been bias-corrected using the methods described in previous sections. Model predictions at most locations are generally in reasonable agreement with measured concentrations. Overall PM2.5 predictions have a slight positive bias.

Figure 5c shows that predicted PM2.5 concentrations are 2-4 times higher than measured values at the monitoring site near Victorville CA (population 121,902) in San Bernardino County. This over-prediction results from over-estimated emissions in this urban location. Food cooking emissions were scaled down to match percapita values in Los Angeles County, but emissions from other area sources were not rescaled. Given the small population in Victorville, this isolated over-prediction in PM2.5 concentrations should not have a large influence on study results.

Seasonal patterns in both predicted and measured PM2.5 concentrations are modest. Most residences in the study region use natural gas or electricity for home heating during winter months, and so the much higher winter concentrations associated with residential wood combustion are generally absent at most sites except around Bakersfield (see for example Figure 6a,c,d). Modest increases in concentrations are observable in winter and summer months due to more stagnant atmospheric conditions compared to spring and fall months.

Figure 2: Locations of PM2.5 mass monitoring sites around the central portion of the study domain that contains the majority of the study population. Full site codes shown in subsequent figures are preceded by the state identification number California=06 and the county FIPS code: Ventura=061, Los Angeles=037, Orange=059, San Diego=073, San Bernardino=071, Riverside=065.

Figure 3: Time series of predicted (solid line) vs. measured (dots) monthly-average PM2.5 concentrations at measurement locations in Los Angeles County. All model concentrations have been bias-corrected. Measurement site codes correspond to names designated by the U.S. EPA monitoring network.

Figure 4: Time series of predicted (solid line) vs. measured (dots) monthly-average PM2.5 concentrations at measurement locations in Orange County and San Diego County. All model concentrations have been biascorrected. Measurement site codes correspond to names designated by the US EPA monitoring network.

Figure 5: Time series of predicted (solid line) vs. measured (dots) monthly-average PM2.5 concentrations at measurement locations in Riverside County and San Bernardino County. All model concentrations have been bias-corrected. Measurement site codes correspond to names designated by the US EPA monitoring network.

Figure 6: Time series of predicted (solid line) vs. measured (dots) monthly-average PM2.5 concentrations at measurement locations in Kern County and Ventura County. All model concentrations have been biascorrected. Measurement site codes correspond to names designated by the US EPA monitoring network.

Figure 7 displays the predicted ground-level daily maximum 1-hr average O3 concentration averaged during each season of the year 2016. The scale in each sub-panel of Figure 7 is adjusted based on seasonal trends, with highest concentrations in the summer and lowest concentrations during the winter. O₃ concentrations generally increase moving from west to east (downwind) in the air basin. Maximum summer concentrations occur in the mountains north of Los Angeles where anthropogenic NOx emissions mix with biogenic VOC emissions leading to enhanced O3 formation. As noted previously, gas-phase concentrations were not bias corrected in the current study, and so the concentrations displayed in Figure 7 may reflect errors associated with under-predicted wind speeds.

Figure 8 illustrates the predicted ground-level PM_{2.5} mass exposure fields over the study domain during each season of the year 2016. The scale in Figure 8 has been adjusted to show concentrations over major population centers. The maximum predicted PM2.5 concentrations over military airports (circled) are off-scale, but this does not significantly affect population-weighted exposures. Maximum PM2.5 mass concentrations occur east of central Los Angeles in San Bernardino County. Elevated concentrations of PM2.5 mass are also predicted to occur along major transportation corridors connecting the Port of Los Angeles and the Port of Long Beach with distribution centers in San Bernardino County.

Figure 9 illustrates the predicted ground-level PM_{2.5} elemental carbon (EC) exposure fields over the study domain during each season of the year 2016. EC is a primary pollutant directly emitted from diesel engines and from gas direct injection (GDI) gasoline engines. The pattern of EC concentrations therefore follows major transportation corridors, with a maximum value once again occurring over distribution centers in San Bernardino County. Increased stagnation in the atmosphere during winter and summer months leads to higher EC concentrations compared to spring and fall months.

Figure 10 illustrates the predicted ground-level $PM_{2.5}$ nitrate concentrations over the study domain during each season of the year 2016. Nitrate is a secondary pollutant formed from atmospheric chemical reactions involving precursor NOx emissions. Regional nitrate patterns are generally more distributed than regional patterns of EC (compare Figure 2 vs. Figure 3). Maximum nitrate concentrations generally occur over a broad area east (downwind) of central Los Angeles. Concentrations are generally higher in the colder winter months because nitrate can evaporate in warmer months.

Figure 11 illustrates the predicted ground-level PM2.5 concentrations associated with primary particulate matter emitted from on-road diesel engines. As expected, the spatial pattern generally follows major transportation corridors, with a noticeable maximum at distribution centers in San Bernardino County. The seasonal pattern of the primary on-road diesel particulate matter is similar to the season pattern for EC (see Figure 2).

Ultrafine particles with diameter less than $0.1 \mu m$ can be emitted directly (primary pollutant) or it can be formed in the atmosphere through either condensation or nucleation processes (secondary pollutant). The PM_{0.1} concentration fields illustrated in Figure 12 show evidence of both pathways. Fall and winter concentrations are highest over distribution centers in San Bernardino County due to primary emissions from goods movement activities. PM0.1 concentrations in the spring are highest over the Port of Los Angeles due to conversion of sulfur emissions to sulfuric acid that subsequently partitions to the particle phase. $PM_{0.1}$ concentrations during summer are highest in the foothills of the mountains to the north of Los Angeles where anthropogenic and biogenic emissions mix. Overall, the $PM_{0.1}$ mass exposure fields have the greatest seasonal variability of all the pollutants considered.

Figure 7: Predicted O3 max exposure fields during four seasons in the year 2016. All units ppb.

Figure 8: Predicted PM_{2.5} mass exposure fields during four seasons in the year 2016. All units µg m⁻³.

Figure 9: Predicted PM2.5 elemental carbon (EC) exposure fields during four seasons in the year 2016. All units μ g m⁻³.

Figure 10: Predicted PM2.5 nitrate exposure fields during four seasons in the year 2016. Note the different maximum values in different seasons. All units μ g m⁻³.

Figure 11: Predicted diesel primary PM2.5 mass exposure fields during four seasons in the year 2016. Note the different maximum values in different seasons. All units μ g m⁻³.

Figure 12: Predicted PM0.1 mass exposure fields during four seasons in the year 2016. Note the different maximum values in different seasons. All units μ g m⁻³.

V. Confounder Analysis

Table 3 below shows the confounders selected for each pollutant based on the 10% criterion.

Table 3: Confounders identified for each exposure based on the 10% change in the pollution coefficient selection rule where FALSE indicates not selected and TRUE indicates selected

VI. Unadjusted hazard ratios

Table 4: Unadjusted hazard ratios

¹HR = Hazard Ratio, CI = Confidence Interval; bold shows p values < 0.05

1 Based on interquartile exposure contrast for

each pollutant or source tracer. **Bolded** entries show

significant p values less than 0.05.

VII. Stratification Analyses

We ran the stratified models and tested for significant interactions with the pollutant models as shown in Table 5-7. The majority of the subgroup analyses were highly insignificant based on the Q statistic shown at the bottom of each table, meaning we did not find significant interactions between the air pollutants and the subgroups.

Stratification by sex

Table 6: Stratification by sex

		F		M				
Characteristic	HR ¹ 95% CI ¹		p-value	HR ¹	95% CI ¹	p-value		
NO ₂ /IOR	1.09	1.00, 1.19	0.056	1.10	1.03, 1.19	0.009		
BMI/IOR	0.66	0.51, 0.87	0.003	0.76	0.59, 0.98	0.035		
BMI*BMI/IOR	1.54	1.23, 1.94	< 0.001	1.39	1.11, 1.75	0.005		
Exercise Vital Sign (median)/IOR	0.95	0.88, 1.01	0.11	0.97	0.94, 1.01	0.15		
NDI ACS2013	1.06	1.00, 1.12	0.034	1.02	0.98, 1.07	0.4		
Relative humidity (%)	0.99	0.98, 0.99	< 0.001	0.99	0.99, 0.99	< 0.001		
Temperature (C)	0.99	0.98, 1.00	0.012	0.98	0.97, 0.99	< 0.001		

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for NO2_stdiqr is: 0.04, df is: 2, and p value is: 0.98"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for O3max_stdiqr is: 0.08, df is: 2, and p value is: 0.961"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for NO2_stdiqr is: 0.054, df is: 2, and p value is: 0.974"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 0.476, df is: 2, and p value is: 0.788"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 0.436, df is: 2, and p value is: 0.804"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5n_v_stdiqr is: 0.011 , df is: 2, and p value is: $0.995"$

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5oc_stdiqr is: 0.602, df is: 2, and p value is: 0.74"

[1] "Q for pm0_1mass_stdiqr is: 2.948, df is: 2, and p value is: 0.229"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5ec_stdiqr is: 0.034, df is: 2, and p value is: 0.983"

		F		М				
Characteristic	HR ¹	$95\% \text{ CI}^{1}$	p-value	HR ¹	95% CI ¹	p-value		
On-road diesel $PM_{2.5}/IOR$	1.06	1.01, 1.13	0.032	1.06	1.01, 1.11	0.012		
BMI/IOR	0.67	0.51, 0.88	0.004	0.78	0.61, 1.02	0.066		
BMI*BMI/IOR	1.54	1.22, 1.93	< 0.001	1.37	1.09.1.72	0.008		
Relative humidity $(\%)$	0.99	0.99, 0.99	< 0.001	0.99	0.99, 1.00	< 0.001		
Temperature (C)	0.99	0.98, 1.00	0.009	0.98	0.97, 0.99	< 0.001		

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer3_stdiqr is: 0.002, df is: 2, and p value is: 0.999"

[1] "Q for pm2_5tracer1_stdiqr is: 0.149, df is: 2, and p value is: 0.928"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer6_stdiqr is: 1.169, df is: 2, and p value is: $0.557"$

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for rmax_k_stdiqr is: 2.062, df is: 2, and p value is: 0.357"

[1] "Q for tmmx_c_stdiqr is: 0.321, df is: 2, and p value is: 0.852"

Stratification by number of disease categories

Table 7: Stratification by number of disease categories

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for NO2_stdiqr is: 2.033, df is: 3, and p value is: 0.566"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for O3max_stdiqr is: 0.72, df is: 3, and p value is: 0.869"

[1] "Q for NO2_stdiqr is: 2.103, df is: 3, and p value is: 0.551"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 6.165, df is: 3, and p value is: 0.104"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 3.651, df is: 3, and p value is: 0.302"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5n_v_stdiqr is: 7.251, df is: 3, and p value is: 0.064"

[1] "Q for pm2_5oc_stdiqr is: 3.622, df is: 3, and p value is: 0.305"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm0_1mass_stdiqr is: 4.96, df is: 3, and p value is: 0.175"

[1] "Q for pm2_5ec_stdiqr is: 2.148, df is: 3, and p value is: 0.542"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer3_stdiqr is: 3.017, df is: 3, and p value is: 0.389"

[1] "Q for pm2_5tracer1_stdiqr is: 3.079, df is: 3, and p value is: 0.38"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer6_stdiqr is: 8.424, df is: 3, and p value is: 0.038"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for rmax_k_stdiqr is: 12.99, df is: 3, and p value is: 0.005"

[1] "Q for tmmx_c_stdiqr is: 0.13, df is: 3, and p value is: 0.988"

Stratification by age

Table 8: Stratification by age

	[18, 53)		[53, 65]			[65, 76]			[76, 105]			
Characteristic	HR ¹	95% CI ¹	$p-$ value	HR ¹	95% CI ¹	$p-$ value	HR ¹	95% CI ¹	p- value	HR ¹	95% CI ¹	$p-$ value
NO ₂ /IQR	0.99	0.80, 1.22	>0.9	1.19	1.05, 1.35	0.007	1.16	1.05, 1.28	0.004	1.05	0.97, 1.13	$0.2\,$
BMI/IQR	1.25	0.69, 2.27	0.5	1.11	0.65, 1.90	0.7	1.12	0.73, 1.71	0.6	0.47	0.34, 0.67	< 0.001
BMI*BMI/IOR	1.04	0.67, 1.61	0.9	1.01	0.64, 1.57	>0.9	0.97	0.67, 1.42	0.9	1.99	1.41, 2.82	< 0.001
Exercise Vital Sign (median)/IQR	0.90	0.81, 1.01	0.078	0.92	0.85, 0.99	0.023	0.96	0.90, 1.02	$0.2\,$	0.99	0.94, 1.04	0.7
NDI ACS2013	1.04	0.92, 1.17	0.5	1.05	0.97, 1.13	0.2	1.11	1.04, 1.17	< 0.001	1.00	0.95, 1.05	0.9
Relative humidity (%)	1.00	0.99, 1.00	0.3	0.98	0.98, 0.99	< 0.001	0.99	0.99, 0.99	< 0.001	0.99	0.99, 1.00	< 0.001
Temperature (C)	0.97	0.95, 0.99	0.006	0.98	0.97, 1.00	0.013	0.98	0.97, 0.99	< 0.001	0.99	0.98, 1.00	0.044

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for NO2_stdiqr is: 4.896, df is: 4, and p value is: 0.298"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for O3max_stdiqr is: 6.175, df is: 4, and p value is: 0.186"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for NO2_stdiqr is: 5.03, df is: 4, and p value is: 0.284"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 5.739, df is: 4, and p value is: 0.22"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5mass_stdiqr is: 5.131, df is: 4, and p value is: $0.274"$

[1] "Q for pm2_5n_v_stdiqr is: 8.318, df is: 4, and p value is: 0.081"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5oc_stdiqr is: 1.985, df is: 4, and p value is: 0.738"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm0_1mass_stdiqr is: 1.887, df is: 4, and p value is: 0.756"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5ec_stdiqr is: 4.505, df is: 4, and p value is: 0.342"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer3_stdiqr is: 0.865, df is: 4, and p value is: 0.93"

[1] "Q for pm2_5tracer1_stdiqr is: 2.172, df is: 4, and p value is: 0.704"

¹HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for pm2_5tracer6_stdiqr is: 2.234, df is: 4, and p value is: 0.693"

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for rmax_k_stdiqr is: 6.136, df is: 4, and p value is: $0.189"$

 1 HR = Hazard Ratio, CI = Confidence Interval

[1] "Q for tmmx_c_stdiqr is: 4.9, df is: 4, and p value is: 0.298"

Stratification by tertile

Figure 13: Stratification of significant pollutants by tertile, controlled by temperature and humidity

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