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Space-time analysis of the effect of air pollution on children's health

Análise espaço-temporal do efeito da poluição do ar na saúde de crianças

Análisis espacio-temporal del efecto de la contaminación del aire en la salud de los niños

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Abstract

The study aimed to investigate the short-term association between air pollution and emergency treatments for respiratory diseases in children 0 to 6 years of age. This was an ecological space-time study in Greater Metropolitan Vitória, Espírito Santo State, Brazil. A Poisson regression general additive model (GAM) used the number of daily treatments for respiratory diseases as the dependent variable, and the independent variables were daily concentrations of air pollutants (PM_{10}, SO_2, NO_2, O_3, and CO), temperature, humidity, and precipitation. Average daily concentrations were used to make estimates for the entire metropolitan area and in loco *analyses considering children residing in a 2km radius around 8 air quality monitoring stations. An increase of 10μg/m³ in the concentration of air pollutants increased the risk of emergency treatment for respiratory disease. In the overall area, for PM_{10}, the increase was 2.43%, 2.73%, and 3.29% in the cumulative values at 5, 6, and 7 days, respectively. For SO_2, the increase was 4.47% on the day of exposure, 5.26% two days later, and 6.47%, 8.8%, 8.76%, and 7.09% for the cumulative values at days 2, 3, 4, and 5 days, respectively. CO showed a significant association for residents around two stations, and O_3 for only one. Even within the limits set by the World Health Organization, the pollutants PM_{10}, SO_2, NO_2, and O_3 are associated with increased risk of treatment for respiratory diseases in children 0 to 6 years of age, and some effects were only identified when disaggregating by neighborhood, i.e.,* in loco*, which allows capturing greater variation in the data.*

Air Pollution; Respiratory Tract Diseases; Child

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Introduction

Respiratory diseases are the principal cause of morbidity and mortality in children and can be caused or aggravated by exposure to air pollutants emitted on a large scale throughout the planet [1,2]. Emissions of particulate matter (PM), nitrogen oxides (NOx), volatile organic compounds (VOCs), sulfur dioxide (SO_2), and photochemical pollutants such as ozone (O_3) have increased in recent decades due to growth of the motor vehicle fleet and increasing industrialization [2]. Studies in large urban areas prove a significant association between levels of these pollutants and the number of emergency treatments and hospitalizations from respiratory causes [3,4,5,6,7,8,9,10,11,12,13,14].

A recent systematic review on Brazilian children's health and the environment identified only 17 time-series studies that correlated air pollution and respiratory causes, all conducted in Southeast Brazil. These studies showed a positive association between levels of pollutants and emergency treatments, hospitalizations, and decreased lung function [15]. Two of these studies were conducted in Greater Metropolitan Vitória, Espírito Santo State, Brazil [12,16].

Greater Metropolitan Vitória is predominantly urban and highly industrialized and is undergoing urban sprawl. Air quality is affected by the emission of pollutants from motor vehicles and large-scale industrial activities, in addition to the logistics sector, with the existence of a large port and airport complex [17]. Emissions from these mobile and fixed sources directly influence the area's air quality [17].

Detection of the association between concentrations of pollutants and respiratory conditions requires statistical techniques that allow isolating the effects of air pollution, since there may be various confounding factors such as temperature and humidity. Time-series models have allowed more precise analyses of such associations.

Epidemiological time-series studies generally use a single fixed monitoring station or the average of stations to represent the entire population's exposure to pollutants. However, this approach may not reflect people's true exposure [18]. Thus, a more realistic analysis might consider a small geographic area close to the monitoring station [19]. Still, a limited number of epidemiological studies use this type of assessment, although there is some evidence that exposure to classification error in time-series analysis tends towards a downward bias in estimates and in this sense does not limit the results' importance for public health [19].

Thus, methodologies in which the areas covered by measurement are better discriminated spatially are important for obtaining more precise inferences. In this context, the current study aimed to assess, via GAM, the short-term relationship between the number of emergency treatments for respiratory problems in children under six years of age and levels of air pollutants in Greater Metropolitan Vitória, considering the temporal variables measured on site (area around monitoring stations) and the average between stations (overall average for Greater Metropolitan Vitória).

Methods

Study area

This was an ecological space-time study conducted in Greater Metropolitan Vitória from January 1, 2005, to December 31, 2010. Greater Metropolitan Vitória consists of 7 municipalities (Vitória, Vila Velha, Cariacica, Serra, Viana, Guarapari, and Fundão), with a territory of 2,318.917km^2 and approximately 1.7 million inhabitants, as one of the main urban and industrial development hubs in the State of Espírito Santo (Instituto Brasileiro de Geografia e Estatística. Censo populacional 2010. https://ww2.ibge.gov.br/home/estatistica/populacao/censo2010, accessed on 19/Oct/2018). The principal polluting activities in Greater Metropolitan Vitória include roadways, various industries (steel, pelletizing, mining, cement mills), ports, airports, and residential and commercial emissions [17].

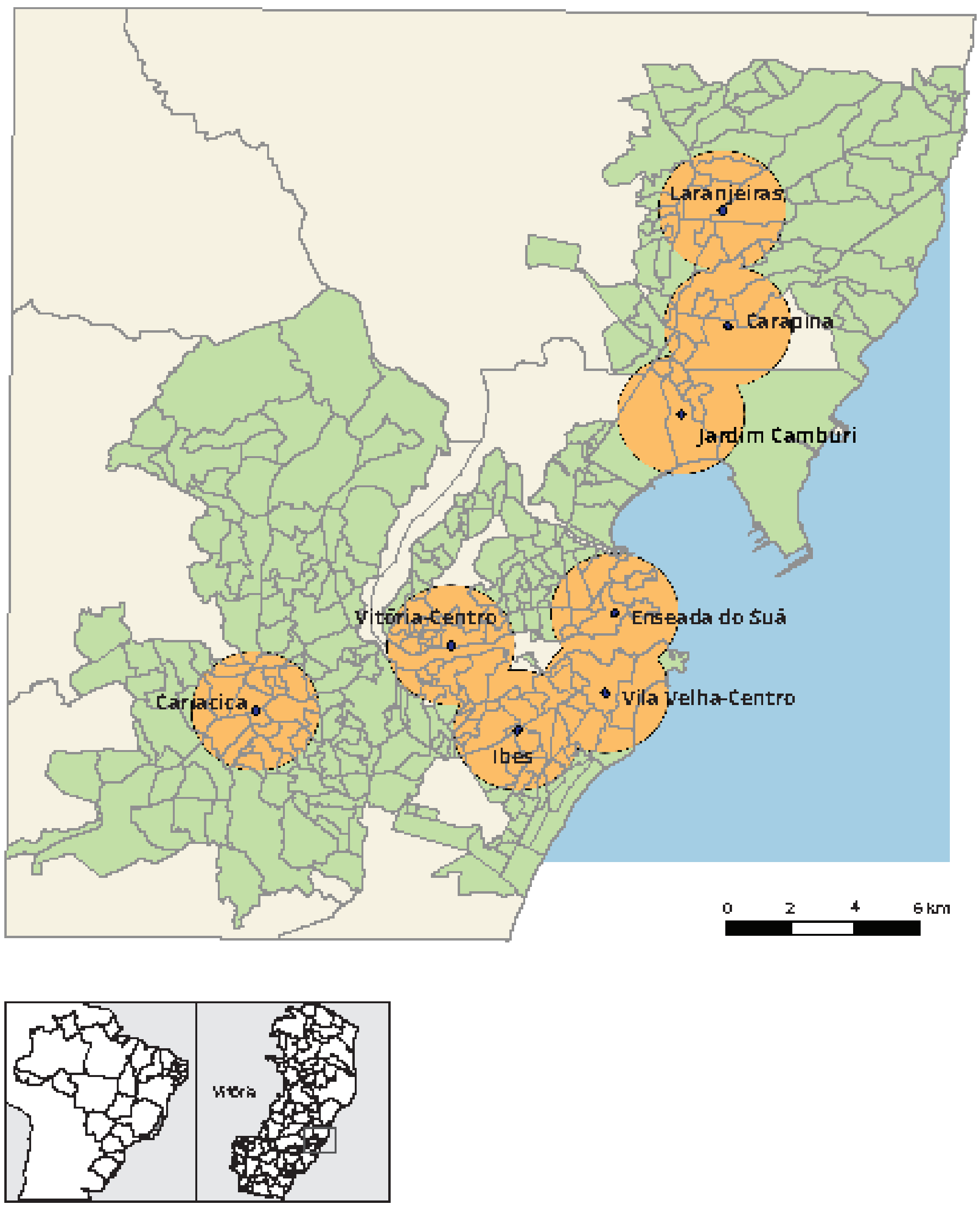
Air quality monitoring in Greater Metropolitan Vitória is done by nine stations which jointly comprise the Automatic Air Quality Monitoring Network (RAMQAr, in Portuguese) managed by the Espírito Santo State Institute for the Environment and Water Resources [17]. The spatial analysis considers each station's area of influence, as proposed by Santolim [20]. The area corresponds to a circle around the station with a radius of approximately 2km. At the time of the study, eight of the nine RAMQAr stations (Figure 1) were functioning.

Health outcome

Data on emergency treatments for respiratory conditions in children under 6 years of age were obtained from the emergency departments of two hospitals, one public and the other private, the Nossa Senhora da Glória Children's Hospital and the Unimed Vitória Integrated Healthcare Center,

Figure 1

Neighborhoods with air quality monitoring stations.



respectively. Respiratory diseases were coded according to the 10th revision of the International Classification of Diseases (ICD-10: J00-J99). We selected the treatments of children that lived in the neighborhoods located in the area of influence of each of the RAMQAr stations.

Environmental pollutants and meteorological variables

The concentrations of particulate matter with aerodynamic volume up to 10 microns (PM_{10}), SO_2, nitrogen dioxide (NO_2), O_3, and carbon monoxide (CO) for the target period were provided by the Espírito Santo State Institute for the Environment and Water Resources (IEMA), which is responsible for the nine RAMQAr stations: Laranjeiras, Carapina, Cidade Continental, Jardim Camburi, Enseada do Suá, Vitória-Centro, Ibes, Vila Velha-Centro, and Cariacica. These automatic stations continuously collect and analyze air samples and process the data as hourly averages, on-site and in real time. The measurement method for PM_{10} is Tapered Element Oscillating Microbalance (TEOM), which measures the mass concentration continuously. Measurement of SO_2 uses the principle of ultraviolet ray fluorescence. Measurement of NO_2 uses a combination of dual crossflow modulation type, also used to measure CO and O_3, with the principle of chemiluminescence and the differential calculus method [17]. We thus calculated the daily averages for PM_{10} and SO_2 and used maximum hourly concentrations of NO_2 and maximum daily concentrations of the eight-hour moving averages for CO and O_3. All pollutants in all the stations were measured in micrograms per cubic meter ($\mu g/m^3$).

The target meteorological variables were: temperature in degrees Celsius (ºC); relative humidity in percentages (%), recorded by the Carapina and Cariacica stations; and precipitation in millimeters (mm), recorded by the Carapina monitor, which are the stations that record these measurements. We used these data to calculate the arithmetic means of the recorded measurements of humidity and temperature (maximum, average, and minimum) and precipitation represented by daily rainfall. We also included for each day the temperature and humidity values from the current medical care day (lag0), the previous day (lag1), two days previously (lag2), and moving averages of the two and three previous days (mm01, mm02).

Missing data

Failures in monitoring of pollutants in the RAMQAr network during the period, both on single days and on consecutive days, caused gaps in the records of concentrations and were corrected by imputation, according to the methodology described by Junger [21]. The estimates obtained with this method are explained by the spatial correlation between the different levels of the same pollutant in the different monitors and by the autocorrelation in the pollutant's levels in the same monitor, over time. The temporal patterns are modeled with a Gaussian autoregressive integrated moving average (ARIMA) model. This algorithm is especially adapted to weather data with missing measurements in some monitors across a given region. The upper and lower limits in the imputation of missing data were the maximum and minimum concentrations, respectively, observed in the historical series for each pollutant's concentrations.

Statistical analysis

The modeling strategy consisted of defining a central model with all the known information (trend, seasonality, days of the week, holidays, and meteorological conditions) in order to explain the variability in the number of treatments for respiratory diseases, except for the concentration of pollutants.

The choice of variables and covariables for the model was based on tests and diagnoses in each stage of the modeling process. The diagnoses were based on residual analysis and the Akaike criterion (AIC) [22].

Generalized additive model

The daily number of medical treatments represents a counting process, and the generalized additive model (GAM) with Poisson marginal distribution was the statistical tool used to estimate the shape of the curve in the relationship between the health outcome and air pollution [5,13,14].

Let $\{Y_t\} \equiv \{Y_t\}_{t \in Z}$ be a counting series, that is, $y_t \in \{0,1,...\}$. The conditional distribution Y_t, given the past F_{t-1} that contains all the available information thus far t - 1, is denoted by:

$$p(y_{t;}\mu_t|F_{t-1}) = \frac{e-^{\mu_t}\mu_t^{y_t}}{y_{t!}} \qquad (1)$$

in which μ_t represents the expected value (average) of Y_t. Thus, given a sample $Y,...,Y_n$, consisting of "n" mutually conditional independent random variables belonging to "Y_t", the conditional log-likelihood function is given by:

$$l(\mu)=\sum_{t=1}^{n} \ln p(y_{t;}\mu_t|F_{t-1}) \propto \sum_{t=1}^{n} (Y_t \ln\mu_t - \mu_t) \qquad (2)$$

in which the vector $\mu = (\mu 1,...,\mu_n)$ depends on the parameters and the process $\{Y_t\}$. Let $X_t = [X_{1t},..., X_{pt}]^T$ be the vector of covariables in the dimension p in time t, in which T denotes the transpose, which can include past values of Y_t and other ancillary information such as pollutants and confounding variables (trend, seasonality, and meteorological variables, among others). In this study, the sequence $X_{1t},..., X_{qt}$ denotes the concentrations of pollutants PM_{10}, SO_2, NO_2, O_3, and CO, thus, q = 5, and $X_{(q+1)t},..., X_{pt}$ indicates the confounding variables in time t, (p > q).

The relationship between the vector is given by:

$$\ln(\mu_t)=\sum_{j=0}^{q} \beta_j X_{jt} + \sum_{j=q+1}^{p} f_j(X_{jt}) \qquad (3)$$

in which (β_0,β), with $\beta = (\beta 1,..., \beta_q)^T$ is the vector of the coefficients to be estimated (β_j it is the j-th covariable coefficient) and fj is the smoothing function for the j-th confounding variable. In addition, β_0 indicates the curve's intercept and is associated with X_{0t}= 1 for every t. The entire modeling process was performed in the R software (http://www.r-project.org) with the ARES package [23].

The relative risk (RR) of a pollutant covariable Xi,j = 1,...,q is given as the relative variation in the expected count of respiratory disease events by the unit variation ξ in the covariable while maintaining the other covariables constant. According to Baxter et al. [24], formula (8), the RR is given by:

$$RR_{X_j}(\xi) = \frac{E(Y|X_j=\xi, X_i, i \neq j)}{E(Y|X_j=0, X_i, i \neq j)} \qquad (4)$$

For the Poisson regression, the RR does not depend on the x_i, $i \neq j$ values of the other covariables and can be expressed as:

$$RR_{X_j}(\xi) = \exp(\beta_j \xi) \qquad (5)$$

For the GAM with Poisson marginal distribution, the RR and its approximate confidence interval (CI, or IC in Portuguese), at level of significance α of a covariable, X_j, j = 1...q, is estimated as follows:

$$RR_{X_j}(\xi)_{X_j} = \exp(\hat{\beta}_j \xi) \qquad (6)$$

$$IC(RR_{X_j}(\xi)) = \exp(\hat{\beta}_j \xi \pm z_{\alpha/2}(\hat{\beta}_j)\xi) \qquad (7)$$

$\hat{\beta}_j$ is the estimated coefficient associated with pollutant Xj in a study with standard error $s(\hat{\beta}_j)$ and $Z_{\alpha/2}$ is the quantile α/2 of the standard normal distribution. At level of significance α, the hypothesis to be tested is defined as H_0: $RR_{xj} = 1$ against H_0: $RR_{xj} > 1$, in which $RR_{xj} = RR_{xj}(1)$, that is, RR of the unit variation in X_j. The rejection of H_0 implies statistically that the respective pollutant has a significant adverse effect on health.

In this study, calculations of the RR(xj) values correspond to an increase of 1,000μg/m^3 in the CO levels and of 10μg/m^3 for the other pollutants. The results are presented as percentage increases in the number of medical treatments and are calculated by the expression:

$$\%RR(x) = (RR(x) - 1)x100 \qquad (8)$$

Lag

The biological manifestation of the effects of pollution on human health apparently display a behavior that shows a lag in relation to the individual's exposure to the pollutants, that is, events that occurred on a given day may be associated with the pollution levels on that day and/or on previous days. Thus, according to previous studies [25,26], we decided to investigate the association between the number of treatments for respiratory diseases and the pollution levels on the day of the emergency treatment (lag0) and on the previous days (lag1, lag2, lag3). The cumulative effect was assessed with the moving averages from two to eight days (MA01, MA02, MA03, MA04, MA05, MA06, MA07) [27,28].

The project was approved by the Institutional Review Board of the Health Sciences Center of the Federal University of Espírito Santo, under number 04/11, on May 14, 2011.

Results

During the study period there were 46,421 emergency treatments recorded for respiratory diseases in children 0 to 6 years of age living in the area of influence of the eight RAMQAr monitoring stations. The average daily number of treatments in Greater Metropolitan Vitória was 21.19 (SD = 9.90), ranging from 1.72 to 4.84 per day, with higher monthly averages from March to June, corresponding to autumn and early winter. The highest number of treatments was in children living in the Enseada do Suá neighborhood.

Average temperature during the period varied from 20.85 to 29.36°C, and rainfall varied from 0mm to 117.80mm (average = 3.78mm) and relative humidity varied from 61.79% to 97.27% (average = 77.47%).

Concentrations of pollutants did not display a uniform behavior between the different RAMQAr stations. The highest average concentrations recorded in the period were: PM_{10} (43.06μg/m^3) in Cariacica, SO_2 (16.32μg/m^3) in Enseada do Suá, O_3 (38.66μg/m^3) in Ibes, and NO_2 (44.10μg/m^3) and CO (1,730.91μg/m^3) in Vitória-Centro. Table 1 shows the pollutants' minimum, average, and maximum concentrations and 25%, 50%, and 75% quartiles and standard deviations (SD).

The series of daily counts of treatments in the overall region was smoothed with a "spline" with 12 degrees of freedom, defined by the Akaike modeling criterion and residual analysis. Non-parametric analysis evidenced seasonality and a downward trend over time, confounding factors that were included in the modeling process. The period from autumn (March) to winter (June) displayed a seasonality with an increase in the number of treatments for respiratory diseases.

Figure 2 shows the goodness-of-fit analysis for the model described previously via the results from Poisson regression for estimation of the effect of PM_{10} on the 6-day moving average for Greater Metropolitan Vitória.

The estimated coefficient for PM10 was 0.0032, with a standard error of 0.0015 and p-value of 0.0301, which we represent as [MA6, Greater Metropolitan Vitória] (0.0032; 0.00145; 0.0301).

The model's fit to the data for the areas *in loco* resulted in [MA6, Vila Velha-Centro] (0.0086; 0.0036; 0.0173), [MA6, Jardim Camburi] (0.0114; 0.0045; 0.0112), [MA6, Cariacica] (0.0044, 0.0021, 0.0331), and [MA6, Carapina] (0.0116; 0.0043; 0.0074). The results for the other sites were not statistically significant.

With the values estimated by the models, we calculated the relative risks corresponding to the estimates and proceeded to the analyses as presented.

We observed no empirical evidence of the model's poor fit, that is, the residuals are not correlated and are approximately normal. The periodogram also proved that the residuals presented characteristics of white noise. These residual graphic analyses provide the necessary support for the model's

Table 1

Descriptive statistics of treatments for respiratory diseases, by daily averages of PM_{10} (μg/m³), SO_2 (μg/m³), and NO_2 (μg/m³) and 8-hour moving averages of O_3 (μg/m³) and CO (μg/m³) in each Automatic Air Quality Monitoring Network (RAMQAr, in Portuguese), 2005-2010.

	Mean	SD	Minimum	Maximum	p25	Median	p75
Carapina							
ADR	2.31	2.10	0	17	1	2	3
PM_{10}	23.02	7.96	5.75	88.25	18.08	21.67	26.50
SO_2	-	-	-	-	-	-	-
Tmpmin	20.85	2.47	13.1	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80
Vila Velha-Centro							
ADR	2.25	1.76	0	12	1	2	3
PM_{10}	23.49	8.22	5.04	90.75	18.04	22.33	27.48
SO_2	11.99	5.80	0.50	54.16	8.61	11.21	13.98
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80
Cariacica							
ADR	2.28	1.91	0	13	1	2	3
PM_{10}	43.06	15.94	8.83	117.88	32.52	41.13	51.46
NO_2	28.06	11.18	4.01	97.64	19.28	26.79	35.78
NO_2 (maximum)	50.65	19.35	8.65	220.25	36.80	49.20	62.36
SO_2	5.50	2.62	0.00	19.82	3.42	5.32	6.98
CO	609.79	266.86	87.28	3700.05	412.67	577.28	769.46
O_3	24.78	9.32	4.50	73.35	18.33	23.76	30.45
O_3 (maximum)	47.90	13.93	12.08	120.00	37.93	46.94	56.40
O_3 (8h)	37.79	12.59	8.54	105.69	28.31	37.30	46.02
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.2	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80
Enseada do Suá							
ADR	4.84	2.86	0	19	3	4	6
PM_{10}	29.39	9.18	7.46	83.58	23.21	28.13	34.46
NO_2	23.69	8.00	5.23	81.40	18.06	22.75	28.35
NO_2 (maximum)	44.10	14.29	9.04	198.80	35.51	42.90	51.40
SO_2	16.32	7.91	1.92	49.81	10.49	15.02	21.99
CO	783.30	276.71	80.22	2250.68	580.37	740.89	944.23
O_3	29.91	8.84	9.08	69.52	24.51	28.51	34.27
O_3 (maximum)	49.05	13.12	10.18	115.03	40.30	46.81	56.08
O_3 (8h)	38.66	10.99	9.40	94.62	31.45	36.72	44.79
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.8	0.00	0.00	1.80

(continues)

Table 1 (continued)

	Mean	SD	Minimum	Maximum	p25	Median	p75
Laranjeiras							
ADR	2.05	1.83	0	12	1	2	3
PM_{10}	32.9	11.39	7.45	106.88	25.21	31.6	38.86
NO_2	22.07	7.17	3.36	59.38	17.12	21.16	25.73
NO_2 (maximum)	41.23	14.85	10.00	115.27	31.19	38.82	47.7
SO_2	12.61	5.79	2.07	52.61	8.59	11.61	15.93
CO	647.58	175.55	212.01	1750.02	529.60	619.98	724.33
O_3	32.58	9.05	10.26	74.18	26.54	30.90	37.05
O_3 (maximum)	52.46	16.34	18.15	139.43	41.26	48.89	60.26
O_3 (8h)	43.34	12.98	14.34	106.38	34.60	40.55	50.01
Tmpmin	20.85	2.47	13.1	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80
Ibes							
ADR	1.72	1.48	0	9	1	1	3
PM_{10}	29.24	9.67	5.00	88.13	23.19	28.13	34.46
NO_2	20.32	5.98	4.80	58.03	16.40	19.69	23.89
NO_2 (maximum)	38.39	11.15	9.60	100.50	31.00	37.70	45.99
SO_2	10.73	6.20	0.25	41.38	5.97	9.79	14.15
CO	657.24	267.07	155.40	2551.97	475.72	608.19	773.41
O_3	40.15	12.23	13.29	102.33	31.36	37.87	47.19
O_3 (maximum)	65.78	17.09	22.20	148.00	53.88	64.01	75.60
O_3 (8h)	54.48	16.38	17.89	140.11	42.34	52.37	64.51
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.8
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.2	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80
Jardim Camburi							
ADR	2.24	1.82	0	12	1	2	3
PM_{10}	26.95	8.06	5.46	78.08	21.50	25.92	31.63
NO_2	24.91	7.85	0.92	56.83	19.06	24.02	30.17
NO_2 (maximum)	42.07	12.76	1.17	127.04	32.50	40.94	49.98
SO_2	14.15	7.49	0.96	54.70	9.73	12.35	16.12
CO							
Tmpmin	20.85	2.47	13.1	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.8	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.7	27.2	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.8	0.00	0.00	1.80

(continues)

Table 1 (continued)

	Mean	SD	Minimum	Maximum	p25	Median	p75
Vitória-Centro							
ADR	3.5	2.39	0	15	2	3	5
PM_{10}	26.09	7.23	6.08	70.42	21.51	25.08	30.08
NO_2	29.87	10.24	6.56	109.68	22.56	28.77	36.28
NO_2 (maximum)	55.78	15.27	13.1	168.35	46.38	54.71	63.83
SO_2	15.77	6.32	2.62	44.63	10.85	15.29	19.85
CO	1730.9	715.30	451.73	4,814.20	1,201.60	1,611.22	2,152.20
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.40	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.8
Greater Metropolitan Vitória							
ADR	21.19	9.9	2	64	14	20	26
PM_{10}	29.27	7.73	7.86	75.9	24.42	28.66	33.59
NO_2 (maximum)	45.37	11.05	19.06	114.93	37.31	44.47	52.26
SO_2	12.44	3.11	4.89	26.48	10.07	12.16	14.57
CO	885.76	231.24	295.17	2141.53	724.83	866.60	1031.10
O_3 (8h)	43.57	10.83	16.93	93.63	35.54	42.21	49.91
Tmpmin	20.85	2.47	13.10	25.98	19.05	21.15	22.80
Tmpmed	24.43	2.45	17.00	30.80	22.63	24.41	26.36
Tmpmax	29.36	3.28	19.4	39.70	27.20	29.43	31.60
Humidity	77.47	6.21	61.79	97.27	73.11	77.10	81.44
Rainfall	3.78	11.31	0.00	117.80	0.00	0.00	1.80

ADR: daily number of treatments for respiratory diseases; SD: standard deviation; Tmpmin: daily minimum temperature; Tmpmed: daily medium temperature; Tmpmax: daily maximum temperature.

Note: "humidity" represents the daily relative air humidity index, "rainfall" is daily precipitation.

good fit and thus for performing inferences. Thus, the quality of the fitted model was guaranteed by the empirical properties shown by the residuals.

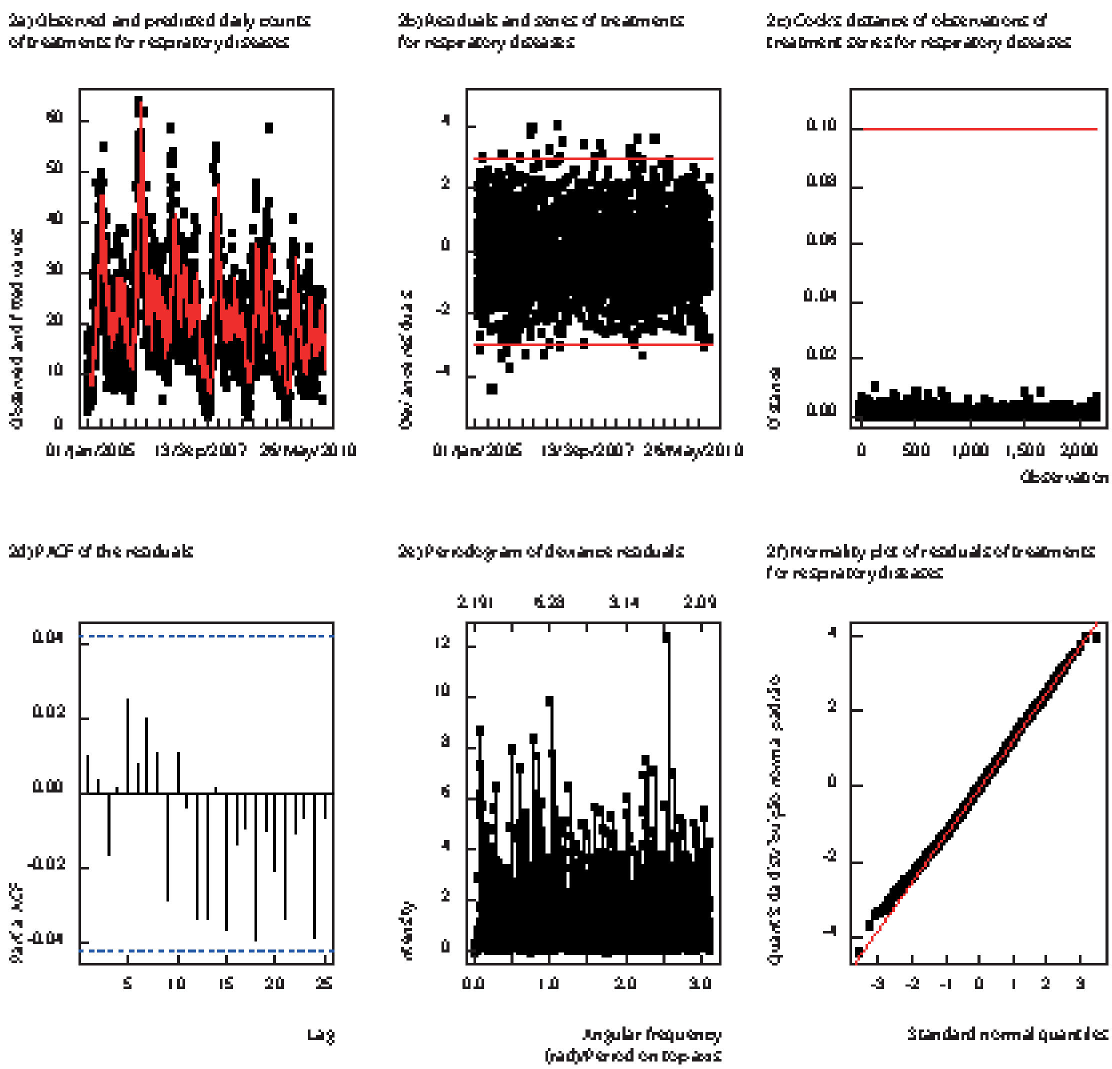
We calculated the relative risks (RR) and confidence intervals (CI) for each model fitted to the station's neighborhood and for the overall region for each pollutant. Table 2 shows the estimated relative risks for an increase of 10 in the concentration of each of the air pollutants for the overall region. When we analyzed the patterns shown in this table, the gradients clearly evidenced the significant effects of PM_{10} on the treatments, for cumulative lags. For SO_2, in the simple lag, the RR values were significant for lag0 and lag2. NO_2, CO, and O_3 did not show statistical significance in the RR for Greater Metropolitan Vitória.

Table 3 presents a summary of the RR values for the effects of each pollutant whose calculations showed statistical significance (the results in bold print are those with the highest magnitudes). For the pollutants PM_{10} and SO_2, the relative risks were higher when estimated for each station separately, compared to the RR for the entire Greater Metropolitan Vitória, that is, the adjusted model in which the covariables correspond to the average concentrations. As seen previously, the effects of NO_2, CO, and O_3 for the aggregate area (Greater Metropolitan Vitória) did not show statistical significance in the RR, which can be considered a spurious result, since the effects of these pollutants for the disaggregated sites led to highly significant relative risks.

The entire analysis was based on the comparison of RR for the different pollutants and spatial points and compared to an average.

Figure 2

Diagnosis of the central model for Greater Metropolitan Vitória, Espírito Santo State, Brazil.



ADR: daily number of treatments for respiratory diseases.

Note: fitted values in red.

Discussion

This study analyzed the effect of air pollution on children's health in Greater Metropolitan Vitória by estimating relative risk in a GAM. Concentrations of PM_{10}, SO_2, NO_2, and O_3, even complying with Brazil's prevailing legislation and WHO guidelines, showed a significant association with increases in emergency treatments for respiratory diseases in children 0 to 6 years of age, proving that there is no limit on these pollutants that is safe for human health [1].

The number treatments increased from March to June, corresponding to autumn to early winter. This expected increase is due to different factors such as low temperatures that predispose to aggravation of preexisting respiratory diseases, higher incidence of viral respiratory diseases, and increased concentration of primary pollutants determined by scarce rainfall and thermal inversion.

Table 2

Relative risk (RR) of treatments for respiratory diseases in children under 6 years of age for 10μg/m3 increases in PM_{10} (μg/m3), SO_2 (μg/m3), NO_2 (μg/m3), O3 (μg/m3), and CO (μg/m3) in Greater Metropolitan Vitória, Espírito Santo State, Brazil, 2005 to 2010.

Exposure	%RR	Lower	Upper	p-value
PM_{10}				
Current day	0.99	-0.50	2.50	0.19
Lag, 1 day	0.04	-1.35	1.46	0.95
Lag, 2 days	0.81	-0.58	2.23	0.25
Lag, 3 days	1.10	-0.29	2.51	0.12
Cumulative, 2 days	0.69	-1.02	2.42	0.43
Cumulative, 3 days	1.13	-0.82	3.12	0.26
Cumulative, 4 days	1.77	-0.44	4.03	0.12
Cumulative, 5 days	2.43	-0.05	4.97	0.05 *
Cumulative, 6 days	2.73	0.00	5.53	0.05 *
Cumulative, 7 days	3.29	0.31	6.36	0.03 *
Cumulative, 8 days	2.50	-0.67	5.77	0.12
SO_2				
Current day	4.47	-0.01	9.14	0.05 *
Lag, 1 day	4.20	-0.20	8.79	0.06
Lag, 2 days	5.26	0.81	9.90	0.02 *
Lag, 3 days	1.43	-2.89	5.94	0.52
Cumulative, 2 days	6.47	0.99	12.26	0.02 *
Cumulative, 3 days	8.80	2.55	15.44	0.01 *
Cumulative, 4 days	8.76	1.93	16.05	0.01 *
Cumulative, 5 days	7.09	-0.13	14.84	0.05 *
Cumulative, 6 days	3.70	-3.71	11.69	0.34
Cumulative, 7 days	2.23	-5.45	10.53	0.58
Cumulative, 8 days	0.00	-7.85	8.52	1.00
NO_2				
Current day	0.25	-0.89	1.40	0.67
Lag, 1 day	-0.90	-2.04	0.25	0.12
Lag, 2 days	-0.45	-1.56	0.67	0.43
Lag, 3 days	-0.16	-1.25	0.94	0.78
Cumulative, 2 days	-0.50	-1.90	0.93	0.49
Cumulative, 3 days	-0.77	-2.39	0.88	0.36
Cumulative, 4 days	-0.82	-2.63	1.01	0.38
Cumulative, 5 days	-0.91	-2.86	1.09	0.37
Cumulative, 6 days	-0.91	-3.02	1.25	0.41
Cumulative, 7 days	-0.37	-2.63	1.95	0.75
Cumulative, 8 days	-0.31	-2.72	2.16	0.81
O_3				
Current day	0.54	-0.54	1.62	0.33
Lag, 1 day	0.46	-0.59	1.52	0.39
Lag, 2 days	0.07	-0.97	1.13	0.89
Lag, 3 days	-0.32	-1.36	0.73	0.55
Cumulative, 2 days	0.74	-0.55	2.05	0.26
Cumulative, 3 days	0.69	-0.78	2.19	0.36
Cumulative, 4 days	0.45	-1.20	2.12	0.60
Cumulative, 5 days	0.34	-1.46	2.17	0.71
Cumulative, 6 days	0.92	-1.04	2.91	0.36
Cumulative, 7 days	0.66	-1.42	2.78	0.54
Cumulative, 8 days	0.60	-1.60	2.86	0.60

(continues)

Table 2 (continued)

Exposure	%RR	Lower	Upper	p-value
CO				
Current day	1.83	-3.25	7.17	0.49
Lag, 1 day	-3.61	-8.21	1.23	0.14
Lag, 2 days	0.39	-4.37	5.39	0.87
Lag, 3 days	4.60	-0.26	9.70	0.06
Cumulative, 2 days	-1.69	-7.76	4.76	0.60
Cumulative, 3 days	-1.24	-8.30	6.37	0.74
Cumulative, 4 days	2.15	-5.97	10.98	0.61
Cumulative, 5 days	3.23	-5.74	13.05	0.49
Cumulative, 6 days	2.53	-7.11	13.17	0.62
Cumulative, 7 days	4.89	-5.72	16.70	0.38
Cumulative, 8 days	5.83	-5.60	18.65	0.33

Table 3

Percentage increase and 95% confidence interval (95%CI) in emergency pediatric treatments for respiratory problems. Greater Metropolitan Vitória, Espírito Santo State, Brazil, 2005-2010.

Exposure	%RR	95%CI	p-value	RAMQAr
PM_{10}				
Cumulative, 5 days	2.43	-0.05; 4.97	0.05	Greater Metropolitan Vitória
Cumulative, 6 days	2.73	-0.00; 5.53	0.05	Greater Metropolitan Vitória
Cumulative, 7 days	3.29	0.31; 6.36	0.03	Greater Metropolitan Vitória
Lag, 1 day	4.49	1.45; 7.62	0.00	Laranjeiras
Cumulative, 2 days	4.5	1.04; 8.08	0.01	Laranjeiras
Cumulative, 3 days	5.17	1.35; 9.13	0.01	Laranjeiras
Cumulative, 4 days	4.66	0.60; 8.89	0.02	Laranjeiras
Lag, 1 day	4.66	0.48; 9.02	0.03	Carapina
Cumulative, 6 days	8.36	0.16; 17.23	0.05	Carapina
Cumulative, 7 days	12.27	3.15; 22.19	0.01	Carapina
Cumulative, 8 days	11.5	1.85; 22.06	0.02	Carapina
Cumulative, 6 days	10.59	1.79; 20.16	0.02	Jardim Camburi
Cumulative, 7 days	12.08	2.63; 22.40	0.01	Jardim Camburi
Cumulative, 8 days	11.82	1.87; 22.73	0.02	Jardim Camburi
Lag, 3 days	2.41	0.17; 4.71	0.03	Enseada do Suá
Current day	4.08	0.54; 7.76	0.02	Vitória-Centro
Cumulative, 6 days	6.58	-0.03; 13.64	0.05	Vitória-Centro
Cumulative, 7 days	7.13	0.01; 14.75	0.05	Vitória-Centro
Cumulative, 7 days	9.05	1.54; 17.12	0.02	Vila Velha-Centro
Cumulative, 8 days	9.01	1.19; 17.42	0.02	Vila Velha-Centro
Lag, 3 days	2.62	0.58; 4.71	0.01	Cariacica
Cumulative, 7 days	4.53	0.36; 8.88	0.03	Cariacica
Cumulative, 8 days	4.77	0.40; 9.34	0.03	Cariacica

(continues)

Table 3 (continued)

Exposure	%RR	95%CI	p-value	RAMQAr
SO_2				
Current day	4.47	-0.01; 9.14	0.05	Greater Metropolitan Vitória
Lag, 2 days	5.26	0.81; 9.90	0.02	Greater Metropolitan Vitória
Cumulative, 2 days	6.47	0.99; 12.26	0.02	Greater Metropolitan Vitória
Cumulative, 3 days	8.8	2.55; 15.44	0.01	Greater Metropolitan Vitória
Cumulative, 4 days	8.76	1.93; 16.05	0.01	Greater Metropolitan Vitória
Cumulative, 5 days	7.09	0.13; 14.84	0.05	Greater Metropolitan Vitória
Current day	10.68	1.09; 21.17	0.03	Laranjeiras
Lag, 2 days	9.71	1.68; 18.37	0.02	Jardim Camburi
Cumulative, 7 days	13.52	-0.24; 29.18	0.05	Jardim Camburi
Current day	8.7	1.12; 16.85	0.02	Vila Velha-Centro
Cumulative, 2 days	11.31	1.23; 22.40	0.03	Vila Velha-Centro
Lag, 3 days	11.9	0.04; 25.17	0.05	Vila Velha-Centro
Lag, 2 days	7.57	1.17; 14.38	0.02	Cariacica
NO_2				
Lag, 2 days	3.85	0.99; 6.80	0.01	Jardim Camburi
Cumulative, 6 days	3.56	0.35; 6.88	0.03	Vitória-Centro
Cumulative, 7 days	3.88	0.46; 7.42	0.03	Vitória-Centro
Cumulative, 8 days	4.32	0.70; 8.06	0.02	Vitória-Centro
CO				
Lag, 3 days	1.78	-0.02; 3.62	0.05	Laranjeiras
Lag, 2 days	2.24	0.72; 3.79	0.00	Ibes
Lag, 3 days	1.97	0.46; 3.51	0.01	Ibes
Cumulative, 4 days	3.01	0.60; 5.48	0.01	Ibes
Cumulative, 5 days	2.96	0.34; 5.65	0.03	Ibes
Cumulative, 6 days	2.99	0.20; 5.86	0.04	Ibes
O_3				
Current day	3.23	0.17; 6.37	0.04	Laranjeiras
Cumulative, 4 days	4.13	-0.08; 8.51	0.05	Laranjeiras

RAMQAr: Automatic Air Quality Monitoring Network; RR: relative risk.

The neighborhood with the most children treated at the emergency departments was Enseada do Suá. This neighborhood is heavily impacted by mobile polluting winds, since it is close to roadways with intense traffic, including a bridge connecting the city of Vitória to Vila Velha, with up to 70,000 motor vehicles circulating per day, as well as fixed sources, mainly an industrial complex inside the urban grid. A recent study showed that the resident population in this neighborhood of Vitória reported the most discomfort and aggravation from sedimented dust [29].

During the study period, the concentrations of pollutants varied between the different RAMQAr stations, which can be explained by each neighborhood's specific polluting activities. The average pollutant levels in these stations are based on on-site data and are usually quite close and significantly different from the overall average. This empirical evidence shows that the local averages, $E(\mu^{L}{}_{t})$, (L = 1,...,8) differ from the Greater Metropolitan Vitória average $E(\mu^{R}{}_{t})$. This result is expected, since the process is not stationary in time, that is, $E(\mu^{L}{}_{t}) \neq E(\mu^{R}{}_{t})$, for L=1,…,8, and justifies the proposed study in the sense of comparing the health outcome to the pollutants in spatially discriminated areas.

PM_{10} and SO_2 were the pollutants that showed the most consistent association with the increase in treatments for respiratory problems. PM_{10} showed a substantial effect on treatments in all the lags and in nearly all the neighborhoods, with the highest magnitude in Jardim Camburi and Carapina. This effect pattern is consistent with other studies. Samoli et al. [10], in Greece, found that an increment of 10μg/m^3 in PM_{10} and SO_2 was associated with increases of 2.54% and 5.98% in the number of hospitalizations from respiratory diseases, respectively. In Itabira, Minas Gerais, Brazil, an increase of 10μg/m³ in the concentration of PM_{10} was associated with a 4% increase in emergency department treatments for respiratory diseases in children for lag0 and lag18. In Greater Metropolitan Vitória, Souza et al. [13] observed a significant relationship between the concentrations of all the pollutants monitored by the RAMQAr (PM_{10}, SO_2, NO_2, O_3, and CO) and the number of emergency treatments for respiratory problems in children up to 6 years of age, through hybrid modeling, vector autoregression (VAR), principal components analysis (PCA), and GAM.

We observed high concentrations of PM_{10} in the Cariacica station, which can be explained by the station's location inside the Espírito Santo Farm Produce Clearinghouse (CEASA/ES), which has intense internal truck traffic and is located close to two federal highways with heavy truck traffic (BR-262 and BR-101).

The higher effect of PM_{10} and SO_2 in the Jardim Camburi, Carapina, and Laranjeiras neighborhoods can be explained by their proximity to heavily travelled roadways and the largest industrial complex in the state of Espírito Santo, both of which are potential sources of PM_{10} and SO_2.

We found the highest RR for SO_2 around the Jardim Camburi and Laranjeiras stations. In Enseada do Suá, the pollutant with the highest average was SO_2, but due to the lack of available data, the RR was only calculated for PM_{10} in this neighborhood, representing a shortcoming in the study.

The adjustments to the model for each of the neighborhoods around the RAMQAr monitoring stations allowed better observation of the effect of all the pollutants on the number of emergency treatments for respiratory diseases. Evidence has shown that in time-series studies, measurements from a central station, compared to statistical or dispersion models or satellite-derived estimates, can be an adequate exposure metric for pollutants distributed homogeneously over the area [30], which does not apply to the current study.

Comparing the estimates when we simulated for the entire Greater Metropolitan Vitória to the analyses around the RAMQAr stations, some effects were only perceptible when the analyses were done in the sites disaggregated by neighborhood, signaling a greater effect compared to the estimate for the entire Greater Metropolitan Vitória. The explanation is that the analysis by the average for all the stations tends to smooth the data and thus decrease their variability, disguising some effects and underestimating air pollution's effects on health. Wilson et al. [31] also concluded that consideration of intraurban variations in concentrations in epidemiological studies allows minimizing exposure errors and uncertainties in the relative risk, but they found that this only applies to long-term studies. However, using this approach we observed short-term effects of NO_2, CO, and O_3 on the number of treatments for respiratory diseases in young children, especially in the Jardim Camburi, Vila Velha-Centro, and Laranjeiras neighborhoods.

Despite the association between the various air pollutants and the risk of emergency treatment for respiratory diseases in children in Greater Metropolitan Vitória, we observed a downward trend in the levels of pollutants over time, which can be explained by better local air pollution control.

For future studies, other susceptible groups could be investigated in the same neighborhood in order to allow elaborating a complete picture of the acute effects of air pollution on the population's health. As an alternative methodology, bootstrap techniques could be used to obtain intervals with the same precision but with a narrower sampling range. Another potential methodology is estimation of variance with heteroscedastic models. The GLARMA [32] and PINAR [33] models, with greater structural complexity, are statistical tools that could be addressed in these studies.

The consistency of associations and the magnitude of the observed effects in the neighborhoods, even in an environment with pollution levels that comply with limits set by regulatory agencies, are extremely relevant to public health. The findings provide backing for measures to minimize health risks, besides contributing to environmental and urban health planning and improvement of public policies.

Contributors

E. P. Matos participated in the study's conception and planning, data collection, analysis, and interpretation, and writing of the draft and final version. V. A. Reisen, F. S. Serpa, P. R. Prezotti Filho and M. F. S. Leite contributed in the study's conception and planning, data analysis and interpretation, and writing of the draft and final version.

Addittional informations

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Conflict of interests

The authors declare that they have no conflict of interests in this study.

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Resumo

O objetivo foi investigar a associação de curto prazo entre a poluição do ar e atendimentos em emergências por doenças respiratórias, em crianças de 0 a 6 anos. Estudo ecológico, espacial e temporal realizado na Região Metropolitana da Grande Vitória, Espírito Santo, Brasil. Utilizou-se o modelo aditivo generalizado (MAG) de regressão de Poisson, com a variável dependente o número diário de atendimentos por doenças respiratórias, e as variáveis independentes, concentrações diárias dos poluentes atmosféricos (MP_{10}*,* SO_2*,* NO_2*,* O_3 *e CO), temperatura, umidade e precipitação pluviométrica. Por meio das médias diárias das concentrações, foram feitas estimativas para toda a região e análises* in loco *com a consideração de crianças residentes no entorno de 2km de oito estações de monitoramento da qualidade do ar. O incremento de 10µg/m*^{3} *nos níveis de concentração dos poluentes atmosféricos aumentou o risco de atendimento em emergência por doença respiratória. Na região geral, para o* MP_{10}*, o aumento foi de 2,43%, 2,73% e 3,29% nos acumulados de 5, 6 e 7 dias, respectivamente. Para o* SO_2*, o acréscimo foi de 4,47% no dia da exposição, 5,26% dois dias após, 6,47%, 8,8%, 8,76% e 7,09% nos acumulados de 2, 3, 4 e 5 dias, respectivamente. O CO apresentou associação significativa para residentes no entorno de duas estações, e o* O_3 *somente em uma. Mesmo dentro dos limites estabelecidos pela Organização Mundial da Saúde, os poluentes* MP_{10}*,* SO_2*,* NO_2 *e* O_3 *estão associados ao maior risco para atendimento por doenças respiratórias em crianças de 0 a 6 anos, e alguns efeitos só foram identificados nas localidades desagregadas por região, isto é,* in loco*, o que possibilita captar maior variabilidade dos dados.*

Poluição do Ar; Doenças Respiratórias; Criança

Resumen

El objetivo fue investigar la asociación de corto plazo entre la contaminación del aire y la atención en urgencias por enfermedades respiratorias, en niños de 0 a 6 años. Estudio ecológico, espacial y temporal realizado en la Región Metropolitana de la Grande Vitória, Espírito Santo, Brasil. Se utilizó el modelo aditivo generalizado (MAG) de regresión de Poisson, con la variable dependiente que es el número diario de consultas por enfermedades respiratorias, y las variables independientes: concentraciones diarias de los contaminantes atmosféricos (MP_{10}*,* SO_2*,* NO_2*,* O_3 *y CO), temperatura, humedad y precipitación pluviométrica. Mediante las medias diarias de las concentraciones, se realizaron estimativas para toda la región y análisis* in loco*, considerando a niños residentes en un entorno de 2km con 8 estaciones de monitoreo de la calidad del aire. El incremento de 10µg/m*^{3} *en los niveles de concentración de los contaminantes atmosféricos aumentó el riesgo de atención en urgencias por enfermedad respiratoria. En la región como un todo, en el caso del* MP_{10}*, el aumento fue de 2,43%, 2,73% y 3,29% en los acumulados de 5, 6 y 7 días, respectivamente. En el* SO_2*, el incremento fue de 4,47% durante el día de la exposición, 5,26% dos días después, 6,47%, 8,8%, 8,76% y 7,09% en los acumulados de 2, 3, 4 y 5 días, respectivamente. El CO presentó asociación significativa para residentes alrededor de dos estaciones, y el* O_3 *solamente en una. Incluso dentro de los límites establecidos por la Organización Mundial de la Salud, los contaminantes* MP_{10}*,* SO_2*,* NO_2 *y* O_3 *están asociados a un mayor riesgo en relación con la atención por enfermedades respiratorias en niños de 0 a 6 años, y algunos efectos sólo se identificaron en las localidades desagregadas por región, esto es,* in loco*, lo que posibilita captar una mayor variabilidad de los datos.*

Contaminación del Aire; Enfermedades Respiratorias; Niño

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