UFSM

CIÊNCIA e NATURA

ISSN 2179-460X
OPEN ACCESS

Ci. e Nat., Santa Maria, v. 46, e69023, 2024 • https://doi.org/10.5902/2179460X69023
Submitted: 13/01/2022 • Approved: 15/08/2023 • Published: 06/11/24

Statistics

Temporal Trends and Statistical Analysis of PM_{10} and TSP Concentrations in the Region of Grande Vitória from 2008 to 2017

Tendências Temporais e Análise Estatística das Concentrações de PM_{10} e PTS na Região da Grande Vitória de 2008 a 2017

Isamara Maria Schmidt [I], **Jaqueline Knaak** [I], **Wanderson de Paula Pinto** [II], **Edson Zambon Monte** [I], **Michel Trarbach Bleidorn** [I], **Gemael Barbosa Lima** [I],

[I] Universidade Federal do Espirito Santo, Vitória, ES, Brazil
[II] Centro Universitário FAVENI, Montanha, ES, Brazil

ABSTRACT

This study aimed to statistically evaluate the PM_{10} and TSP time series data in the RGV, between 2008 and 2017, verifying whether the series of each pollutant are generated by the same stochastic process. For that, the tests proposed by Coates and Diggle (1986), by Quenouille (1958) and the series difference procedure developed by Silva, Ferreira and Sáfadi (2000) were used. PM_{10} time series for Laranjeiras (E1), Carapina (E2), Jardim Camburi (E3), Enseada do Suá (E4), Vitória (E5), IBES (E6) and Cariacica (E8) stations were compared two by two, and for TSP time series of stations E3, E4, E5, E6 and E8 the same was done. It was found that, for a 5% significance level, stations E2, E3, E4, E5 and E6 for PM_{10} and, E3, E4, E5 and E6, for the TSP, present time series generated by the same stochastic process. After analyse the results, it's suggested that the monitoring equipments of PM_{10} in E2 station and the monitoring equipments of PM_{10} and TSP for E3, E5 and E6 stations can be installed in a new site to expand the monitored area.

Keywords: Comparison Tests; Time Series; Air Pollution; Region of Grande Vitória; Statistics

RESUMO

Este estudo teve como objetivo avaliar, estatisticamente, os dados de séries temporais de PM_{10} e PTS na RGV, entre 2008 e 2017, a fim de verificar se estas são geradas por um mesmo processo estocástico. Para tanto, utilizaram-se os testes propostos por Coates e Diggle (1986), por Quenouille (1958) e o procedimento de diferença de séries desenvolvido por Silva et al. (2000). Compararam-se, duas a duas, as séries das estações Laranjeiras (E1), Carapina (E2), Jardim Camburi (E3), Enseada do Suá (E4), Vitória (Centro) (E5), IBES (E6) e Cariacica (E8), para o poluente PM_{10}, e as séries das estações E3, E4, E5, E6 e E8, para o PTS. Verificou-se que, para um nível de significância de 5%, as estações E2, E3, E4, E5 e E6 para

PM$_{10}$ e E3, E4, E5 e E6 para PTS apresentam séries temporais geradas pelo mesmo processo estocástico. Após analisar os resultados, sugere-se que os equipamentos de monitoramento de PM$_{10}$ na estação E2 e os equipamentos de monitoramento de PM$_{10}$ e PTS nas estações E3, E5 e E6 podem ser instalados em um novo local para expandir a área monitorada.

Palavras-chave: Testes de Comparação; Séries Temporais; Poluição do Ar; Região da Grande Vitória; Estatística

1 INTRODUCTION

Numerous studies have extensively linked airborne particulates to various health disorders. Airborne particulate pollution is often described and quantified using terms such as 'suspended particulate matter' (SPM) and 'total suspended particles' (TSP). SPM refers to the overall airborne particle count, while TSP indicates that a gravimetric method was used to determine SPM. Additionally, terms like 'respirable particles' and 'inhalable particles' are used to characterize dusty atmospheres, indicating specific particle sizes and potential health risks. Inhalable particles are those that enter the respiratory system during breathing, while respirable particles are capable of reaching the gas exchange regions of the lungs. These distinctions help in understanding the potential impacts on human health (Pooley and Mille, 1999).

Recent attention has been directed towards the gravimetric measurement of the PM$_{10}$ and PM$_{2.5}$ fraction of airborne particulate matter due to the potential health impact suggested by numerous recent studies. PM$_{10}$ refers to a fraction of airborne matter containing particles with an aerodynamic diameter of less than 10 μm and is also known as respirable particles while PM$_{2.5}$ refers to a fraction of airborne matter containing particles with an aerodynamic diameter of less than 2.5 μm and is also known as inhalable particles (Seinfeld and Pandis, 2006).

Among the carried studies, the main consequences observed prove the relationship between PM concentration in environment and increase in daily cases of mortality and morbidity, making PM pollution a growing public health problem (Vardoulakis and Kassomenos, 2008; Wang et al., 2019). Most common studies refer to respiratory and cardiovascular morbidities associated with PM exposure, which can be observed at short and medium term, as for example, the study conducted by Freitas et al. (2016), in Vitória city, Southeastern Brazil, in which, using time series models via Poisson Regression, the authors analysed the air pollution impact on respiratory and cardiovascular morbidity of children and adults, from 2001 to 2006, reaching the conclusion that, for each 10 $\mu g.m^{-3}$ increment of PM_{10} pollutant, there is an increase in the percentage of relative risk for hospitalizations due to total respiratory diseases of 9.67 and for respiratory diseases in children under the age of five years the increase is 6.60. In addition to this, can be cited the studies carried by Nascimento et al. (2017) and Zhu et al. (2019), that too found evidence between an increase in the rate of respiratory diseases and exposure to PM.

However, recent long-term studies have shown an association between exposure to PM pollution and greater chances of a child having Autism Spectrum Disorder (Raz et al., 2015), cognitive, structural and metabolic impacts on children brain development and constitution of a risk factor for the development of Alzheimer's disease and multiple sclerosis throughout life (Calderón-Garcidueñas et al., 2016), changes in human cognitive performance (Zhang et al., 2018), constitution of modifiable cerebrovascular and neurodegenerative risk factor, since PM contributes to about one third of the global burden of stroke and one fifth of the global burden of dementia (Béjot et al., 2018), the increased risk of the incidence of diabetes melitus (Bowe et al., 2018), constitution of a risk factor for the development of lung cancer (Raaschou-Nielsen et al., 2016; Zhu et al., 2019) and cardiovascular system diseases (Hamanaka and Mutlu, 2018).

Given the above, air quality monitoring, through so-called monitoring networks, stands out as a tool of great importance for air quality management. However, for economic and administrative reasons, the number of measurement points in a network is limited and, above all, its spatial arrangement may not have been studied carefully, may be positioned in unrepresentative locations (Moreira et al., 2008). Because of this, is possible that the time series measured by the stations of an air quality monitoring network were generated by the same stochastic process, that is, present similar behaviour patterns, from the statistical point of view, for a specific monitored pollutant, as described studies by Costa and Sáfadi (2010) analysing PM_{10} time series in São Paulo city, Zamprogno et al. (2020) studying PM_{10} and SO_2 concentrations in Region of Grande Vitória, and Cotta et al. (2020) evaluating PM_{10} time series, also for the Region of Grande Vitória, Espírito Santo state.

If was proven that two or more stations have the same behaviour pattern for a pollutant in common, it's possible relocate the measurement equipment for that pollutant to another station (Cotta et al., 2020; Pires et al., 2008), thus, the number of monitoring sites that constitute the network should be optimised helping to reduce expenses and expanding the coverage area, at the same time guarantying the adequate characterisation of the regional air quality (Pires et al., 2008), what justifies the present study. Therefore, this work aims to evaluate, statistically, respirable particles (PM_{10}) and Total Suspended Particles (TSP) concentration data, in the Region of Grande Vitória (RGV), between 2008 and 2017, to detect whether the concentration pollutants time series are generated by the same stochastic process.

2 METHODOLOGY

2.1 Characterization of the study area

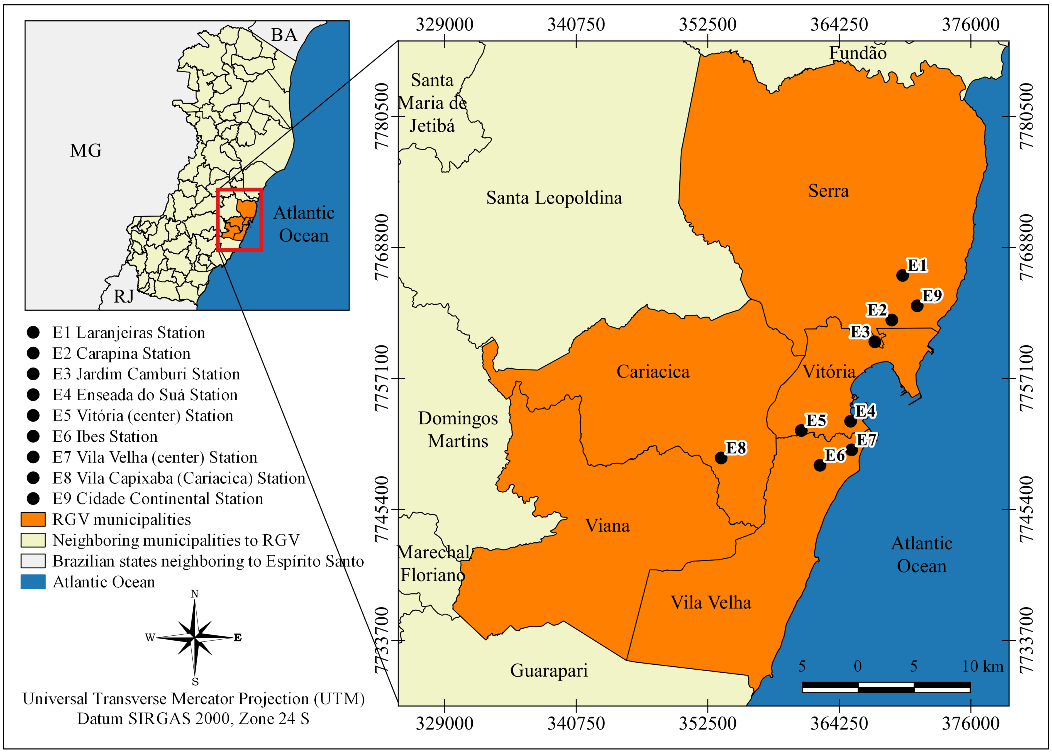
The Region of Grande Vitória (RGV) is located on the coast of Espírito Santo state, Southeastern Brazil, and comprises Vitória, Vila Velha, Cariacica, Serra and Viana municipalities. Has an Aw (warm tropical) climate whose temperatures vary between 24º and 30ºC, according to Köppen climate classification (Köppen, 1900). Has an area of 1,456 km^2, with about 1,738,173 inhabitants representing 45.34% of total population from Espírito Santo state, with 98.6% of that population living in urban areas (IBGE, 2023). RGV has an Automatic Air Quality Monitoring Network (RAMQAr), owned by State Institute of Environment and Water Resources (IEMA), composed of nine stations distributed over four RGV municipalities, whose spatial location is represented in the Figure 1.

Table 1 shows IEMA identification codes for each RAMQAr station, identification nomenclature adopted in this study, neighborhoods where each station is located, start operation year and plane coordinates (UTM).

2.2 Data

Analyses were carried out from January 1, 2008 to December 31, 2017, with data referring to PM_{10} and TSP concentration in RGV provided in hourly averages of 24 hours and collected through IEMA (2018) database. Initially, analysis of raw database was performed to identify missing data and impute them via EM algorithm

Figure 1 – Location of the RAMQAr stations at RGV, Espírito Santo, Southeastern Brazil



Source: Elaborated by the authors (2022)

Table 1 – RAMQAr stations information

Station Code	ID	Neighborhood	Operation start	Coordinate (m)	
				Easting	Northing
RAMQAr 1	E1	Laranjeiras	2000	369917	7766305
RAMQAr 2	E2	Carapina	2000	368945	7762315
RAMQAr 3	E3	Jardim Camburi	2000	367429	7760371
RAMQAr 4	E4	Enseada do Suá	2000	365266	7753279
RAMQAr 5	E5	Centro (Vitória)	2005	360857	7752450
RAMQAr 6	E6	IBES	2000	362532	7749346
RAMQAr 7	E7	Centro (Vila Velha)	2000	365354	7750721
RAMQAr 8	E8	Vila Capixaba (CEASA)	2000	353697	7749998
RAMQAr 9	E9	Cidade Continental	2011	371218	7763588

Source: Elaborated by the authors (2022) adapted from IEMA (2021)

(expectation-maximization), through mstdi platform, implemented by Junger (2008) in R software (R Development Core Team, 2018). The missing data percentage accepted to the series of a given station be used was 35%. After imputing missing data, daily pollutant concentration averages were calculated, thus considering, for the analysed period, 3,653 PM_{10} concentration observations at stations E1, E2, E3, E4, E5, E6 and E8, and 3,653 TSP concentration observations at stations E3, E4, E5, E6 and E8.

2.3 Statistical Analyses

To analyse the studied pollutants concentrations, statistical methodologies were used in form of descriptive methods, for summary and organization data, and inferential methods, for estimation and hypotheses verification. All statistical analysis was performed at a 5% significance level using the free software R 3.4.4 (R Development Core Team, 2018).

Stationarity of a time series is related to the series development around an average (Morettin and Toloi, 2006; Wei, 2006). The non-stationarity of a time series, a very common fact, results from the presence of intrinsic factors to the studied phenomenon that are described in theoretical models as seasonal components, trends and heterogeneity of variances (Amaral, 2014). In this way, tests were applied to verify trend and seasonality to assess the need previous data treatment before analysis. For trends detection in PM_{10} and TSP concentration series, Mann-Kendall (Kendall, 1975; Mann, 1945) and Cox-Stuart (Wei, 2006) tests were used.

Assessment of periodicity existence, also called seasonality, in the series under study was carried out using Fisher's G test (Wei, 2006). Bearing in mind that this test is based on series periodicity evaluation by checking periodograms, it's necessary present some concepts regarding the spectral analysis for better understanding.

Consider $Z(t), t \in T$ a stochastic process that obeys an asymptotic independence condition of the form shown in Equation (1).

$$\sum_{\tau=-\infty}^{\infty} |\gamma(\tau)| < \infty \quad (1)$$

The Fourier transform of $\gamma(\tau)$, also called spectral density function $f(\lambda)$, is given by Equation (2).

$$f(\lambda) = \frac{1}{2\pi} \sum_{\tau=-\infty}^{\infty} \gamma(\tau) e^{-i\lambda\tau}, -\infty \leq \lambda \leq \infty \quad (2)$$

where $e^{-i\lambda} = cos\lambda + isin\lambda$, with $i = \sqrt{-1}$ and λ is equal to the frequency value that will be used to verify a period to be analyzed. Function $f(\lambda)$ is pair, periodic with period 2π and its representation is given in the interval $[0, \pi]$. Since the interest is verify periods in discrete and finite time series, the finite Fourier transform of a stationary process with zero mean, $Z_t, t = 1, ..., N$, is defined according to Equation (3).

$$d^{(N)}(\lambda) = \frac{1}{\sqrt{2\pi N}} \sum_{t=1}^{N} Z_t e^{-i\lambda\tau}, -\infty < \lambda < \infty \tag{3}$$

If $\lambda_j = \frac{2\pi j}{N}$ and $-\left[\frac{N-1}{2}\right] \leq j \leq \left[\frac{N}{2}\right]$, where j is the index of each observation of any trajectory Z_t, the discrete Fourier transform is obtained using Equation (4).

$$d_j^{(N)}(\lambda) = \frac{1}{\sqrt{2\pi N}} \sum_{t=1}^{N} Z_t e^{\left(\frac{-i2\pi jt}{N}\right)} \longrightarrow$$

$$d_j^{(N)}(\lambda) = \frac{1}{\sqrt{2\pi N}} \sum_{t=1}^{N} Z_t \cos\left(\frac{2\pi jt}{N}\right) + i\frac{1}{\sqrt{2\pi N}} \sum_{t=1}^{N} Z_t \sin\left(\frac{2\pi jt}{N}\right) \tag{4}$$

with $j = 0, 1, ..., \left[\frac{N}{2}\right]$.

For a realization of the stationary process $\{Z_t, t = 1, ..., N\}$, the aim is finding an estimator for $f(\lambda_j)$. Under asymptotic independence assumption, established according to Equation (5), one has that

$$I_j^{(N)}(\lambda) = \left|d_j^{(N)}(\lambda)\right|^2 = \frac{1}{\sqrt{2\pi N}} \left|\sum_{t=1}^{N} Z_t e^{-i\lambda jt}\right|^2 \tag{5}$$

is called periodogram, a non-additive estimator of $f(\lambda_j)$ whose asymptotic distribution is defined by Theorem 1, according to Morettin and Toloi (2006).

Theorem 1. *Periodogram ordinates $I_j^{(N)}(\lambda)$ are asymptotically independent random variables with multiple asymptotic distribution of a random variable with chi-square distribution, that is,*

$$I_j^{(N)}(\lambda) \xrightarrow{D} \left\{ \begin{array}{ll} \frac{1}{2} f(\lambda_j)\chi_2^2, & j \neq 0, \frac{N}{2}, \\ f(\lambda_j)\chi_1^2, & j = 0, \frac{N}{2}. \end{array} \right\}$$

Given the periodogram, according to Equation (5), Fisher's G test is used to verify the seasonal period of the time series under study, testing the hypotheses:

H_0: There is no seasonality, for all $I_j^{(N)}(\lambda)$;
H_1: There is seasonality for some $I_j^{(N)}(\lambda)$.

Fisher G test statistic is given by Equation (6),

$$G = \frac{max\left[I_j^{(N)}(\lambda)\right]}{\sum_{j=1}^{\left(\frac{N}{2}\right)} I_j^{(N)}(\lambda)} \tag{6}$$

where $I_j^{(N)}(\lambda)$ represents the periodogram value in ordinate j; and, N the number of observations in the series.

G exact distribution is given by $Z_\alpha = 1 - \left(\frac{\alpha}{c}\right)^{\frac{1}{c-1}}$, with $c = \frac{N}{2}$ and α beings the adopted significance level. If $G > Z$, hypothesis H_0 is rejected and the series presents periodicity in period i. Seasonal period (s) determination consists of checking which frequency is associated with the highest value $I_j^{(N)}(\lambda)$ and then dividing 1 by this frequency value, according to Equation (7). For details, see Morettin and Toloi (2006), Wei (2006) and Brockwell and Davis (2006).

$$s = \frac{1}{\lambda} \tag{7}$$

A recurring problem in practical areas of knowledge that use time series is that the use of theory about them is not always sufficient for certain studies (Amaral, 2014). Thus, the comparison of these series has great interest on time series studies collected in near locations. To carry out this analysis, were applied the tests proposed by Coates and Diggle (1986) and by Quenouille (1958), being these two univariate tests for comparing the spectral density and autocorrelation functions, respectively. The series difference procedure proposed by Silva et al. (2000) also was applied in this work.

2.3.1 Cumulative Sum Test (Coates and Diggle, 1986)

Consider the periodogram $I_j^{(N)}(\lambda)$ of $\{Z_i(t); t = 1, ..., N\}$ series, with $i = 1, 2$. Asymptotically, $I_j^{(N)}(\lambda) \sim f_j(\lambda)\chi_2^2/2, \lambda \not\equiv 0, \pi$, according to Theorem 1. Thus, the spectral ratios are defined as given by Equations (8) and (9),

$$J(\lambda) = \frac{I_1^{(N)}(\lambda)}{I_2^{(N)}(\lambda)} \tag{8}$$

$$U(\lambda) = \frac{f_1(\lambda)}{f_2(\lambda)}, 0 < \lambda < \pi \tag{9}$$

for independent $Z_1(t)$ and $Z_2(t)$, $J(\lambda) = \frac{I_1^{(N)}(\lambda)}{I_2^{(N)}(\lambda)} \sim U(\lambda)F_{2,2}$, where, F is Fisher-Snedecor distribution.

According to Coates and Diggle (1986) methodology, it is possible demonstrate like show Equation (10), that

$$z_i = ln\left(1 + J^{-1}(\lambda_j)\right) \sim U(\lambda_j)exp(1) \tag{10}$$

where $\lambda_j = \frac{2\pi j}{N}(j = 1, ..., m)$, $m = \left[\frac{(N-1)}{2}\right]$ and $exp(1)$ is the exponential distribution of mean 1.

If $f_1(\lambda)$ and $f_2(\lambda)$ are spectral density functions of $Z_1(t)$ and $Z_2(t)$ time series, respectively, the hypotheses will be tested:

H_0: $f_1(\lambda) = f_2(\lambda)$ for all $0 < \lambda < \pi$;
H_1: $f_1(\lambda) \neq f_2(\lambda)$ for all $0 < \lambda < \pi$.

Considering the H_0 hypothesis of Coates and Diggle (1986), $U(\lambda_j) = 1$ and $exp(1)$ is the exponential distribution to which the z_i random samples belong, asymptotically. Thus, $c_j = \sum_{i=1}^{j} z_i$ compose the points of a Poisson process and, therefore, the ratio $o_j = \frac{c_j}{c_m}, j = 1, ..., m$, is the vector of the statistics order of uniform distribution $[0, 1]$.

This test proposed by Coates and Diggle (1986), basically consists in constructing the o_j statistics and using the Kolmogorov-Smirnov test to evaluate deviations from $U(0, 1)$ distribution. If the p-value is greater than α, H_0 hypothesis isn't rejected, at the level of significance α. The test presented requires that the two series to be tested have same size (N).

2.3.2 Equality Autocorrelation Functions Test (Quenouille, 1958)

Equality of Autocorrelation Functions test, proposed by Quenouille (1958), has to purpose verifying if two distinct time series present the same correlation structure. For this, consider $\rho_1(j)$ and $\rho_2(j)$ the autocorrelation functions of the series $Z_1(t)$ and $Z_2(t)$, respectively. Will be tested the hypotheses:

H_0: $\rho_1(j) = \rho_2(j)$ for all $j = \pm1, \pm2, ...$,
H_1: $\rho_1(j) \neq \rho_2(j)$ for all $j = \pm1, \pm2, ...$.

The procedure for applying Quenouille (1958) proposed method consists in the following methodology, as described by Toloi and Echeverry (2000): (i) obtain the autocorrelation functions $\hat{\rho}_1(j)$ and $\hat{\rho}_2(j)$, with $j = 0, 1, ..., J$, of $Z_1(t)$ and $Z_2(t)$ series, respectively; (ii) calculate the autocorrelation function common to both series, using Equation (11), where n_1 and n_2 are the observations number of series $Z_1(t)$ and $Z_2(t)$, respectively;

$$\hat{\rho}(j) = \frac{n_1\hat{\rho}_1(j) + n_1\hat{\rho}_2(j)}{n_1 + n_2} \tag{11}$$

(iii) calculate the estimated common partial autocorrelation function $\left(\hat{\Phi}(k)\right)$, from the common autocorrelation function $(\hat{\rho}(j))$; (iv) identify the autoregressive order, p, using $\hat{\Phi}(k)$; (v) estimate the p autoregressive model coefficients solving the Yule-Walker equations. For details, see Costa (2010); (vi) adjust the autoregressive model to $Z_1(t)$ and $Z_2(t)$ series with the coefficients obtained in (v), thus finding the residual series $\hat{a}_1$ and $\hat{a}_2$; (vii) calculate the partial autocorrelation functions v_j and v'_j for the residual series $\hat{a}_1$ and $\hat{a}_2$, respectively; $(viii)$ test whether $\frac{v_j - v'_j}{\sqrt{\frac{1}{n_1-j}+\frac{1}{n_2-j}}}$ has approximately $N(0,1)$ distribution, or equivalently, test whether (Equation (12))

$$SQ = \sum_{j=1}^{J} \frac{\left(v_j - v'_j\right)^2}{\frac{1}{n_1-j} + \frac{1}{n_2-j}} \sim \chi_j^2 \tag{12}$$

(xi) if $SQ > C_\alpha$, where C_α is such that $P\left(\chi_j^2 > C_\alpha\right) = \alpha$, H_0 is reject at the significance level α.

2.3.3 Method for comparing time series (Silva, Ferreira and Sáfadi, 2000)

The procedure for comparing time series $Z_1(t)$ and $Z_2(t)$, as proposed by Silva et al. (2000), consists in taking the difference between the two series under study, as shown in Equation (13),

$$Z_d = Z_1(t) - Z_2(t), t = 1, 2, 3, ..., N \tag{13}$$

resulting in the residual series Z_d, in which applies Cox-Stuart test for verifying trends, Fisher G test for verifying seasonality and Box e Pierce test (Box and Pierce, 1970) to verify whether residuals are independent and identically distributed, with zero mean and constant variance.

If Z_d is stationary, that is, it doesn't show trend or seasonality, and residuals behave like white noise, it is concluded that the two series come from the same stochastic process, that is, are the same in the analysed period.

3 RESULTS AND DISCUSSION

For studied average hourly PM_{10} and TSP concentrations better understanding, each station descriptive statistics are presented in Table 2. For PM_{10}, the highest mean was recorded at E8 (40.31 $\mu g.m^{-3}$), followed by E1 (32.73 $\mu g.m^{-3}$), and, for TSP, the highest mean value was also found at E8 (72.14 $\mu g.m^{-3}$). All stations showed high standard deviation and coefficient of variation, suggesting that the data average is not very representative. Among PM_{10} maximum values observed, all exceeded the guidelines established by the World Health Organization (WHO, 2021) and, the maximum value recorded in E8 for PM_{10} (120.83 $\mu g.m^{-3}$) and for TSP (275.21 $\mu g.m^{-3}$) exceeded Intermediate Standard 1 (PI1) determined by CONAMA Resolution 491/2018 (CONAMA, 2018) and Intermediate Goal 1 (MI1) established by State Decree nº 3463 - R/2013 (ESPÍRITO SANTO, 2013), which is alarming, since, even though these pollutants are found in concentrations below the permitted standards, damage to human health are already observed Dapper et al. (2016); Freitas et al. (2016); Nascimento et al. (2017); WHO (2021). Asymmetry and kurtosis coefficients suggest that the series under study do not belong to a normal probabilities distribution.

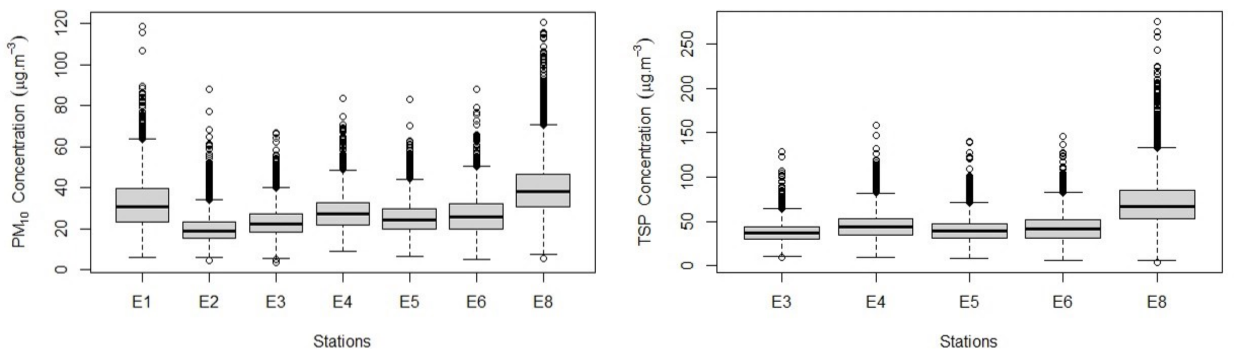
Table 2 – Descriptive measures of the PM_{10} and TSP concentrations

Descriptive measures	PM_{10} Stations							TSP Stations				
	E1	E2	E3	E4	E5	E6	E8	E3	E4	E5	E6	E8
Mean ($\mu g.m^{-3}$)	32.73	20.35	23.45	28.15	25.48	26.93	40.31	45.22	38.38	40.15	43.32	72.14
Median ($\mu g.m^{-3}$)	31.04	19.12	22.61	27.21	21.42	25.96	38.34	43.96	37.08	39.08	41.21	67.32
Standard deviation ($\mu g.m^{-3}$)	13.17	7.28	7.43	8.74	8.08	9.54	15.22	15.55	11.99	14.23	16.58	31.31
Coefficient of variation (%)	40.23	35.81	31.67	31.06	31.70	35.43	37.75	34.38	31.25	35.43	38.27	43.41
Maximum ($\mu g.m^{-3}$)	118.79	88.25	66.88	83.58	83.12	88.13	120.83	157.79	128.79	139.92	146.04	275.21
Minimum ($\mu g.m^{-3}$)	5.97	4.42	3.54	8.83	6.79	5.00	5.50	9.12	10.08	8.75	6.45	3.63
Asymmetry	1.00	1.83	0.95	0.95	1.03	0.95	1.19	1.11	1.32	1.14	0.99	1.30
Kurtosis	1.93	6.87	2.00	2.14	2.21	2.08	2.63	3.09	4.36	3.45	1.83	3.26

Source: Elaborated by the authors (2022)

Figures 2 (a) and 2 (b) outline the spatial variation between PM_{10} and TSP concentrations, respectively. Can be seen that E8 stands out for presenting higher values for both pollutants. For PM_{10}, in addition to E8, E1 is significantly different from other stations. Regarding the TSP monitoring, E3 has the lowest monitored concentrations of the pollutant, and stations E4, E5 and E6 have similar values.

Figure 2 – Time series boxplot for each station observed in relation to the spatial distribution for pollutants (a) PM_{10} and (b) TSP.



(a) (b)

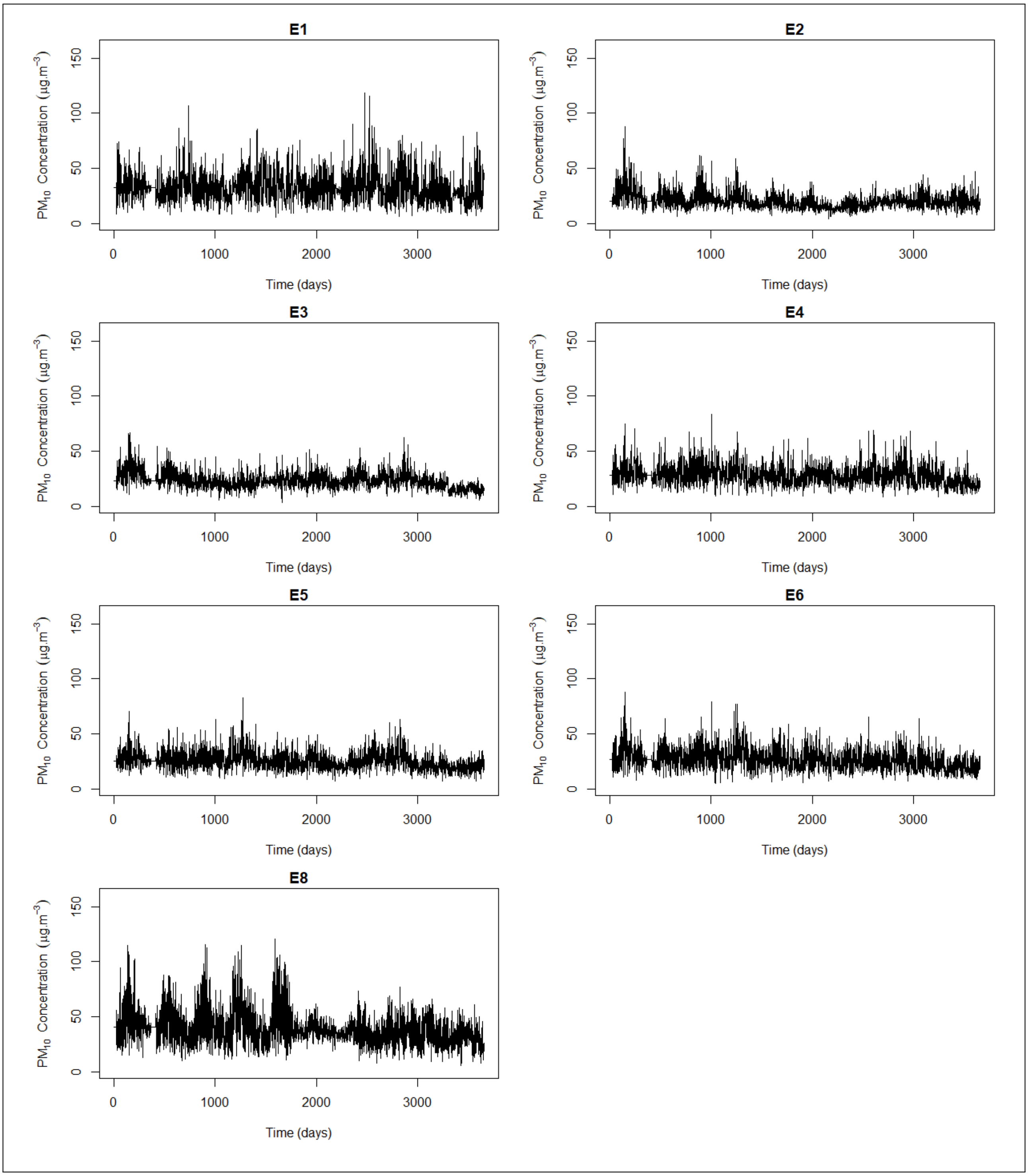
Source: Elaborated by the authors (2022)

It's possible visualize that all stations presented outliers, that are basically the data points not near to other data points. They are uncommon values in a dataset indicative atypical concentration levels (Khan et al., 2022; Torres et al., 2020), above average standard of data set, which, in air pollution time series can occur due to excessive emissions from pollution sources, in short periods of time, or due to adverse weather conditions (Sgrancio, 2015). PM_{10} and TSP high average values and maximum concentration for E8 are associated with its location in RGV, because it's near to Espírito Santo Supply Centers (CEASA/ES), where is an intense flow of vehicles and, consequently, a higher level of pollution due to emission from vehicle combustion process and, also, the resuspension of pollutants.

Figures 3 and 4 show PM_{10} and TSP time evolution series for stations under study. Performing a visual analysis, it is possible to verify that the series behaviour of analysed pollutants was of stability, presenting, however, a slight tendency of decay, mainly, in last years, hypothesis confirmed by Mann Kendell and Cox-Stuart tests.

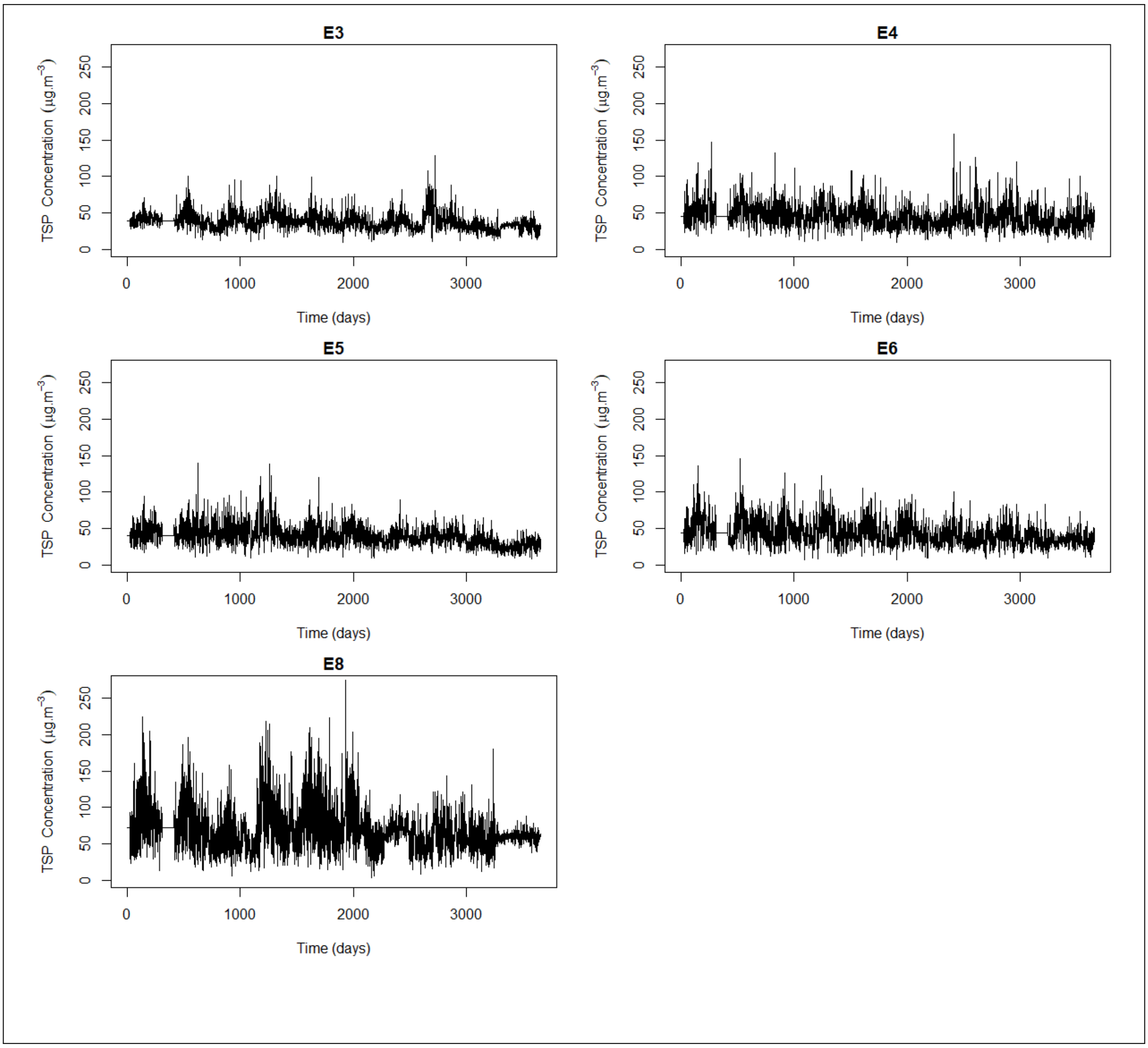
According to Mann-Kendal and Cox-Stuart trend tests results, in all seasons and, for both pollutants, there is a negative trend at 5% significance level, that is, there was a decrease in concentrations along the time. Such reduction tendency in PM_{10} and TSP concentrations suggest that more restrictive measures imposed by Decree 3463 - R/2013 ESPÍRITO SANTO (2013) in relation to federal legislation in force in that period, influenced pollutant concentrations reduction. Similar results are found in Ramachandra and Shwetmala (2009), Nesamani (2010), Petro and Konečný (2017), Oliveira (2017) and Abe and Miraglia (2018) studies, which show the relationship between adoption of programs to control air pollution and decreased main air pollutants concentration levels.

Figure 3 – PM_{10} time evolution series in each RAMQAr station



Source: Elaborated by the authors (2022)

Figure 4 – TSP time evolution series in each RAMQAr station

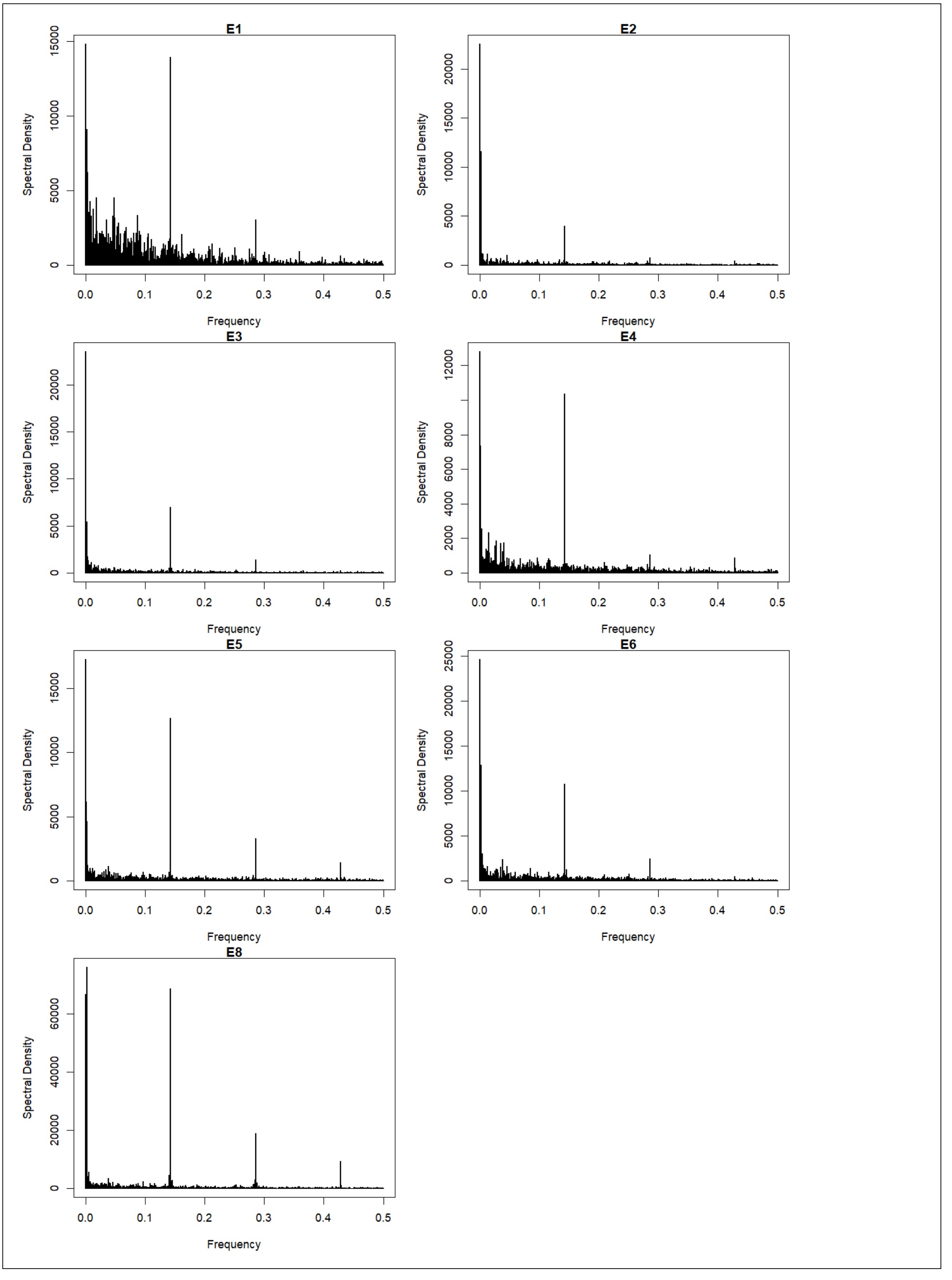


Source: Elaborated by the authors (2022)

It is also important analyse the seasonality component, in order to understand PM_{10} and TSP concentrations behaviour over time and possible factors responsible for their emissions. Normally, natural phenomena data show oscillations that are repeated in a certain identical period of time. Thus, to verify the data seasonality property, PM_{10} and TSP series spectral decomposition was performed, as shown in Figures 5 and 6.

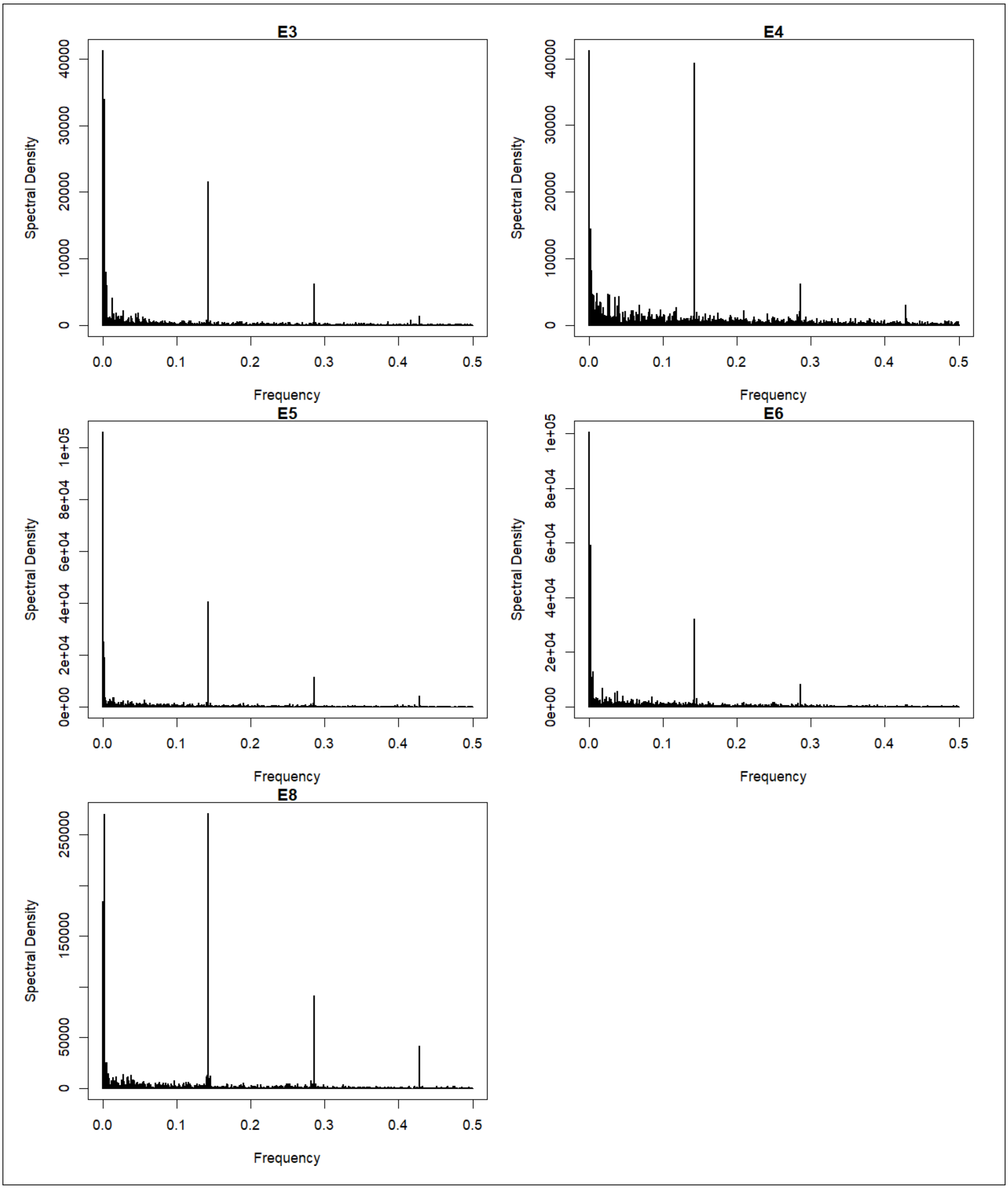
PM_{10} periodogram (Figure 5) shows that the highest peak is associated with the 0.14293 frequency in all seven stations studied, which implies $s = \frac{1}{0.14293} = 6.99$, that is, a seasonal component with 7 days periodicity. According to Fisher's G test results, in all

Figure 5 – PM_{10} series periodograms for each RAMQAr station



Source: Elaborated by the authors (2022)

Figure 6 – TSP series periodograms for each RAMQAr station



Source: Elaborated by the authors (2022)

seasons G value is higher than Z, therefore, H_0 hypothesis is rejected, confirming seasonality existence with 7 days periods at 5% nominal significance level. Seasonality presence analysis in TSP data can be done through Figure 6 and, as in PM_{10} periodogram, the time series showed the highest peak at 0.14293 frequency, implying a behavior repeating pattern with a 7 days period. Fisher's G test application proved seasonality existence for this period in all seven seasons under study for TSP.

This behaviour presented by both pollutants is expected because, according to RGV atmospheric emissions inventory, the main source of particulate matter in the region are motor vehicles, representing approximately 70% of emissions, resulting from particles resuspension at road (ECOSOFT, 2019). Thus, seasonal variation presented can be explained by transport movement pace, that is, PM_{10} and TSP highest concentrations measured, occur during working days, when vehicles flow are greater, and the opposite occurs at weekends, due to vehicular circulation reduction through the streets.

Celis et al. (2007) found a similar result for the city of Chillán, Chile, where the concentration of PM_{10} was 40% higher on weekdays (Monday to Friday) than on weekends, reflecting the influence of anthropogenic activity such as traffic, construction works, and industrial processes, which are generally more intense on weekdays. According to the authors, city traffic strongly contributes to this variation through the elevation of dust from the streets and the release of fine particles from combustion engine exhaust.

Stadlober et al. (2008) fitted multiple linear regression models combining information from the current day with meteorological forecasts for the next day to predict daily PM_{10} concentrations for the provinces of South Tyrol, Carinthia, and Styria. This approach was adopted because in winter, unfavorable dispersion conditions lead to above-average PM_{10} concentrations in these locations. According to the authors, special emphasis was placed on selecting appropriate predictor variables readily available as measured values, factors, or suitable meteorological forecasts. One of the factors used was the impact of human activity, reflected by the differences in PM_{10} concentration between weekdays and weekends. As indicated by the authors, there is a significant reduction in concentration on Sundays and holidays in the three cities, most likely associated with a decrease in traffic load.

Leite et al. (2011) conducted a study analyzing the atmospheric air quality in Uberlândia, Minas Gerais, using simple logistic regression models. The authors found that in the analysis of air quality based on the days of the week when the data were collected, only Saturday and Sunday showed a significant relationship. Based on the Odds Ratio results, it can be concluded that on Sunday, there is a 2.194 times greater chance of having good air quality compared to the other days of the week, while on Saturday, this chance was three times greater. According to the authors, this result can be explained by the fact that vehicle movement is less intense on weekends.

Reina and Olaya (2012) characterized the behavior of PM_{10} in the air throughout a day, taking into account the day of the week and precipitation levels in Cali, Colombia, using a non-parametric smoothing model. Based on the study, it was observed that PM_{10} concentrations show a conditioned behavior based on the day of the week. According to the authors, Mondays are characterized by presenting low pollution in the early hours of the morning, in harmony with the reduction of work activities and the exodus of people from the previous day. Meanwhile, PM_{10} pollution levels are higher from Tuesday to Saturday, related to increased work activities and vehicular traffic. On Sundays and holidays, PM_{10} concentrations are low starting from 10 a.m., most likely due to the cessation of work activities and reduced vehicular flow.

Monte et al. (2016) examined the impacts of meteorological variables such as temperature, relative humidity, wind speed, and precipitation on air quality in the Greater Vitória Region, Espírito Santo, Brazil, considering PM_{10}, using the Logit model from January 2005 to December 2010. Air quality was classified as "non-good" and "good". The authors also estimated the effects of the days of the week and the seasons on the probability of "non-good" air quality occurrences. According to the results, on Tuesdays, Wednesdays, Thursdays, and Fridays, the probability of "non-good" air quality was much higher than on weekends (Sunday and Saturday). For example, on Sunday, the chance of "non-good" air quality decreased by 15.44 percentage points. On the other hand, on Friday, the probability of "non-good" air quality increased by 9.61 percentage points. According to the authors, the lower probability of "non-good" air quality on weekends was expected, as Saturdays and Sundays see a reduction in industrial production, logistics services, and a decrease in vehicle circulation.

Tables 3 and 4 show, respectively, means comparison tests results applied for all combinations between studied stations for PM_{10} and TSP pollutants. In order for the series compared between two stations be considered to come from different stochastic processes, was adopted the condition that at least two tests must have the same result, that is, among the three tests applied, two must be should agree, for H_0 rejection condition.

Analysing the presented result, series measured in E1 is, statistically different, from series measured in other stations with which was compared, that is, time series comparison tests results showed p-value lower than adopted significance level, indicating that E1 series is generated by a stochastic process different from the other RAMQAR stations. According to IEMA (2021), this can be explained by the fact that E1, in addition to receiving direct influences from Ponta de Tubarão industries, when South winds occur, is the only one belonging to RAMQAr that covers areas under influence of CIVIT (Vitória Industrial Center) industries, when there are Northeast winds competition, main direction taken by winds in the Region (for more details, see IEMA (2021), p. 26). Also is possible observe that E8 presented a time series statistically different from other stations to which was compared, except E5. This is basically due to the fact that E8 covers areas directly influenced by vehicular emissions, because is located near to CEASA, a place characterized by intense vehicular traffic.

After tests application, was verified that the monitoring performed in E2 just for PM_{10} and E3, E4, E5 and E6 for PM_{10} and TSP data, when compared to each other, are generated by the same stochastic process, which suggests that these stations, despite operating in different RGV locations, follow similar patterns or random behaviors over time. Although the series may have different specific values at each point in time, they exhibit similar statistical characteristics, such as trends, seasonalities, variations, and correlations.

Table 3 – PM_{10} time series comparison tests results

Stations	COATES & DIGGLE	QUENOUILLE	SANTOS et al.
$E1 \times E2$	3.230×10^{-8}	7.429×10^{-5}	2.220×10^{-16}
$E1 \times E3$	3.863×10^{-6}	9.102×10^{-3}	2.220×10^{-16}
$E1 \times E4$	2.738×10^{-5}	5.936×10^{-1}	2.220×10^{-16}
$E1 \times E5$	1.182×10^{-8}	1.677×10^{-7}	2.220×10^{-16}
$E1 \times E6$	1.912×10^{-4}	8.859×10^{-1}	2.220×10^{-16}
$E1 \times E8$	3.737×10^{-5}	2.220×10^{-16}	2.220×10^{-16}
$E2 \times E1$	4.359×10^{-5}	7.429×10^{-5}	2.220×10^{-16}
$E2 \times E3$	2.778×10^{-1}	9.999×10^{-1}	2.220×10^{-16}
$E2 \times E4$	2.778×10^{-1}	9.999×10^{-1}	2.220×10^{-16}
$E2 \times E5$	4.252×10^{-1}	9.886×10^{-1}	2.220×10^{-16}
$E2 \times E6$	1.366×10^{-1}	9.856×10^{-1}	2.220×10^{-16}
$E2 \times E8$	9.754×10^{-1}	1.411×10^{-5}	2.220×10^{-16}
$E3 \times E1$	4.774×10^{-3}	9.102×10^{-3}	2.220×10^{-16}
$E3 \times E2$	4.598×10^{-2}	9.999×10^{-1}	2.220×10^{-16}
$E3 \times E4$	3.570×10^{-1}	9.999×10^{-1}	2.220×10^{-16}
$E3 \times E5$	5.502×10^{-2}	9.980×10^{-1}	2.220×10^{-16}
$E3 \times E6$	5.266×10^{-1}	9.944×10^{-1}	2.220×10^{-16}
$E3 \times E8$	3.789×10^{-1}	1.928×10^{-4}	2.220×10^{-16}
$E4 \times E1$	1.039×10^{-2}	5.936×10^{-1}	2.220×10^{-16}
$E4 \times E2$	2.613×10^{-2}	9.999×10^{-1}	2.220×10^{-16}
$E4 \times E3$	5.502×10^{-2}	9.999×10^{-1}	2.220×10^{-16}
$E4 \times E5$	1.286×10^{-2}	9.059×10^{-1}	2.220×10^{-16}
$E4 \times E6$	8.476×10^{-1}	1.000×10^{-1}	2.220×10^{-16}
$E4 \times E8$	7.195×10^{-1}	7.164×10^{-5}	2.220×10^{-16}
$E5 \times E1$	8.905×10^{-6}	1.647×10^{-7}	2.220×10^{-16}
$E5 \times E2$	8.699×10^{-1}	9.886×10^{-1}	2.220×10^{-16}
$E5 \times E3$	1.366×10^{-1}	9.980×10^{-1}	2.220×10^{-16}
$E5 \times E4$	9.186×10^{-2}	9.059×10^{-1}	2.220×10^{-16}
$E5 \times E6$	3.168×10^{-2}	6.189×10^{-1}	2.220×10^{-16}
$E5 \times E8$	7.467×10^{-1}	5.627×10^{-1}	2.220×10^{-16}
$E6 \times E1$	5.502×10^{-2}	8.859×10^{-1}	2.220×10^{-16}
$E6 \times E2$	5.044×10^{-4}	9.856×10^{-1}	2.220×10^{-16}
$E6 \times E3$	1.837×10^{-3}	9.944×10^{-1}	2.220×10^{-16}
$E6 \times E4$	5.266×10^{-1}	1.000×10^{-1}	2.220×10^{-16}
$E6 \times E5$	1.110×10^{-3}	6.189×10^{-1}	2.220×10^{-16}
$E6 \times E8$	1.169×10^{-1}	2.399×10^{-4}	2.220×10^{-16}
$E8 \times E1$	2.340×10^{-5}	2.220×10^{-16}	2.220×10^{-16}
$E8 \times E2$	5.044×10^{-4}	1.411×10^{-5}	2.220×10^{-16}
$E8 \times E3$	2.348×10^{-3}	2.232×10^{-4}	2.220×10^{-16}
$E8 \times E4$	3.570×10^{-1}	7.164×10^{-5}	2.220×10^{-16}
$E8 \times E5$	2.917×10^{-4}	5.627×10^{-1}	2.220×10^{-16}
$E8 \times E6$	2.601×10^{-1}	2.399×10^{-4}	2.220×10^{-16}

Source: Elaborated by the authors (2022)

Table 4 – TSP time series comparison tests results

Stations	COATES & DIGGLE	QUENOUILLE	SANTOS et al.
$E3 \times E4$	1.234×10^{-5}	9.568×10^{-6}	$< 2.220 \times 10^{-16}$
$E3 \times E5$	2.220×10^{-16}	1.688×10^{-14}	$< 2.220 \times 10^{-16}$
$E3 \times E6$	5.910×10^{-5}	$< 2.220 \times 10^{-16}$	$< 2.220 \times 10^{-16}$
$E3 \times E8$	2.220×10^{-16}	2.220×10^{-16}	$< 2.220 \times 10^{-16}$
$E4 \times E3$	2.220×10^{-16}	9.568×10^{-6}	$< 2.220 \times 10^{-16}$
$E4 \times E5$	2.220×10^{-16}	3.404×10^{-4}	$< 2.220 \times 10^{-16}$
$E4 \times E6$	2.220×10^{-16}	3.462×10^{-9}	$< 2.220 \times 10^{-16}$
$E4 \times E8$	7.979×10^{-5}	8.329×10^{-11}	$< 2.220 \times 10^{-16}$
$E5 \times E3$	2.220×10^{-16}	1.684×10^{-14}	$< 2.220 \times 10^{-16}$
$E5 \times E4$	2.220×10^{-16}	3.404×10^{-4}	$< 2.220 \times 10^{-16}$
$E5 \times E6$	2.220×10^{-16}	2.327×10^{-1}	$< 2.220 \times 10^{-16}$
$E5 \times E8$	2.220×10^{-16}	3.696×10^{-7}	$< 2.220 \times 10^{-16}$
$E6 \times E3$	2.220×10^{-16}	$< 2.220 \times 10^{-16}$	$< 2.220 \times 10^{-16}$
$E6 \times E4$	2.220×10^{-16}	3.462×10^{-9}	$< 2.220 \times 10^{-16}$
$E6 \times E5$	2.220×10^{-16}	2.327×10^{-1}	$< 2.220 \times 10^{-16}$
$E6 \times E8$	5.033×10^{-2}	1.968×10^{-4}	$< 2.220 \times 10^{-16}$
$E8 \times E3$	2.220×10^{-16}	$< 2.220 \times 10^{-16}$	$< 2.220 \times 10^{-16}$
$E8 \times E4$	2.220×10^{-16}	8.329×10^{-11}	$< 2.220 \times 10^{-16}$
$E8 \times E5$	2.220×10^{-16}	3.696×10^{-7}	$< 2.220 \times 10^{-16}$
$E8 \times E6$	2.220×10^{-16}	1.968×10^{-4}	$< 2.220 \times 10^{-16}$

Source: Elaborated by the authors (2022)

Similar results are presented by Zamprogno et al. (2020) that, aiming to identify redundant particulate matter measurements in RGV using Principal Component Analysis (PCA) from January 2005 to December 2009 found that, for the eight stations that comprise de RGV monitoring network, only three (namely: Ibes, Laranjeiras and Jardim Camburi) would be maintained cause the other five presented similar patterns and, the authors suggest move the equipment of these five stations to alternative areas of interest to cover a larger area of the RGV. Cotta et al. (2020) applies robust PCA to identify air quality monitoring stations that present similar behavior in the management of the automaticair quality monitoring network of the RGV to PM_{10} between 2005 and 2009. It was found by the authors that Ibes, Enseadado Suá, and Vitória Centro presented a similar behavior and thus can be grouped. Also, Jardim

Camburi and Enseada do Suá form another group. Therefore, two stations, Vitória Centro and Enseada do Suá, are the candidates to be moved to a newsite to provide a better use of public resources and to enlarge the monitored area.

Based on this results and analysis, it's suggested that the monitoring equipments of PM_{10} in E2 station and the monitoring equipments of PM_{10} and TSP for E3, E5 and E6 stations may be selected to be moved to a new area to enlarge the total monitored area by RAMQAr. It is highlighted that although E4 station results being generated by the same stochastic process that E2, E3, E5 and E6, it's important to have, at last one station located in Vitória municipality and, the E4 station it's presented by IEMA (2021) as the main station in the installed monitoring network, as it is strategically located in the RGV, providing a large spatial coverage area. Furthermore, it is directly influenced by emissions from the industrial sources at Ponta de Tubarão and by mobile sources converging into that natural corridor of the region IEMA (2021), therefore, E4 must be kept.

The statistical similarity between two temporal series of the same variable measured at different locations is crucial for understanding common patterns, conducting comparative analyses, and making forecasts and valid inferences in diverse contexts. This similarity allows researchers to generalize results from one location to others with similar properties, enabling evidence-based decision-making and efficient resource utilization. It aids in identifying potential causal relationships between variables in different locations and supports regional and comparative studies for various issues (Toloi and Echeverry, 2000). While statistical similarity provides valuable insights, it is essential to remember that it does not imply direct causality, and further analyses may be necessary to identify specific causal relationships. Overall, this similarity enhances the understanding of phenomena, facilitates reliable projections, and informs informed decision-making.

However, it is essential to emphasize that stochastic similarity between two or more temporal series does not provide detailed information about the nature of pollution sources in a region. To confirm that monitoring stations in different locations are indeed observing the same pollution source and gain a better understanding of the situation, more detailed analyses are required, such as dispersion modelling or source apportionment studies, for instance. These approaches can help differentiate between different sources and identify the relative contribution of each one to the PM_{10} and TSP concentration at each monitoring station, like was done in Santos et al. (2017), Galvão et al. (2019) and Monticelli et al. (2020).

4 CONCLUSION

This work evaluated PM_{10} and TSP daily average concentrations measured in different RGV monitoring stations, Espírito Santo state, Southeastern Brazil, through application of descriptive and inferential statistical methods, between 2008 and 2017, to detect whether the concentration pollutants time series are generated by the same stochastic process.

Regarding the particles time series analysis, was possible observe that the concentrations of both pollutants sometimes exceeded the limits established by both state and national standards, as well as by international guidelines, a fact that must be treated with attention, considering that even in low concentrations, mainly PM_{10}, has potential to cause adverse health effects. Among sources, motor vehicle traffic is presented as the main contributor to respirable particles and total particles in suspension emission at RGV.

However, a decreasing trend in pollutant concentrations has also been observed for all stations in recent years, which suggests that to improve air quality, more restrictive measures should be taken in relation to atmospheric contaminants emission limits, as in the case of State Decree 3463-R/2013.

According to the found results by time series comparison tests applied in this study, stations E2, only for pollutant PM_{10}, and E3, E4, E5 and E6, for pollutants PM_{10} and TSP, when compared to each other, were generated by the same stochastic process, therefore monitoring equipments of PM_{10} in E2 station and the monitoring equipments of PM_{10} and TSP for E3, E5 and E6 stations may be selected to be moved to a new area to enlarge the total monitored area by RAMQAr.

Thus, the present work can be used as an indication of need to reanalysis the initial RAMQAr project, stating whit the relocating of PM_{10} and TSP monitoring equipments. However, to choose the new locations to receive this equipments, in order to expand RAMQAr coverage area, a contaminants dispersion study must be carried out in order to guide pollutants monitoring, since a dispersion study makes possible verify their behavior in atmosphere and the scope of environmental impact. In addition, is suggested study the need to expand the network to cover entire RGV, with emphasis to Viana municipality that, actually, integrates RGV and does not have any stations for monitoring air quality, providing an even more reliable and adequate database to be used in planning and managing studies and strategies related to air pollution control, in order to minimize and/or prevent possible harmful population and the environment impacts.

For future works, it is suggested to apply the time series comparison methodologies used in this study to other pollutants monitored by RAMQAr, as well as to conduct statistical analyses of comparison and trend for a more recent data period, including the Covid-19 pandemic, in order to verify if this event has altered, in any way, the stochastic structure of the monitored series in the RGV.

REFERENCES

Abe, K. C. and Miraglia, S. G. K. (2018). Avaliação de impacto à saúde do Programa de Controle de Poluição do Ar por veículos automotores no município de São Paulo, Brasil. *Revista Brasileira de Ciências Ambientais (Online)*, (47):61–73. DOI: 10.5327/z2176-947820180310.

Amaral, M. V. S. G. (2014). Ajuste de modelos e comparação de séries temporais para dados de vazão específica em microbacias pareadas. Mestrado em ciências, Escola Superior de Agricultura Luiz de Queiroz, Universidade de São Paulo, Piracicaba, São Paulo.

Béjot, Y., Reis, J., Giroud, M., and Feigin, V. (2018). A review of epidemiological research on stroke and dementia and exposure to air pollution. *International Journal of Stroke*, 13(7):687–695. DOI: 10.1177/1747493018772800.

Bowe, B., Xie, Y., Li, T., Yan, Y., Xian, H., and Al-Aly, Z. (2018). The 2016 global and national burden of diabetes mellitus attributable to $PM_{2.5}$ air pollution. *The Lancet Planetary Health*, 2(7):e301–e312. DOI: 10.1016/s2542-5196(18)30140-2.

Box, G. E. P. and Pierce, D. A. (1970). Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models. *Journal of the American Statistical Association*, 65(332):1509–1526. DOI: 10.1080/01621459.1970.10481180.

Brockwell, P. and Davis, R. (2006). *Time Series: Theory and Methods*. Springer, New York, 2 edition.

Calderón-Garcidueñas, L., Leray, E., Heydarpour, P., Torres-Jardón, R., and Reis, J. (2016). Air pollution, a rising environmental risk factor for cognition, neuroinflammation and neurodegeneration: The clinical impact on children and beyond. *Revue Neurologique*, 172(1):69–80. DOI: 10.1016/j.neurol.2015.10.008.

Celis, J. E., Morales, J. R., Zaror, C. A., and Carvacho, O. F. (2007). Contaminación del aire atmosférico por Material Particulado en una ciudad intermedia: El caso de Chillán (Chile). *Información tecnológica*, 18(3). DOI: 10.4067/s0718-07642007000300007.

Coates, D. S. and Diggle, P. J. (1986). Tests for comparing two estimated spectral densities. *Journal of Time Series Analysis*, 7(1):7–20. DOI: 10.1111/j.1467-9892.1986.tb00482.x.

CONAMA (2018). Resolução nº 491, de 19 de novembro de 2018. Dispõe sobre padrões de qualidade do ar. Technical report, Brasília.

Costa, F. M. (2010). Comparação estatística de duas séries de Material Particulado (MP_{10}) na cidade de São Paulo. Mestrado em estatística e experimentação agronômica, Universidade Federal de Lavras, Lavras, Minas Gerais.

Costa, F. M. and Sáfadi, T. (2010). Comparação estatística de duas séries de Material Particulado (MP_{10}) na cidade de São Paulo. *Revista Brasileira de Biometria*, 28(3):23–38.

Cotta, H. H. A., Reisen, V. A., Bondon, P., and Filho, P. R. P. (2020). Identification of redundant air quality monitoring stations using Robust Principal Component Analysis. *Environmental Modeling & Assessment*, 25(4):521–530. DOI: 10.1007/s10666-020-09717-7.

Dapper, S. N., Spohr, C., and Zanini, R. R. (2016). Poluição do ar como fator de risco para a saúde: uma revisão sistemática no estado de São Paulo. *Estudos Avançados*, 30(86):83–97. DOI: 10.1590/s0103-40142016.00100006.

ECOSOFT (2019). Inventário de emissões atmosféricas da região da grande vitória ano base - 2015. Technical report, Vitória.

ESPÍRITO SANTO (2013). Decreto no 3463-r, de 16 de dezembro de 2013. Technical report, Vitória.

Freitas, C. U., Leon, A. P., Junger, W., and Gouveia, N. (2016). Air pollution and its impacts on health in Vitoria, Espirito Santo, Brazil. *Revista de Saúde Pública*, 50(0). DOI: 10.1590/s1518-8787.2016050005909.

Galvão, E. S., Reis, N. C., Lima, A. T., Stuetz, R. M., Orlando, M. T. D., and Santos, J. M. (2019). Use of inorganic and organic markers associated with their directionality for the apportionment of highly correlated sources of particulate matter. *Science of The Total Environment*, 651:1332–1343. DOI: 10.1016/j.scitotenv.2018.09.263.

Hamanaka, R. B. and Mutlu, G. M. (2018). Particulate Matter Air Pollution: Effects on the Cardiovascular System. *Frontiers in Endocrinology*, 9. DOI: 10.3389/fendo.2018.00680.

IBGE (2023). Panorama do Censo 2022. Technical report, Rio de Janeiro.

IEMA (2018). Qualidade do ar. Technical report, Vitória.

IEMA (2021). Relatório da qualidade do ar da Região da Grande Vitória - 2021. Technical report, Vitória.

Junger, W. L. (2008). *Análise, imputação de dados e interfaces computacionais em estudos de séries temporais epidemiológicas*. Doutorado em saúde coletiva, Instituto de Medicina Social, Universidade do Estado do Rio de Janeiro, Rio de Janeiro.

Kendall, M. (1975). *Rank Correlation Methods*. Charles Griffin, London.

Khan, N. U., Shah, M. A., Maple, C., Ahmed, E., and Asghar, N. (2022). Traffic flow prediction: An intelligent scheme for forecasting traffic flow using air pollution data in smart cities with bagging ensemble. *Sustainability*, 14(7):4164. DOI: 10.3390/su14074164.

Köppen, W. (1900). Versuch einer klassifikation der klimate, vorzugsweise nach ihren beziehungen zur pflanzenwelt. *Geographische Zeitschrift*, 6(12):657–679.

Leite, R. C. M., Guimarães, E. C., de Lima, E. A. P., de Souza Barrozo, M. A., and Tavares, M. (2011). Utilização de regressão logística simples na verificação da qualidade do ar atmosférico de Uberlândia. *Engenharia Sanitaria e Ambiental*, 16(2):175–180. DOI: 10.1590/s1413-41522011000200011.

Mann, H. B. (1945). Nonparametric Tests Against Trend. *Econometrica*, 13(3):245. DOI: 10.2307/1907187.

Monte, E. Z., de Almeida Albuquerque, T. T., and Reisen, V. A. (2016). Impactos das Variáveis Meteorológicas na Qualidade do Ar da Região da Grande Vitória, Espírito Santo, Brasil. *Revista Brasileira de Meteorologia*, 31(4):546–554. DOI: 10.1590/0102-7786312314b20150100.

Monticelli, D. d. F., Santos, J. M., Dourado, H. O., Moreira, D. M., and Jr, N. C. R. (2020). Assessing particle dry deposition in an urban environment by using dispersion models. *Atmospheric Pollution Research*, 11(1):1–10. DOI: 10.1016/j.apr.2019.07.010.

Moreira, D. M., Tirabassi, T., and de Moraes, M. R. (2008). Meteorologia e poluição atmosférica. *Ambiente & Sociedade*, 11(1):1–13. DOI: 10.1590/s1414-753x2008000100002.

Morettin, P. and Toloi, C. (2006). *Análise de Séries Temporais*. Edgard. Blücher, São Paulo, 2ª edition.

Nascimento, A. P., Santos, J. M., Mill, J. G., de Souza, J. B., Júnior, N. C. R., and Reisen, V. A. (2017). Association between the concentration of fine particles in the atmosphere and acute respiratory diseases in children. *Revista de Saúde Pública*, 51(0). DOI: 10.1590/s1518-8787.2017051006523.

Nesamani, K. (2010). Estimation of automobile emissions and control strategies in India. *Science of The Total Environment*, 408(8):1800–1811. DOI: 10.1016/j.scitotenv.2010.01.026.

Oliveira, L. M. d. (2017). Contribuição do programa Despoluir para a redução das emissões atmosféricas pela frota de ônibus da Região Metropolitana de Natal. Mestrado em uso sustentável de recursos naturais, Instituto Federal de Educação, Ciência e Tecnologia do Rio Grande do Norte, Rio Grande do Norte.

Petro, F. and Konečný, V. (2017). Calculation of emissions from transport services and their use for the internalisation of external costs in road transport. *Procedia Engineering*, 192:677–682. DOI: 10.1016/j.proeng.2017.06.117.

Pires, J., Sousa, S., Pereira, M., Alvim-Ferraz, M., and Martins, F. (2008). Management of air quality monitoring using principal component and cluster analysis—part I: SO_2 and PM_{10}. *Atmospheric Environment*, 42(6):1249–1260. DOI: 10.1016/j.atmosenv.2007.10.044.

Pooley, F. D. and Mille, M. (1999). *Composition of Air Pollution Particles*, pages 619–634. Academic Press, London.

Quenouille, M. H. (1958). The Comparison of Correlations in Time-Series. *Journal of the Royal Statistical Society: Series B (Methodological)*, 20(1):158–164.

R Development Core Team (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria.

Raaschou-Nielsen, O., Beelen, R., Wang, M., Hoek, G., Andersen, Z., Hoffmann, B., Stafoggia, M., Samoli, E., Weinmayr, G., Dimakopoulou, K., Nieuwenhuijsen, M., Xun, W., Fischer, P., Eriksen, K., Sørensen, M., Tjønneland, A., Ricceri, F., de Hoogh, K., Key, T., Eeftens, M., Peeters, P., de Mesquita, H. B., Meliefste, K., Oftedal, B., Schwarze, P., Nafstad, P., Galassi, C., Migliore, E., Ranzi, A., Cesaroni, G., Badaloni, C., Forastiere, F., Penell, J., Faire, U. D., Korek, M., Pedersen, N., Östenson, C.-G., Pershagen, G., Fratiglioni, L., Concin, H., Nagel, G., Jaensch, A., Ineichen, A., Naccarati, A., Katsoulis, M., Trichpoulou, A., Keuken, M., Jedynska, A., Kooter, I., Kukkonen, J., Brunekreef, B., Sokhi, R., Katsouyanni, K., and Vineis, P. (2016). Particulate Matter air pollution components and risk for lung cancer. *Environment International*, 87:66–73. DOI: 10.1016/j.envint.2015.11.007.

Ramachandra, T. and Shwetmala (2009). Emissions from India's transport sector: Statewise synthesis. *Atmospheric Environment*, 43(34):5510–5517. DOI: 10.1016/j.atmosenv.2009.07.015.

Raz, R., Roberts, A. L., Lyall, K., Hart, J. E., Just, A. C., Laden, F., and Weisskopf, M. G. (2015). Autism Spectrum Disorder and Particulate Matter Air Pollution before, during, and after Pregnancy: A nested case–control analysis within the nurses' health study II cohort. *Environmental Health Perspectives*, 123(3):264–270. DOI: 10.1289/ehp.1408133.

Reina, J. and Olaya, J. (2012). Curve fitting nonparametric methods for studying behavior from air pollution PM_{10}. *Revista EIA*, (18):19–31.

Santos, J. M., Reis, N. C., Galvão, E. S., Silveira, A., Goulart, E. V., and Lima, A. T. (2017). Source apportionment of settleable particles in an impacted urban and industrialized region in Brazil. *Environmental Science and Pollution Research*, 24(27):22026–22039. DOI: 10.1007/s11356-017-9677-y.

Seinfeld, J. H. and Pandis, S. N. (2006). *Atmospheric chemistry and physics: from air pollution to climate change*. John Wiley & Sons, Chichester.

Sgrancio, A. M. (2015). *Análise fatorial em series temporais com long-memory, outliers e sazonalidade : aplicação em poluição do ar na região da Grande Vitória-ES*. Doutorado em engenharia ambiental, Universidade Federal do Espírito Santo, Vitória.

Silva, R. B. V., Ferreira, D. F., and Sáfadi., T. (2000). Modelos de séries temporais aplicados à série dos índices de preços ao consumidor na região de Lavras, MG, no período de 1992 a 1999. *Organizações Rurais & Agroindustriais*, 2(2):44–55.

Stadlober, E., Hörmann, S., and Pfeiler, B. (2008). Quality and performance of a PM_{10} daily forecasting model. *Atmospheric Environment*, 42(6):1098–1109. DOI: 10.1016/j.atmosenv.2007.10.073.

Toloi, C. M. C. and Echeverry, G. (2000). Testes para comparação de séries temporais: uma aplicação a séries de temperatura e salinidade da água, medidas em profundidades diferentes. *Revista Brasileira de Estatística*, 61(215):51–80.

Torres, J. M., Pérez, J. P., Val, J. S., McNabola, A., Comesaña, M. M., and Gallagher, J. (2020). A functional data analysis approach for the detection of air pollution episodes and outliers: A case study in Dublin, Ireland. *Mathematics*, 8(2):225. DOI: 10.3390/math8020225.

Vardoulakis, S. and Kassomenos, P. (2008). Sources and factors affecting PM_{10} levels in two European cities: Implications for local air quality management. *Atmospheric Environment*, 42(17):3949–3963. DOI: 10.1016/j.atmosenv.2006.12.021.

Wang, B., Jiang, Q., and Jiang, P. (2019). A combined forecasting structure based on the L1 norm: Application to the air quality. *Journal of Environmental Management*, 246:299–313. DOI: 10.1016/j.jenvman.2019.05.124.

Wei, W. (2006). *Time Series Analysis: Univariate and Multivariate Methods*. Addison Wesley, Boston.

WHO (2021). Who global air quality guidelines. Technical report, Copenhagen, Denmark.

Zamprogno, B., Reisen, V. A., Bondon, P., Cotta, H. H. A., and Reis, N. C. (2020). Principal component analysis with autocorrelated data. *Journal of Statistical Computation and Simulation*, 90(12):2117–2135. DOI: 10.1080/00949655.2020.1764556.

Zhang, X., Chen, X., and Zhang, X. (2018). The impact of exposure to air pollution on cognitive performance. *Proceedings of the National Academy of Sciences*, 115(37):9193–9197. DOI: 10.1073/pnas.1809474115.

Zhu, F., Ding, R., Lei, R., Cheng, H., Liu, J., Shen, C., Zhang, C., Xu, Y., Xiao, C., Li, X., Zhang, J., and Cao, J. (2019). The short-term effects of air pollution on respiratory diseases and lung cancer mortality in Hefei: A time-series analysis. *Respiratory Medicine*, 146:57–65. DOI: 10.1016/j.rmed.2018.11.019.

Author contributions

1 – Isamara Maria Schmidt (Corresponding Author)
Master’s student in Environmental Engineering at Federal University of Espírito Santo (UFES)
https://orcid.org/0000-0003-3107-2931 • isamaraschmidt@gmail.com
Contribution: Conceptualization – Methodology – Software – Validation – Formal Analysis – Resources – Data Curation – Writing – Original Draft – Writing – Review & Editing – Visualization – Project Administration

2 – Jaqueline Knaak
Master of Science in Environmental Engineering by Federal University of Espírito Santo (UFES)
https://orcid.org/0000-0001-8980-7289 • jaquelineknaak@gmail.com
Contribution: Conceptualization – Methodology – Formal Analysis – Resources – Data Curation – Writing – Original Draft – Writing – Review & Editing – Visualization – Project Administration

3 – Wanderson de Paula Pinto
Doctor in Environmental Engineering by Federal University of Espírito Santo (UFES)
https://orcid.org/0000-0001-5267-227X • wandersondpp@gmail.com
Contribution: Conceptualization – Methodology – Software – Validation – Formal Analysis – Resources – Writing – Review & Editing – Supervision – Project Administration

4 – Edson Zambon Monte
Doctor in Environmental Engineering by Federal University of Espírito Santo (UFES);
https://orcid.org/0000-0002-6878-5428 • edsonzambon@yahoo.com.br
Contribution: Formal Analysis – Writing – Review & Editing

5 – Michel Trarbach Bleidorn
Master of Science in Environmental Engineering by Federal University of Espírito Santo (UFES)
https://orcid.org/0000-0003-4773-3546 • michelbleidorn@gmail.com
Contribution: Formal Analysis – Writing – Review & Editing

6 – Gemael Barbosa Lima
Doctor’s student in Environmental Engineering at Federal University of Espírito Santo (UFES)
https://orcid.org/0000-0003-3675-4720 • gemaelbl@yahoo.com.br
Contribution: Formal Analysis – Writing – Review & Editing

How to cite this article

Schmidt, I. M., Knaak, J., Pinto, W. de P., Monte, E. Z., Bleidorn, M. T. & Lima, G. M. (2024). Temporal Trends and Statistical Analysis of PM_{10} and TSP Concentrations in the Region of Grande Vitória from 2008 to 2017. *Ciência e Natura*, Santa Maria, v.46. DOI: https://doi.org/10.5902/2179460X69023.