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The relationship between the number of COVID-19 cases, meteorological variables, and particulate matter concentration in a medium-sized Brazilian city

A relação entre o número de casos de COVID-19, variáveis meteorológicas e concentração de material particulado em uma cidade média brasileira

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ABSTRACT

The COVID-19 disease was first identified at the end of 2019 and spread rapidly around the world in 2020. Its symptom includes an acute respiratory crisis and the disease has claimed millions of victims. According to the literature, the relationship between COVID-19 transmission, and climatic factors and air pollutants is still unclear. Therefore, studies aiming to clarify this correlation are essential. This study aims to determine the correlation between the number of COVID-19 cases, particulate matter (PM) concentration, and meteorological variables in the city of Limeira, Brazil. The statistical analyses used were a generalized model with gamma distribution, Spearman's correlation, and cluster analysis, followed by the Mann-Whitney test. The variables included were rainfall, temperature, wind speed, relative humidity, and atmospheric pressure, in addition to social distancing compliance rate, dummy variables for business opening flexibility, and the weekday. The concentration of the coarse inhalable particulate matter (PM_{10}) fraction showed an inverse correlation with relative humidity, rainfall, and pressure. The Total Suspended Particulate matter (TSP) had an inverse correlation with relative humidity, rainfall, weekends, and social distancing compliance rate. A correlation was also found between the number of COVID-19 cases and pressure, PM_{10}, and TSP. Finally, the calculated relative risk showed that the reduction in PM_{10} concentrations directly affects health, which implies an estimate of almost 13 deaths avoided in Limeira, during the pandemic. The results obtained provide important information as to improving air quality and strategies to contain

RESUMO

A doença COVID-19 surgiu no final de 2019 e espalhou-se rapidamente pelo mundo em 2020, tendo como sintoma uma crise respiratória aguda e causando milhões de vítimas. De acordo com a literatura, ainda não está clara a relação entre a transmissão de COVID-19 e fatores climáticos e poluentes do ar, sendo portanto fundamentais estudos que visem esclarecer essa correlação. Esta pesquisa tem como objetivo determinar a correlação entre o número de casos de COVID-19, a concentração de material particulado (MP) e variáveis meteorológicas na cidade de Limeira, Brasil. As análises estatísticas utilizadas foram um modelo generalizado com distribuição gama, correlação de Spearman e análise de *cluster*, seguida do teste de Mann-Whitney. As variáveis incluídas foram pluviosidade, temperatura, velocidade do vento, umidade relativa e pressão atmosférica, além da taxa de isolamento, variáveis *dummy* para flexibilidade de abertura de estabelecimentos e dia da semana. A concentração de material particulado inalável grosso (MP_{10}) apresentou correlação inversa com umidade relativa, pluviosidade e pressão. O particulado total em suspensão (PTS) teve correlação inversa com umidade relativa, pluviosidade, fins de semana e taxa de isolamento. Também foi encontrada correlação entre o número de casos de COVID-19 com pressão, MP_{10} e PTS. Finalmente, o risco relativo calculado mostrou que a redução das concentrações de MP_{10} afeta diretamente a saúde, o que implica quase 13 mortes evitadas em Limeira, no período da pandemia. Os resultados obtidos fornecem informações importantes para melhorar a qualidade do ar e estratégias para conter a

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COVID-19 transmission. Besides, albeit on a small scale, they confirm the relationship between the social distancing compliance rate, PM concentration, and COVID-19 cases.

Keywords: SARS-CoV-2; social distancing compliance rate; air pollution; aerosol.

transmissão da COVID-19. Além disso, embora em pequena escala, eles confirmam a relação entre taxa de isolamento, concentração de MP e casos de COVID-19.

Palavras-chave: SARS-CoV-2; taxa de isolamento; poluição do ar; aerossol.

Introduction

The new coronavirus (SARS-CoV-2), which causes COVID-19, was first detected in Wuhan, China, in December 2019. This virus spread rapidly all over the world, such that in March 2020, the World Health Organization (WHO) declared the disease a pandemic (OPAS, 2020; WHO, 2021a). Transmission can occur through direct contact or being as close as 1 m to an infected person, through saliva and secretions, and through indirect contact, as well as by touching contaminated surfaces (Wang and Du, 2020). In addition, some studies indicate that transmission also occurs through aerosols suspended in the air, mainly in closed and poorly ventilated spaces (Domingo et al., 2020; Tang et al., 2020; Thaper, 2020).

Atmospheric aerosol is composed of solid and/or liquid material that remains suspended in the atmosphere and it is categorized into size fractions: Total Suspended Particulate matter (TSP), whose aerodynamic diameter is less than or equal to 50 μm, and Particulate Matter (PM_{10}), whose aerodynamic diameter is less than or equal to 10 μm (Seinfeld and Pandis, 2016; Brasil, 2018). Particulate matter (PM) concentration is strongly correlated with meteorological variables (Yotova et al., 2016; Godoy et al., 2020). As expected, in rainy periods, the concentration is usually lower, since wet depositions remove the particulate matter suspended in the atmosphere (Zu et al., 2017; Kayes et al., 2019).

As COVID-19 causes breathing difficulty and PM can also cause respiratory problems, studies suggested that high PM concentrations can aggravate symptoms and consequently increase the lethality of COVID-19 (Conticini et al., 2020; Maleki et al., 2021; Zhu et al., 2021). In addition to aggravating the symptoms, PM concentration in conjunction with weather conditions also directly influences the number of cases of the disease, since the virus can be transported by PM (Zhu et al., 2020; Tung et al., 2021).

Besides, several studies suggested a positive association between meteorological variables and the number of COVID-19 cases, such as temperature (Holtmann et al., 2020; Pani et al., 2020; Tosepu et al., 2020; Xie and Zhu, 2020), relative air humidity, (Ahmadi et al., 2020; Bashir et al., 2020; Habeebullah et al., 2021) and precipitation (Menebo, 2020). Regarding wind speed, there is no consensus on its influence, since some studies have established an inverse correlation (Ahmadi et al., 2020; Pani et al., 2020), while others have established a direct correlation with the cases of COVID-19 (Bashir et al., 2020; Huang et al., 2020; Menebo, 2020).

Several social distancing measures have been adopted worldwide in an attempt to contain the advance of the COVID-19 outbreak, and, in general, had a direct impact on anthropogenic activities, such as decreased vehicular traffic and reduced industrial activities (Chen et al., 2020; Selvam et al., 2020; Rosse et al., 2021), changing the atmospheric emissions and improving the air quality in several countries (Chauhan and Singh, 2020), such as Spain (Tobías et al., 2020), China (Chu et al., 2021) and India (Singh and Chauhan, 2020).

Vehicle emission is one of the main sources of air pollutants in Brazil (Andrade et al., 2017). Although newer vehicles have technology that makes them less polluting, the large increase in the number of vehicles circulating on the streets still causes an increase in PM due to the resuspension of soil. It is noteworthy that the state of São Paulo has about 40% of Brazil's entire vehicle fleet in the country, showing its relevance in the emission and resuspension of PM (CETESB, 2018). In addition, several studies have shown that social distancing measures, during the pandemic, improved air quality conditions, mainly due to reduced vehicular emissions (Chauhan and Singh, 2020; Mahato et al., 2020; Nakada and Urban, 2020; Siciliano et al., 2020).

It is crucial to highlight that fires are also a considerable source of TSP and PM_{10} in some cities in the state of São Paulo. According to the Fire Monitoring Program of the National Institute for Space Research (INPE), the state of São Paulo recorded 6,123 active fires in 2020. The months of March, April, May, June, and July had, respectively, 127, 252, 262, 262, and 558 fires. When added together, these represent 23.8% of the total for the year. Despite being an expressive number in the months in which the samples were taken, they were not the most critical, when compared to September, for example, which had a total of 2,254 fires (INPE, 2022).

In Latin America, some studies have also been carried out, such as in Ecuador (Zambrano-Monserrate and Ruano, 2020) and Brazil (Dantas et al., 2020; Nakada and Urban, 2020; Rosse et al., 2021; Rudke et al., 2021). In a way, the measures adopted during the pandemic provided an opportunity to investigate the behavior of air pollutants, such as in situations of lower vehicle traffic (Krecl et al., 2020; Rosse et al., 2021; Rudke et al., 2021).

In general, this study aimed to assess the impacts on air quality during the social distancing measures implemented to combat the COVID-19 pandemic in a medium-sized Brazilian city, Limeira, which had one of the lowest rates of compliance with social distancing measures in the state of São Paulo. More specifically, the goals were:

- to assess the role of meteorological conditions and COVID-19 control variables on air pollution levels in Limeira;
- to analyze/explore variations in meteorological variables and TSP and PM_{10} concentrations, concerning the number of daily cases of COVID-19;
- to quantify health impacts due to reduced PM_{10} concentration.

Methods

Study location

The city of Limeira, located in the state of São Paulo (Figure 1), had an estimated population, in 2020, of 308,482 people, with an approximate area of 580.711 km^2, and a climate characterized as subtropical (IBGE, 2020). The city has a wide variety of industries, mainly in the jewelry sector. In the agricultural sector, it stands out for having extensive areas of sugarcane plantation and citriculture (Prefeitura de Limeira, 2020). The production and economic activities mostly developed in the city are directly associated with TSP and PM emissions (Martins et al., 2019).

Data collection and description

PM samples were collected from March 17, 2020 to July 7, 2020, at the "Meteorological and Air Quality Monitoring Station", located at the Universidade de Campinas School of Technology (22º33'43.81"S; 47º25'20.84"W). The entire sampling process lasted 24 hours, starting at midnight on one day and ending at midnight on the other, with a timer programmed to turn the equipment on and off.

We collected 36 PM_{10} samples using 20 x 25 cm fiberglass filters (Equipo, Brazil) with a Hi-Vol sampler (Energética, model AGVMP101, No. MP10-0071, Brazil and Tisch Environmental, model TE-6001-25; No. 13612, USA) with a constant flow of 1.13 m^3/min. We also collected 36 TSP samples with 20 × 25 cm fiberglass filters, using another Hi-Vol sampler (Energética, model AGVPTS1, No. HVP-0575, Brazil) with a flow rate varying between 1.1 and 1.7 m^3/min. The fiberglass filters (Equipo, Brazil) were weighed before and after sampling and were placed in desiccators for 24 h before and after each sampling to remove moisture. The PTS and PM_{10} concentrations were calculated using a gravimetric method.

In this study, we used filters collected manually using a Hi-Vol sampler instead of using CETESB's automatic monitoring data due to the location of the samplers. CETESB's data are collected within "Limeira City Park", which is a highly wooded area, and this could interfere with PM concentration. The samplers used are located next to a roundabout with traffic lights, which connects the municipal ring road to a highway through which vehicles can leave the city. The highway also passes through the city and has a high daily traffic rate, thus being more compatible with the objectives of this research.

Some meteorological variables, such as Rainft (*Rainf$_t$*, mm), Temperature (*Temp$_t$*, ºC), and Wind Speed (*WS$_t$*, km/h) were obtained at the "Meteorological and Air Quality Monitoring Station", located at the School of Technology, while Relative Humidity (*RH$_t$*, %) and Pressure (*Pres$_t$*, mmHg) were obtained from the QUALAR database of the São Paulo State Environmental Company (CETESB, 2020). This database monitors these parameters using the automatic station located in the City of Limeira Park (22º33'48.97"S; 47º24'51.53"W). The straight-line distance between the two monitoring stations is 851.8 m, as shown in Figure 1.

Figure 1 – Sampling locations: PM and meteorological variables (Limeira-SP, Brazil).

History of governmental measures

The social distancing compliance rates ($SDCR_t$) for the city of Limeira, provided by the government of the state of São Paulo, indicate the extent to which the population practiced social distancing as recommended by public authorities. This rate is obtained using the location of cell phones, provided by telecommunication service providers. A person is considered to have violated social distancing measures when their cell phone moves away from the place it was at night (São Paulo, 2020a). During the pandemic, Limeira was one of the cities that had the lowest social distancing rates, below 40%, when the government recommended it should be at least 55% (G1 Piracicaba e Região, 2020a; 2020b).

In the state of São Paulo, a plan to resume business activities was designed (Figure 2). In the plan's red phase, only essential businesses were allowed to open, while, in the orange phase, the reopening of shopping malls (except food courts), retail businesses, and services in general was allowed, with restricted opening hours and occupancy capacity. In addition, all the necessary precautions to prevent the virus from spreading had to be taken (São Paulo, 2020b). Finally, data on new daily COVID-19 cases were provided by the city of Limeira.

In Limeira, the red phase started in March 2020, followed by the orange phase. The city then returned to the red phase and later moved on to the yellow phase. Details of each phase are shown in Figure 3 (São Paulo, 2020b). Thus, of the 36 samples collected for each fraction, two samples of each were collected before any action was implemented, 25 of each were collected during the red phase and nine of each were collected during the orange phase.

Statistical analysis

Some dummy (binary) variables were considered in the statistical models. The following binary variables were considered: Weekends (Wkd_t), indicating 1 for samples taken on Saturday or Sunday and 0 for the rest of the week (Hrdličková et al., 2008); and Weekdays ($Week_t$), indicating 1 for normally open businesses and 0 for restrictions on businesses. The $Week_t$ variable was included in the analyses, according to the measures taken and the reopening plan of the São Paulo state government (Figure 2) for the city of Limeira.

We used the generalized linear model with gamma distribution with identity-link function (McCullagh and Nelder, 1989) to adjust the concentration of TSP and PM_{10}, as already applied in the studies of Hrdličková et al. (2008) and Huebnerova and Michalek (2014). The models were called M1 and M2, and the response variable was the daily concentration of PM_{10} (M1) and the daily concentration of TSP (M2). We considered the RH_t, $Rainf_t$, $Pres_t$, $Temp_t$ and WS_t meteorological variables as predictor variables of the gamma model. In addition, COVID-19-related control variables, Wkd_t, $Week_t$ and $SDCR_t$, were also included. The considered generalized linear model with gamma distribution with identity-link function is expressed by Equation 1.

$$\mu t = \beta_0 + \beta_1 RH_t + \beta_2 Rainf_t + \beta_3 Pres_t + \beta_4 Temp_t + \beta_5 WS_t + \beta_6 Wkd_t + \beta_7 Week_t + \beta_8 SDCR_t \quad (1)$$

In which:
μt = the conditional expectation of the response variable (daily concentration of PM_{10}, in M1 and daily concentration of TSP, in M2);
$\beta_0, \beta_1, ..., \beta_8$ = unknown parameters that must be estimated.

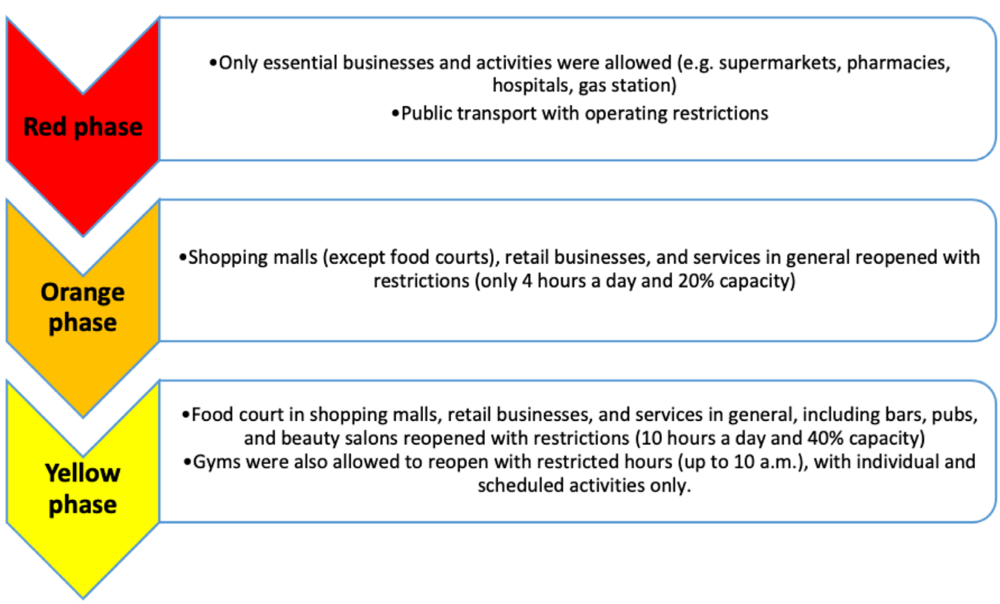

Figure 2 – Details of the reopening plan phases for the state of São Paulo.

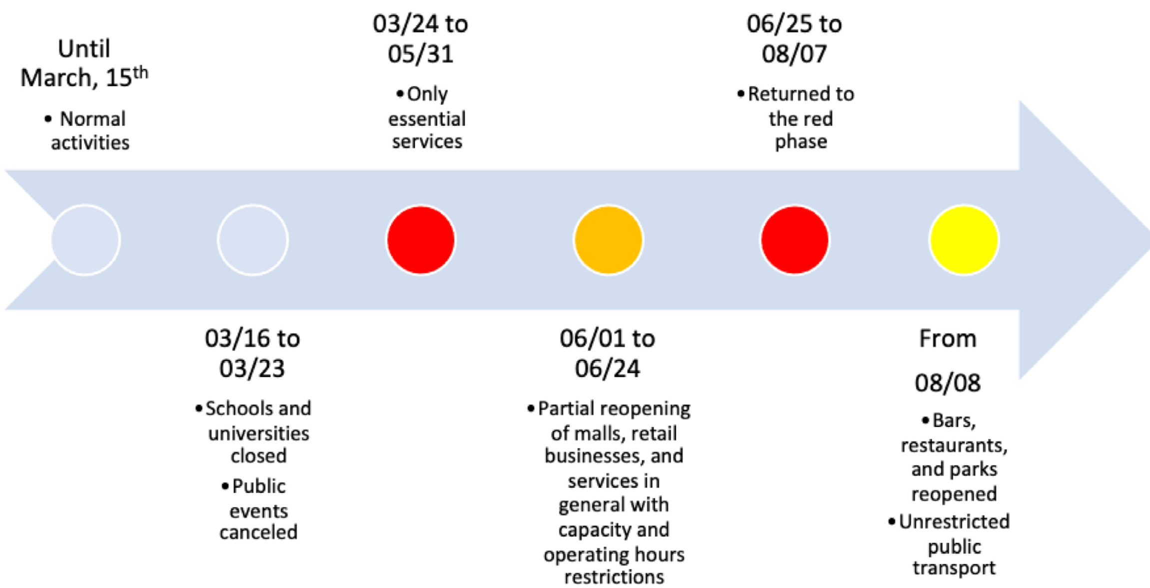

Figure 3 – Characteristics* of the study period in the city of Limeira.
*According to the São Paulo State Government's reopening plan.

Initially, we considered all the predictor variables described both in M1 and M2. For the final model chosen, only the significant variables (at least 10% level) in each of them were considered. The performance of the models was examined by analyzing the standardized residuals obtained. The normality of the residuals was assessed using the qq-plot and the Shapiro-Wilk test (Hrdličková et al., 2008; Ravindra et al., 2019). In addition, the residual plot was analyzed to verify the random distribution around zero, in amplitude from -3 to 3 (Chuang et al., 2011).

The Spearman's correlation and cluster analysis were used to evaluate the number of new cases of COVID-19, followed by the Mann-Whitney test. The meteorological, air pollution, and COVID-19-related variables were correlated with the number of daily cases through Spearman's rank correlation. This correlation was used because the data did not follow normal distribution. The Spearman's correlation test was also used to evaluate significant correlations (Tosepu et al., 2020; Zhang et al., 2020). Also, we examined the lag effects of air pollution concentration on the daily cases of COVID-19 by analyzing the correlation between the daily cases on the current day (lag 0) and up to 7 days (lag 1 – lag 7) with meteorological and air pollution variables (Yao et al., 2020). This analysis was carried out to consider the average time of virus incubation in the human body, the appearance of symptoms, and the time of testing in Brazil.

We used Hierarchical Agglomerative Cluster Analysis (HACA), with Ward's method, and we used the Euclidean distance to measure similarity (Han and Kamber, 2006; Austin et al., 2012). In HACA, firstly each individual object is in separate clusters. Then pair-wise distances between clusters are calculated and the pair with the smallest distance is grouped forming a new cluster (Dominick et al., 2012; Latif et al., 2014). In the cluster analysis (CA) of this study, the days were grouped according to the levels of similarity of the meteorological variables, air pollution variables (PM_{10} and TSP concentration), and social distancing compliance rate.

After grouping, we determined whether the data on the number of daily cases followed a normal distribution, using the Shapiro-Wilk test. Due to the non-normality of the number of daily cases, we considered the Mann-Whitney test (Riondato et al., 2020) to compare the number of daily cases (lag 0 until lag 7) across the groups obtained. We performed all statistical analyses in the R software, version 3.5.1 (R Core Team, 2018).

Health risk assessment

Because of the social distancing measures implemented as a result of the pandemic, there was a reduction in PM_{10} concentration. To assess the extent to which reduced PM_{10} impacted health, we used the relative risk (RR) function. This function quantified the impacts of PM_{10} pollution on health during social distancing (Equation 2). RR is an epidemiological concept that indicates the probability of mortality associated with exposure to a pollutant (Debone et al., 2020; Leirião et al., 2020).

$$RR = exp[\beta(\Delta X)] \quad (2)$$

In which:
ΔX = the variation in PM_{10} concentration observed in each CA group;
β = the coefficient for PM_{10}-related mortality.

The coefficient β is assumed to be equal to 0.0008 as recommended by the WHO (Ostro et al., 2004).

In addition, RR was used to estimate the Impacted Fraction (IF), according to Equation 3. The IF expresses the proportion of deaths attributed to PM_{10} exposure (Debone et al., 2020; Leirião et al., 2020).

$$IF = (RR - 1)/RR \quad (3)$$

The relative risk approach did not consider some factors, such as age group or race. The studies of Kumar et al. (2020) and Sharma et al. (2020) calculated the relative risk to compare the effects of air pollution exposure in periods with and without lockdown using other parameters. In this sense, RR and IF are a general estimate of PM_{10} exposure during the study period. The all-cause mortality between March 2020 and July 2020 was obtained from the Brazilian Health Database (Brasil, 2022). The daily mean of the all-cause mortality was calculated and multiplied by the IF to estimate the all-cause mortality avoided per day (Leirião et al., 2020) due to reduced PM_{10} observed during the pandemic.

Results and Discussion

Figure 4 shows the concentration of PM_{10} and TSP (μg/m³), and the SDCR (%) during the sample campaign. It is possible to note that most of the samples were taken during the red phase.

As shown in Figure 4, all PM_{10} samples collected in Limeira had concentrations below 100 μg/m³, which is the limit value established by the Brazilian National Environmental Council (CONAMA) Resolution No. 491 (Brasil, 2018), which provides the Brazilian Air Quality Standards. In terms of international legislation, all samples were also within the standard established by the United States Environmental Protection Agency (EPA, 2020), which is 150 μg/m³. However, seven of the 36 PM_{10} samples exceeded the limit concentration value suggested by the European Commission (EC, 2008), which has the most restrictive value of 50 μg/m³, and 12 samples exceeded the limit established by World Health Organization (WHO, 2021b), which has the most restrictive value of 45 μg/m³. For this reason, studying PM levels in the city is seen as highly important due to the high concentrations.

Tables 1, 2, and 3 show the estimates of the parameters estimated by the gamma model for PM_{10} and TSP, respectively. For PM_{10}, only the $Week_t$, RH_t, $Rainf_t$, and $Pres_t$ variables were significant at 1%, and the RH_t variable was significant at 5% (Table 1). In contrast, the TSP, RH_t, and $Rainf_t$ variables were significant at 5%, and the Wkd and SDCR variables were significant at 10% (Table 3).

Flexibility as to the reopening of businesses was observed to increase PM_{10} concentration (Table 1). In this case, with businesses open, people left their houses and did not comply with social distancing measures. Consequently, there was higher vehicle traffic, causing increased PM_{10} concentration.

The RH_t, $Rainf_t$, and $Pres_t$ meteorological variables had a negative influence on PM_{10} concentration (Table 1). Precipitation washes the atmosphere, removing particles suspended in the air. Relative humidity, when added to the presence of PM, acts in the formation of condensation nuclei, helping to remove pollutants by wet means (Dos Santos et al., 2018, 2019). Regarding the atmospheric pressure variable, Li et al. (2019) also found a significant inverse correlation between PM_{10} and $Pres_t$, while Zu et al. (2017) found high PM_{10} concentrations with moderate pressure. In our study sample, about 72% of the days had wind speeds below 1 km/h. In general, low pressure is accompanied by low wind speed, both of which contribute to PM accumulation (Li et al., 2019).

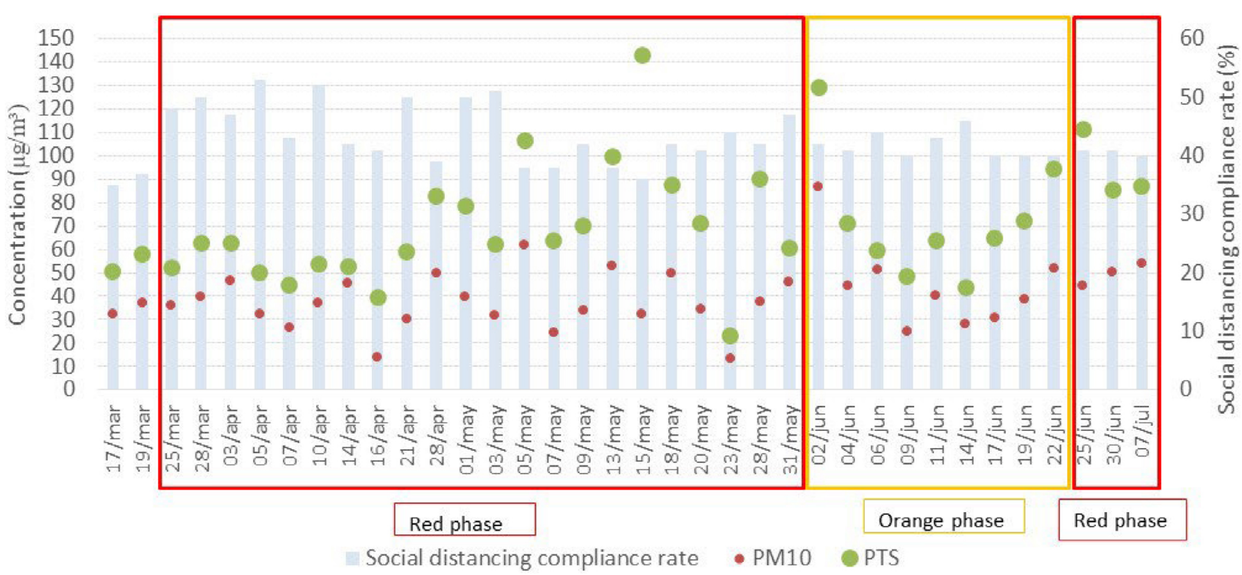

Figure 4 – Social distancing compliance rate (%) and daily average concentration (μg/m³) of PM_{10} and TSP during the sampling campaign.

Regarding TSP, all variables had a negative influence on the concentration (Table 2). It is observed that the RH_t and $Rainf_t$ meteorological variables have the same effect as that observed for PM_{10}. There was also a reduction in TSP concentration during weekends, which was expected, considering the lower vehicle traffic (Yousefian et al., 2020). The COVID-19-related control variable, social distancing compliance rate, interfered with TSP variability. In this case, the increased compliance rate of the population led to lower concentrations of this pollutant. That is, when the population complied with social distancing measures, air quality improved, with reduced TSP concentration, similarly to what occurred with PM_{10}.

Table 3 shows the Spearman's correlation coefficient between the daily cases of COVID-19 and the other study variables. The correlation was significant with PM_{10} and TSP, all positively. Thus, increased PM_{10} (on the 0-day lag, 1-day lag, and 7-day lag) and TSP concentrations (except on the 4-day lag) were associated with an increased number of COVID-19 cases, in Limeira, São Paulo. Similarly, Xu et al. (2020) and Zhu et al. (2020) also found a direct association between the number of cases and air pollution. Besides, the correlation was positively significant with pressure on all day lags. On the other hand, rainfall was negatively significant on the 4-day lag and 6-day lag, while the temperature was negatively significant on the 2-day lag and 7-day lag. Notice that on the 7-day lag, almost all variables were significant concerning the number of COVID-19 daily cases after 7 days. This was probably due to the incubation time of the virus (Elias et al., 2021).

In the CA, collection days were divided into two groups, called C1 and C2. Table 4 shows the number of observations in each group, as well as the average social distancing compliance rate, average temperatures, pressure, relative humidity, wind speed, rainfall, PM_{10}, and TSP for each of the two groups. These results enable the characterization of each of the two groups. C1, with 25 observations, had a social distancing compliance rate of 44.2%, higher than that of C2, with 39.91%. In C1, we also observed higher averages for meteorological variables in relation to C2. On the other hand, PM_{10} and TSP concentrations were higher in C2, with 51.90 $\mu g/m^3$ and 101.46 $\mu g/m^3$, respectively (Table 4). In general, the days grouped in C1 had better air quality conditions (lower averages for PM_{10} and TSP). In addition, these days had higher social distancing compliance rates, that is, when the population stayed home and did not go out to the streets.

To examine how these variables can interfere with COVID-19 cases, we considered the number of cases on lag 0 up to lag 7. The Shapiro-Wilk test indicated non-normality of all data (i.e., $p < 0.0001$ on all lag effects) thus, the Mann-Whitney test was applied to determine whether there were differences in the number of COVID-19 cases between the two groups on lag 0 until lag 7. The Mann-Whitney test indicated differences between the two groups on the 0-day lag, 1-day lag, 2-day lag, 3-day lag, and 7-day lag (Table 5). Figure 5 shows the boxplot of the number of daily cases in groups 1 and 2 for all the lag effects.

Table 1 – Estimates of the parameters with respective standard errors and p-value of the significance test for the model using PM_{10} concentration as a response variable (M1).

M1	Estimate	Standard Error	p-value	
Intercept	2313.76	813.40	0.0078	**
$Week_t$	14.69	5.04	0.0065	**
RH_t	-0.50	0.19	0.0127	*
$Rainf_t$	-0.78	0.22	0.0017	**
Pres	-3.18	1.14	0.0091	**

*Significance at 5%; **significance at 1%.

Table 2 – Estimates of the parameters with respective standard errors and p-value of the significance test for the model using TSP concentration as a response variable (M2).

M2	Estimate	Standard Error	p-value	
Intercept	181.89	43.07	0.0002	***
Wkd	-13.78	8.04	0.0963	*
RH_t	-0.75	0.31	0.0232	**
$Rainf_t$	-0.96	0.39	0.0194	**
SDCR	-1.74	0.87	0.0538	*

*Significance at 10%; **significance at 5%; ***significance at 1%.

Table 3 – Spearman's correlation coefficients between meteorological, air pollution, and social distancing compliance rate variables and COVID-19 daily cases on the current day (lag 0) up to 7 days (lag 1 – lag 7).

Variable	0-day lag		1-day lag		2-day lag		3-day lag	
SDCR	-0.2504		-0.3090		-0.2777		-0.1978	
Temp	-0.2577		-0.1832		-0.2956	*	-0.2715	
Pres	0.3458	**	0.3147	*	0.3929	**	0.4158	**
RH_t	-0.0918		-0.0733		-0.0496		-0.0889	
$Rainf_t$	-0.1972		-0.1350		-0.1864		-0.1841	
PM_{10}	0.3176	*	0.3166	*	0.2572		0.2782	
TSP	0.4651	***	0.4270	***	0.4236	**	0.4170	**
Variable	**4-day lag**		**5-day lag**		**6-day lag**		**7-day lag**	
SDCR	-0.0620		-0.1435		-0.1912		-0.2866	*
Temp	-0.2026		-0.2275		-0.2710		-0.2926	*
Pres	0.3578	**	0.4948	***	0.3936	**	0.3156	*
RH_t	-0.1600		-0.0015		-0.1245		0.0120	
$Rainf_t$	-0.2890	*	-0.1691		-0.2791	*	-0.0934	
PM_{10}	0.1719		0.1809		0.1450		0.3077	*
TSP	0.2375		0.3071	*	0.2891	*	0.3788	**

*Significance at 10%; **significance at 5%; ***significance at 1%.

It is noted that the number of cases in C2 was greater than in C1. On average, for example, C1 had 12.92 cases per day, while C2 had 46.27 cases per day on the 0-day lag.

When comparing the averages between the two groups, TSP and rainfall showed higher percentage variation (Table 4). Regarding rainfall, it did not rail for several days, resulting in zero values. We can state that the number of cases of the disease was lower on the days when meteorological and air quality conditions were more favorable. The relaxation of social distancing measures, measured here by the social distancing compliance rate, was also an important factor in this reduction of cases.

Finally, considering the variation obtained between PM_{10} concentrations in groups C1 and C2 (Table 4), RR and IF were calculated. RR was equal to 1.01408, while IF was 1.39%. Debone et al. (2020) found RR values between 1.001 and 1.023, while Leirião et al. (2020) found RR values between 1.00481 and 1.00593, both during a truckers' strike in Brazil. During the pandemic, Kumar et al. (2020) found RR values of 1.000014 and 1.000041 for $MP_{2.5}$ exposure in India. During March 2020 and July 2020, 383 deaths occurred considering all-cause mortality (Brasil, 2022) on 152 days. The daily mean all-cause mortality in Limeira between March 2020 and July 2020 was 2.52, while the IF was estimated at 1.39%.

Table 4 – Characterization of the groups obtained by cluster analysis, and absolute (Δx) and percentage (Δ%) variation of the comparison between the averages of the variables in each group.

Clusters	C1	C2	Δx	Δ%
No. samples	25	11		
SDCR (%)	44.20	39.91	-4.29	-9.71
Temp (°C)	21.54	20.40	-1.14	-5.29
Pres (mmHg)	708.47	708.35	-0.13	-0.02
RH_t (%)	43.72	37.82	-5.90	-13.50
WS (km/h)	0.96	0.62	-0.34	-35.34
$Rainf_t$ (mm)	2.49	0.12	-2.37	-95.26
PM_{10} (μg/m³)	34.42	51.90	17.48	50.77
TSP (μg/m³)	57.53	101.46	43.93	76.35

Table 5 – Results of the Mann-Whitney test for comparison of groups and COVID-19 daily cases on the current day (lag 0) and up to 7 days (lag 1 – lag 7).

Daily cases	p-value	
0-day lag	0.0218	**
1-day lag	0.0102	**
2-day lag	0.0567	*
3-day lag	0.0529	*
4-day lag	0.1555	
5-day lag	0.1432	
6-day lag	0.2413	
7-day lag	0.0419	*

*Significance at 10%; **significance at 5%.

Thus, the number of daily deaths avoided was 0.03. Considering a one-year period (365 days), the number of deaths avoided during a one-year period in Limeira would be 12.77 deaths considering the reduced PM_{10} concentration during the COVID-19 pandemic. A study in the metropolis of São Paulo (Leirião et al., 2020), considering workdays, found values of avoided deaths between 1.03-1.27.

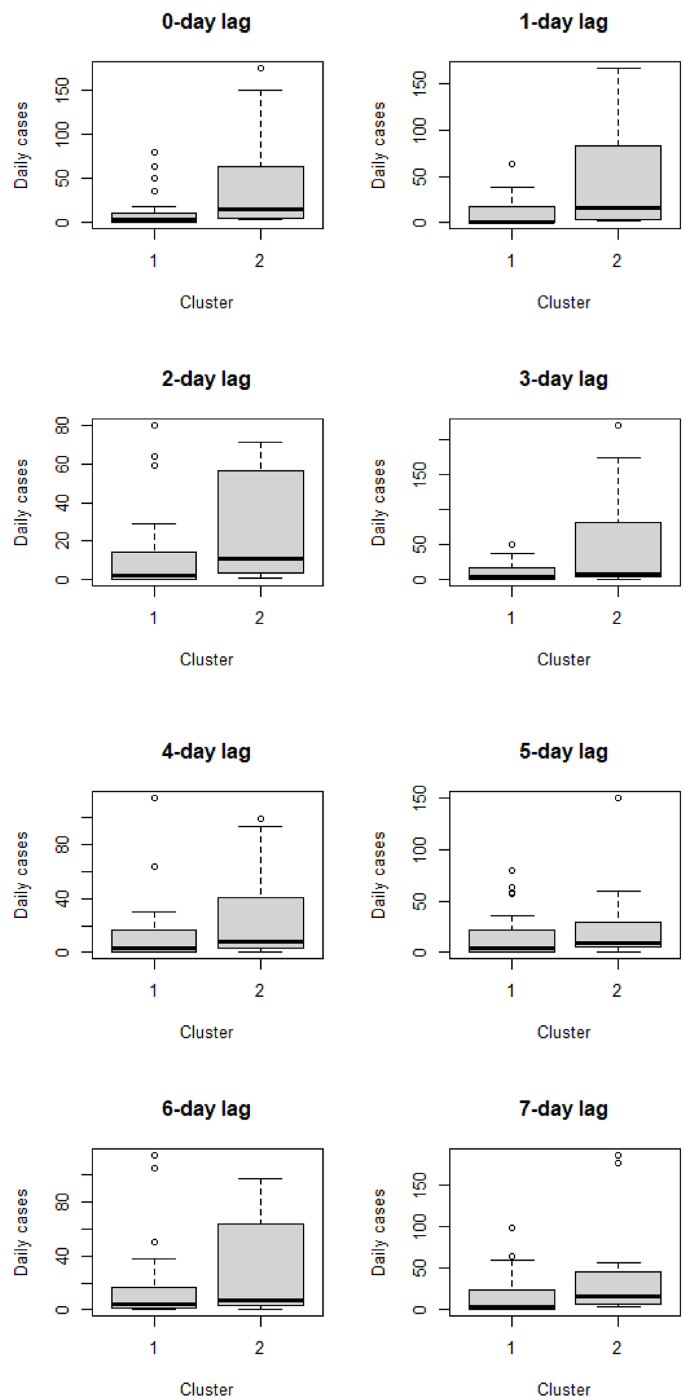

Figure 5 – Boxplot of the number of daily cases — on the current day (lag 0) and up to 7 days (lag 1 – lag 7) — per group obtained in cluster analysis (C1 and C2).

With the results of this study, we observed that PM_{10} exposure directly impacted health risks. In addition, the reduction occurred during a short period of time, just a few days, and thus continuous PM_{10} emission control measures, such as public policies and incentives for alternative transport, can lead to better air quality and, consequently, lower human health impacts (Coelho Junior et al., 2016).

Conclusions

We confirmed that PM concentration and meteorological conditions were associated with the number of registered cases of COVID-19 during the periods (lag effects) and in the location evaluated. This was possible because there was a positive correlation between the number of cases of the disease caused by the coronavirus, and PM_{10} (on the 0-day lag, 1-day lag, and 7-day lag) and TSP (on all day lags). We also observed that while the PM_{10} fraction showed an inverse correlation with relative humidity, rainfall, and pressure, TSP had an inverse correlation with relative humidity, precipitation, weekends, and the social distancing compliance rate. Thus, we can state that meteorological factors and air pollution are important in determining COVID-19 infection rates. Such information is also important for the management of future pandemics or events that alter the characteristics of the emission of air pollutants.

Finally, the new coronavirus causing COVID-19 spread very rapidly in Brazil, and the results of this study can be useful for efforts to better understand the routes of transmission of this disease and to design strategies to contain its transmission. On the other hand, the social distancing measures adopted during the pandemic provided an opportunity to assess air quality and its impacts on health. Continuous PM_{10} emission control measures could be taken to reduce public health impacts.

Despite the results obtained in this study, further research is necessary to better understand the relationship between meteorological variables and daily cases of COVID-19. Considering that the number of samples is small, we need to examine the lag effect to minimize this study limitation. Several other factors can interfere, such as virus resistance, population mobility, compliance with social distancing measures, government interventions, among others. More in-depth conclusions require a longer sampling time and/or a large dataset (Tosepu et al., 2020).

Data availability

The data that support the findings of this study are available from the corresponding author upon request.

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GONÇALVES, P. B.: Methodology; Formal Analysis; Data Curation; Investigation; Resources; Writing — Original Draft; Writing — Review and Editing. NOGAROTTO, D. C.: Methodology; Software; Formal Analysis; Data Curation; Investigation; Resources; Writing — Original Draft. CANTERAS, F. B.: Conceptualization; Methodology; Writing — Original Draft; Writing — Review and Editing; Supervision; Project Administration. POZZA, S. A.: Conceptualization; Methodology; Writing — Original Draft; Writing — Review and Editing; Supervision; Project Administration.

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