# The impact of air pollution on COVID-19 pandemic varied within different cities in South America using different models

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**Research Article**

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# Abstract

There is a rising concern that air pollution plays an important role in the COVID-19 pandemic. However, the results weren't consistent on the association between air pollution and the spread of COVID-19. In the study, air pollution data and the confirmed cases of COVID-19 were both gathered from five severe cities across three countries in South America. Daily real-time population regeneration ($R_t$) were calculated to assess the spread of COVID-19. Two frequently used model, generalized additive models (GAM) and multiple linear regression, were both used to explore the impact of environmental pollutants on the epidemic. Wide ranges of all the six air pollutants were detected across the five cities. Spearman's correlation analysis confirmed the positive correlation within six pollutants. $Rt$ value showed a gradual decline in all the five cities. Further analysis showed that the association between air pollution and COVID-19 varied across five cities. Multiple linear regression and GAM did not give the same trend in a specific city. For example, in Sao Paulo, the GAM model shows that $PM_{10}$ has a nonlinear negative correlation with $R_t$, while $PM_{10}$ has no significant correlation in the multiple linear model. According to our research results, even for the same region, varied models gave inconsistent results. Moreover, in the case of multiple regions, current used models should be selected according to local conditions.

## 1. Introduction

In late December 2019, a novel coronavirus, named COVID-19, was first reported in Wuhan, Hubei Province, China (Daraei et al. 2020, Lu et al. 2020, Wu et al. 2020). Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV2) (Lu et al. 2020) is the pathogenic agent of COVID-19 and most of the infected had clinical manifestations of fever and shortness of breath (Chen et al. 2020). It has been confirmed COVID-19 can be transmitted through direct contact (Human-to-human) (Chan et al. 2020). 20,871,160 patients with Covid-19 had been confirmed worldwide as of August 13, 2020, 81 countries have more than 10,000 confirmed cases. (https://www.hopkinsmedicine.org/coronavirus). South America accounts for about 27% of the world's confirmed cases, making it the region with the highest number of confirmed cases.

Previous studies showed that droplets with virus can stay suspended in the air for a short time, and these particles may pose a threat of infection if they are inhaled by nearby persons. This approach makes it possible for people infected with COVID-19 to facilitate the spread of infection (Anfinrud et al. 2020, Meselson 2020). Lab experiments have demonstrated that the SARS-CoV-2 virus can survive in aerosols for days or weeks, making the virus susceptible to airborne contamination (Liu et al. 2020). Particulate matters such as $PM_{10}$ and $PM_{2.5}$, due to their small size, can easily penetrate into the lower respiratory tract and can carry the virus directly into the alveoli and tracheobronchial region (Qu et al. 2020). Several studies have proven that air pollutants act as a carrier to transmit virus reducing the level of immune system and therefore make human bodies more vulnerable to virus infection (Becker &Soukup 1999, Glencross et al. 2020, Xie et al. 2019, Xu et al. 2020). Air pollutants have been shown to affect the transmission and severity of respiratory viral infections including, but not limited to severe acute respiratory syndrome (SARS), the emergence of the Middle East respiratory syndrome (MERS), as well as

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SARS-CoV-2 (Cui et al. 2003, Domingo &Rovira 2020, Silva et al. 2014). It has been shown that air pollution is positively correlated with the mortality of SARS in China (Cui et al. 2003). The environment around us is filled with contaminants that can inadvertently expose humans to viruses (Daraei et al. 2020). Although risk factors for COVID-19 are still under investigation, it is possible that environmental factors, such as air pollution, may play a significant role in affecting the spread of the epidemic among the population. In terms of SARS-CoV-2, there are multiple studies showing the significant association between air pollution and the spread rate of the COVID-19. Generalized additive models (GAM) showed that six air pollutants ($PM_{2.5}$, $PM_{10}$, $SO_2$, CO, $NO_2$ and $O_3$) were significantly related to the confirmed cases in 120 cities from Jan 23, to Feb 29, 2020 in China (Zhu et al. 2020). In Europe, the most severely affected region is the same as that possessed the highest concentrations of $PM_{10}$ and $PM_{2.5}$ (Martelletti &Martelletti 2020). Furthermore, most fatality cases occurred in the regions with the highest $NO_2$ concentration (Ogen 2020). The relations were also confirmed in California, USA and India (Bashir et al. 2020b, Sharma et al. 2020).

The impact of air pollution on the epidemic varies from study to study. Thus, the findings have been inconsistent and there were limited compelling reasons on the shape and magnitude of those relationships. Therefore, it is necessary to explore the effect of air pollution on the spread of COVID-19. Tracking the epidemic data and the dynamic variations of these values can help to estimate the spread of this emerging pandemic (Merl et al. 2009). Here, we assemble the datasets of the spread of COVID-19 pandemic in five regions of South America. The time-dependent reproduction number ($R_t$) in each area was estimated to assessing the expected number of secondary cases arising from a primary case infected during the t period (Thompson et al. 2019). In order to evaluate the impact of pollutants on epidemic spread more objectively and comprehensively, we collected as much epidemic and pollutant data as we could, and referred to the previous epidemiological studies, two frequently used models, generalized additive models (GAM) and multiple linear regression were both used for each city, and the results from both models were compared to explore the impact of air pollution on the spread of the virus, in addition, we also compared the differences in the results of the two models.

## 2. Materials And Methods

## 2.1 Data collection

The confirmed cases in South America until August 13, 2020, are shown in Fig. 1. Data of confirmed cases and the corresponding air pollution were obtained in five regions from three countries in South America from March 28 to June 10. The list is as follows, Brazil, including Sao Paulo, Sao Jose dos Campos and Vitoria, https://covid.saude.gov.br/, Guayaquil in Ecuador, https://coronavirusecuador.com/data/, Bogota in Colombia, https://www.ins.gov.co/Noticias/Paginas/Coronavirus.aspx). Time series data of air pollution including six major air pollutants $PM_{2.5}$, $PM_{10}$, $O_3$, nitrogen dioxide ($NO_2$), sulfur dioxide ($SO_2$) and carbon monoxide (CO), were obtained from aqicn.org/data-platform/covid19/. This website uses the standard

for air pollutants from the US Environmental Protection Agency (EPA) and the daily air quality index (AQI) data were then converted to mass concentrations (EPA https://www3.epa.gov/airnow/aqi-technical-assistance-document-sept2018.pdf)

## 2.2 Estimation of the time-dependent reproduction number ($R_t$)

The $R_t$, a time-dependent reproduction number, which can reflect the transmission of infectious diseases in the population (Cowling et al. 2010, Wallinga &Teunis 2004), was estimated with the using of package of "EpiEstim" in the R software. Based on the research of the Chinese CDC (Li et al. 2020b), we set an offset gamma distribution with mean 7.5 days and standard deviation 3.4 days. The smoothing time was set to 10 days. The epidemic grows when $R_t$ is above 1 and the outbreak will die out once $R_t$ stays below 1. Cross-sectional analysis was performed to examine the spatial association between air pollutants and $R_t$ of COVID-19, and longitudinal analysis was used to examine the temporal associations of air pollutants with $R_t$.

## 2.3 Statistical analysis

To determine the relationship between each air pollutants, and the correlation between air pollutants and the transmission of COVID-19 ($R_t$), we used Spearman correlation to assess the associations of air pollutants with $R_t$ with detection level α = 0.05 (bilateral). Based on the analysis of correlation, two frequently used model, multiple linear regression and generalized additive models (GAM), were both used in the study. For multiple linear regression model, the number of $R_t$ were used as dependent variables, and the daily air pollution were selected as independent variables. The formula used was as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

In this model, outcome variable, Y, is thought to be a linear function of a set of predictor variables, where n is the number of predictor variables, α is a numerical constant that represents an intercept. βs stand for the partial regression coefficients of X, each β reflects that how Y will change with the X, which associated with the β, when all other X variables constant (Jaccard et al. 2006). Among them, Xs stand for the parameters of air pollution that are significantly associated with Rt.

GAM, which developed by Hastie and Tibshirani (Hastie &Tibshirani 1995), was also used to estimate the association between $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, CO and the $R_t$. The fitting of GAM uses nonlinear smoothing term, the regression equation of GAM to predict a regressed variable is shown below:

$$g(E(Y)) = \beta X_1 + \sum_{i=2}^{p} S_i\left(X_i\right)$$

where $Y$ is the predicted values of the dependent variable, $R_t$; $Xi$ represent the levels of air pollution, independent variables, and Si is nonparametric smoothing function.

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According to the different data distribution of dependent variables, different methods are used to fit the model. Popularly used distributions in GAM modeling are Normal, Gamma and Poisson distributions (Ravindra et al. 2019). In this paper, we applied Poisson distributions to examine the moving average lag effect (7 days) of air pollutions on daily values of $R_t$ of COVID-19 and all Poisson regression analyses were performed in R (version 3.6.2) with the using of "mgcv" package.

# 3. Results

## 3.1 Daily pollutant data

As shown in Fig. 2, the median concentration of particulate matter in Sao Jose dos Campos ($PM_{2.5}$, 11.040 µg/m$^3$, $PM_{10}$, 19.440 µg/m$^3$), $O_3$ (0.020 ppm) and CO (6.453 ppb) in Colombia, $NO_2$ (4.558 ppb) in Guayaquil and $SO_2$ (10.706 ppb) in Sao Paulo were the highest within the five cities, respectively. The concentrations of other pollutants are at similar levels through these five cities. According to Spearman's correlation coefficient, there are positive correlation within six pollutants, most of which are extremely significant ($p < 0.01$), except $O_3$, which has negative correlation, or weak positive correlation (in Vitoria) with other pollutants in three Brazilian cities (Fig. 3A-3C). In Bogota (Fig. 3D), there are strong positive correlations ($p < 0.01$) between each pollutant, except $O_3/NO_2$, $SO_2/CO$. In Guayaquil (Fig. 3E), the correlation between any of the two pollutants were statistically significant ($p < 0.05$).

## 3.2 Epidemiological data in the selected regions

The calculated $R_t$ (Fig. 4) values showed a gradual decline in all the five regions, particularly in Sao Jose dos Campos, where the peak was 5.56, and then went down to 1.16 on June 10. The $R_t$ value of Guayaquil decreased from the peak of 1.72 to 0.24. By contrast, the $R_t$ in Victoria fluctuated, and it remained above 1 until June 10, indicating that the epidemic situation in the region was still serious.

## 3.3 Model fitting

The results of GAM and multiple linear models were shown in Fig. 5 and **Table 2**, respectively. By establishing GAM models between the pollutant factors (explanatory variables) and the $R_t$ response variables, the smooth regression function of explanatory variables is obtained, as well as the effect diagram of influencing factors on $R_t$ (Fig. 5). The results show that there is a nonlinear relationship between $R_t$ and each explanatory variable in Sao Paulo (Fig. 5A), and $R_t$ value decreases gradually with the increase of $PM_{10}$ concentration. $R_t$ increases monotonically when $O_3$ concentration is less than 0.012 ppm or between 0.014 ppm and 0.018 ppm. When $SO_2$ concentration is less than 0.6 ppb, $R_t$ shows a slow decreasing trend. However, $R_t$ increases with the elevation of $SO_2$ when $SO_2$ concentration is higher than 0.6 ppb, In Sao jose dos Campos (Fig. 5B), $R_t$ showed an increasing trend when $PM_{10}$ concentration was between 15 µg/m$^3$ and 20 µg/m$^3$. $R_t$ shows a fluctuating decreasing trend with the increase of $O_3$ and $NO_2$ concentration, while it shows a weak change with the increase of $SO_2$ concentration. In Victoria trend with the increase of $PM_{10}$ and $NO_2$ concentrations.

When $O_3$ concentration is less than 0.012 ppm, $R_t$ decreases gradually; when $O_3$ concentration is higher than 0.012 ppm, $R_t$ changes relatively gently. When $SO_2$ concentration is lower than 4.0 ppb, $R_t$ shows a large fluctuation change, while when $SO_2$ concentration is higher than 4 ppb, $R_t$ shows almost no significant change. $R_t$ increases monotonically when CO concentration is higher than 0.11 ppb. In Bogota (Fig. 5D), with the increase of $PM_{10}$ and $NO_2$ concentration, $R_t$ shows a certain fluctuation, but the value doesn't change a lot. When $O_3$ concentration is less than 0.004 ppm, $R_t$ shows a monotonically increasing trend, while when $O_3$ concentration is higher than 0.008 ppm, $R_t$ shows a decreasing trend. When $SO_2$ concentration is less than 0.35 ppb, $R_t$ tends to decrease slowly, while when it is higher than this concentration, $R_t$ increases gradually. $R_t$ shows a fluctuating rising trend with the increase of CO concentration. When CO concentration was higher than 0.42 ppb, there is no obvious change. In Guayaquil (Fig. 5E), $R_t$ decreases slowly when the concentration of $PM_{10}$ is lower than 17 μg/m$^3$, and increases slowly when it is higher than 17 μg/m$^3$. $R_t$ increases when $O_3$ concentration is less than 0.03 ppm, and decreases when $O_3$ concentration is higher than 0.03 ppm. $R_t$ value shows a relatively slow change with the increase of $SO_2$ concentration. The correlation between CO concentration and Rt shows a certain linear relationship, and when CO concentration increases, $R_t$ decreases monotonically.

However, based on the results of multiple linearity (**Table 2**), the magnitudes of β reflect the influence of the corresponding variable, there is a positive correlation between the $R_t$ value and $O_3$ (β = 13.135) in Sao Paulo and a negative correlation with $SO_2$ (β= -0.320). In Victoria, $R_t$ was negatively correlated with $NO_2$ (β= -0.147) and $SO_2$ (β=-0.053). There is a negative correlation between $R_t$ and $PM_{10}$ in Bogota (β= -0.013). For Sao jose dos Campos and Guayaquil, there is no linear correlation.

# 4. Discussion

The epidemic situation in five regions of South America were analyzed in this study. Our calculated $R_t$ values showed that, until 10 June, in five regions, Vitoria's $R_t$ remained at alarming levels while the outbreak in Guayaquil was effectively contained.

At present, the research on the adverse effects of air pollution exposure is limited, and the conclusion is controversial. Due to different environmental conditions, even the impact of the same pollutant will vary. Previous results indicated that air pollution can increase the spread of diseases (Bell et al. 2004, Goings et al. 1989, Wei et al. 2019). However, the results of these studies did not follow the expected model. According to our results, air pollution ($PM_{2.5}$, $PM_{10}$, $O_3$, $SO_2$, $NO_2$, CO) and $R_t$ do not have consistent results.

There may be regional differences that could have a potential impact on the epidemic transmission, including variation in the timing and coverage of public health interventions (Dalziel et al. 2018). We pooled data from similar studies in the past, and summarized the types of pollutants, the study area, the study time and the fitting model used (Table 3). Our data spans a wider range of time and space, and

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more types of pollutants than previous studies, referred to the previous studies, two frequently used models, generalized additive models (GAM) and multiple linear regression were both used for each city. Our findings do not reveal a clear effect of pollutants on the virus's ability to spread, but our data are broader in space and time than previous studies, and more diverse than most studies, this can give an indication that the effects of pollutants on disease may not be specific, and the results of GAM and multiple linear model in individual cities cannot be directly replicated in other regions. The social intervention, as well as population immunity may have a greater impact on the virus's ability to spread compared to air pollution (Baker et al. 2020).

Table 3

| Region | Model formula | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|
| Sao Paulo | $Y_{Rt} = 1.163 + 13.135X_{O3} - 0.320X_{SO2}$ | 0.142 | 0.069 |
| Sao jose dos Campos | / | / | / |
| Vitoria | $Y_{Rt} = 2.120 - 0.148X_{NO2} - 0.053X_{SO2}$ | 0.306 | 0.246 |
| Bogota | $Y_{Rt} = 1.257 - 0.013X_{PM10}$ | 0.182 | 0.111 |
| Guayaquil | / | / | / |
| Comparison of correlational studies between air pollution and COVID-19 in various studies. | | | |

For each region, we adopted two commonly used models for fitting, and our results were quite different from those of previous studies. At the same time, the results of the two models in the same region were also different. There are shortcomings in the current used models. The conclusions drawn from a single fitting result cannot be directly applied, and more models can be used in future research.

There are some limitations of this study. First, there may be differences in the timing of the acquisition of epidemic data across regions. Second, there are many other models for this kind of prediction, in this paper, GAM and multiple linear models are adopted, and there may be other more appropriate models. Third, there are many other factors that contribute to outbreaks, such as individual behavior, government control measures, and so on, in this paper, only air pollution is considered. For actual disease prediction, these factors should be included in the model as far as possible.

# 5. Conclusion

The association between air pollution and the spread of COVID-19 differed in varied cities with specific status of air pollution. Inconsistent results were obtained from GAM and multiple linear regression model for one city. Model optimization is still warranted for determining the contribution of air pollution to the COVID-19 pandemic.

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# Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing Interests** The authors declare that they have no competing interests.

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# Tables 1 And 2

### Table 1

Summary of the models

| Region | Model | Significant independent variables |
|---|---|---|
| Sao Paulo | GAM | $PM_{10}$, $SO_2$, $O_3$ |
| | multiple linear regression | $SO_2$, $O_3$ |
| Sao joe dos Campos | GAM | $PM_{10}$, $SO_2$, $NO_2$, $O_3$ |
| | multiple linear regression | / |
| Vitoria | GAM | $PM_{10}$, $SO_2$, CO, $NO_2$, $O_3$ |
| | multiple linear regression | $SO_2$, $NO_2$ |
| Bogota | GAM | $PM_{10}$, $SO_2$, CO, $NO_2$, $O_3$ |
| | multiple linear regression | $PM_{10}$ |
| Guayaquil | GAM | $PM_{10}$, $SO_2$, CO, $O_3$ |
| | multiple linear regression | / |

/, no significant independent variables in the model.

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Statistical data of the multiple linear regression equation

| Region | Model formula | $R^2$ | Adjusted $R^2$ |
|---|---|---|---|
| Sao Paulo | $Y_{Rt}= 1.163+13.135X_{O3}-0.320X_{SO2}$ | 0.142 | 0.069 |
| Sao jose dos Campos | / | / | / |
| Vitoria | $Y_{Rt}= 2.120-0.148X_{NO2}-0.053X_{SO2}$ | 0.306 | 0.246 |
| Bogota | $Y_{Rt}=1.257-0.013X_{PM10}$ | 0.182 | 0.111 |
| Guayaquil | / | / | / |

# Figures
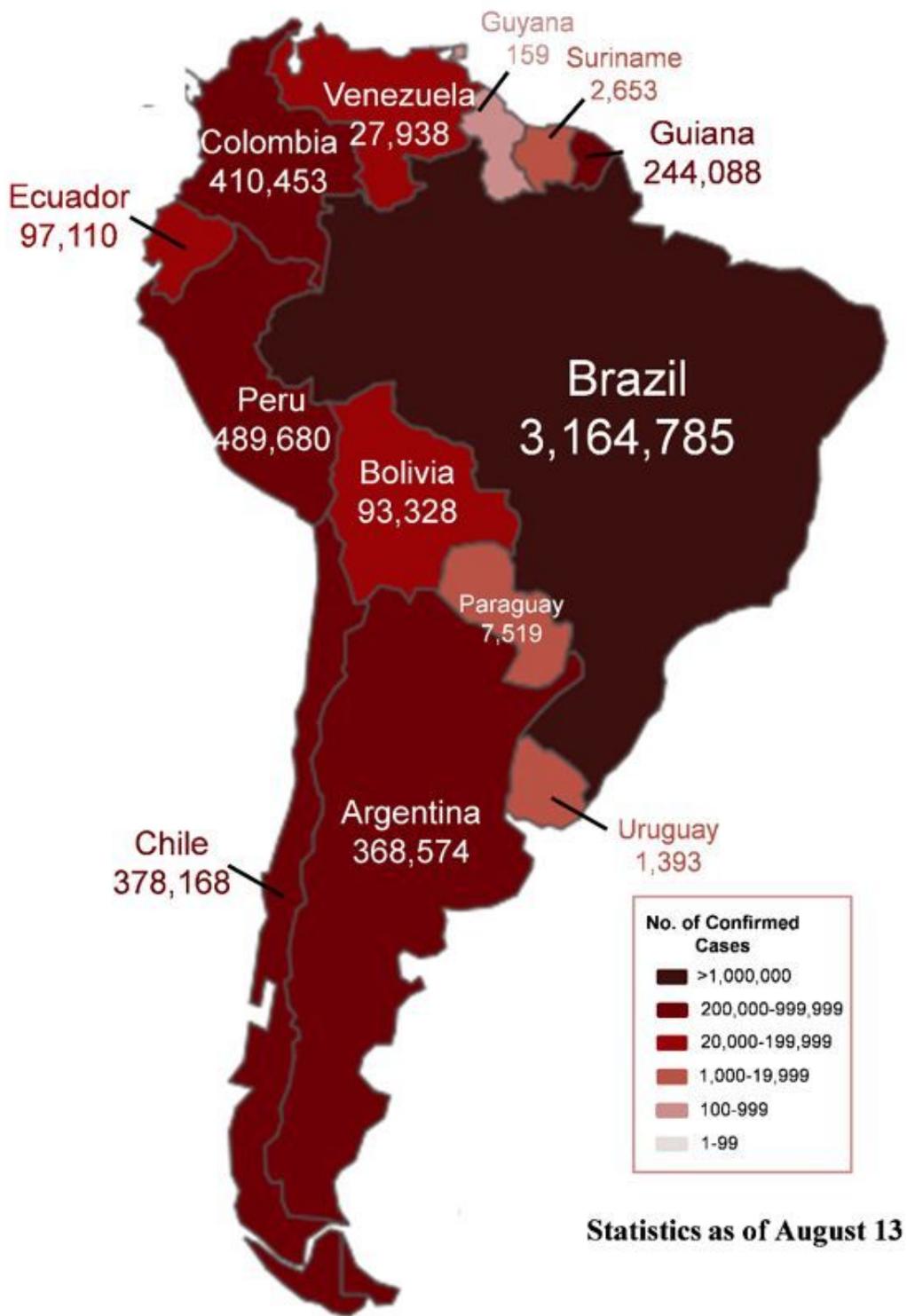
**Figure 1**

Confirmed cases of COVID-19 across South America until 13 August.
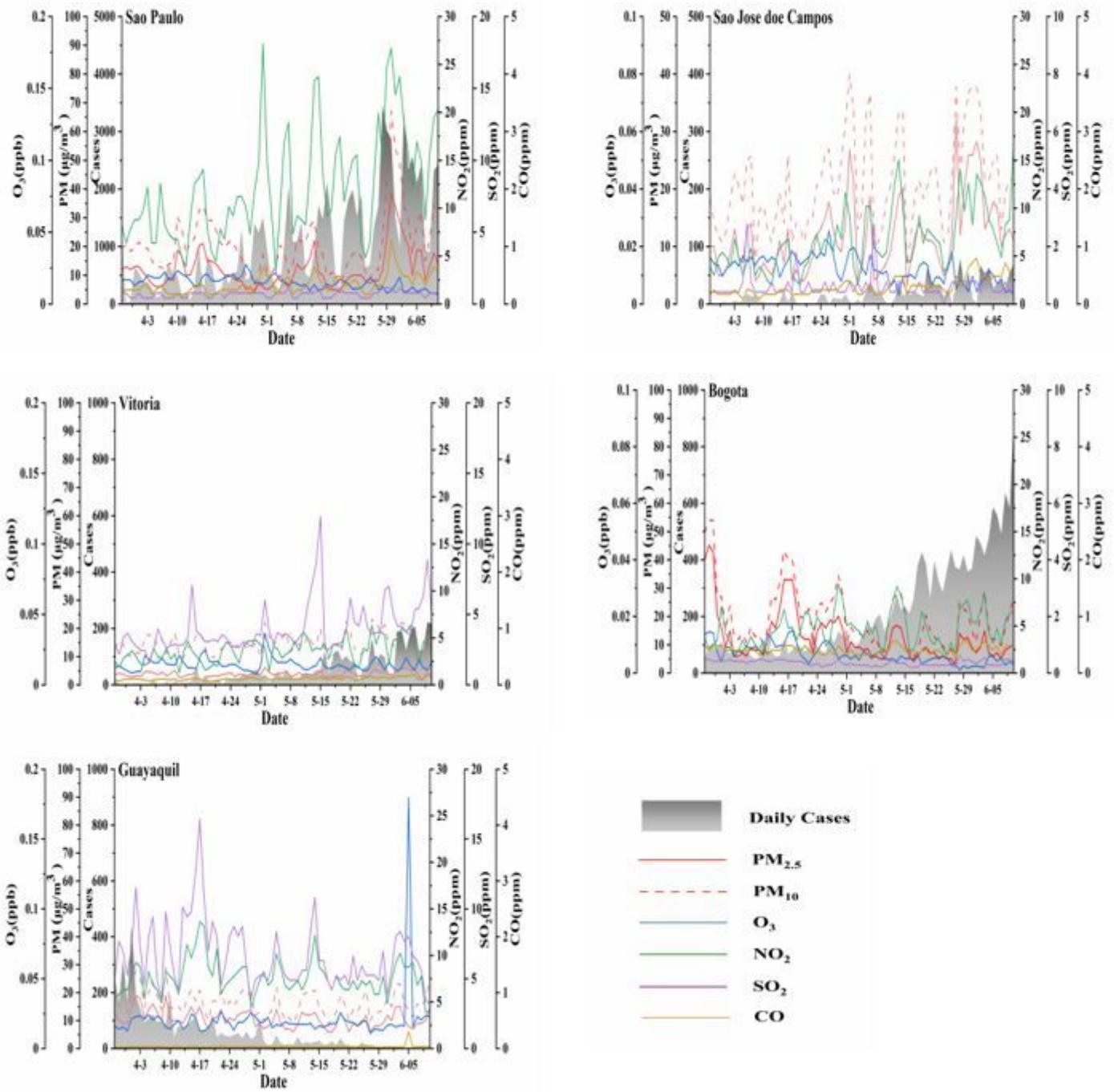
## Figure 2

Daily changes in the number of confirmed COVID-19 cases and air pollution in the selected regions.
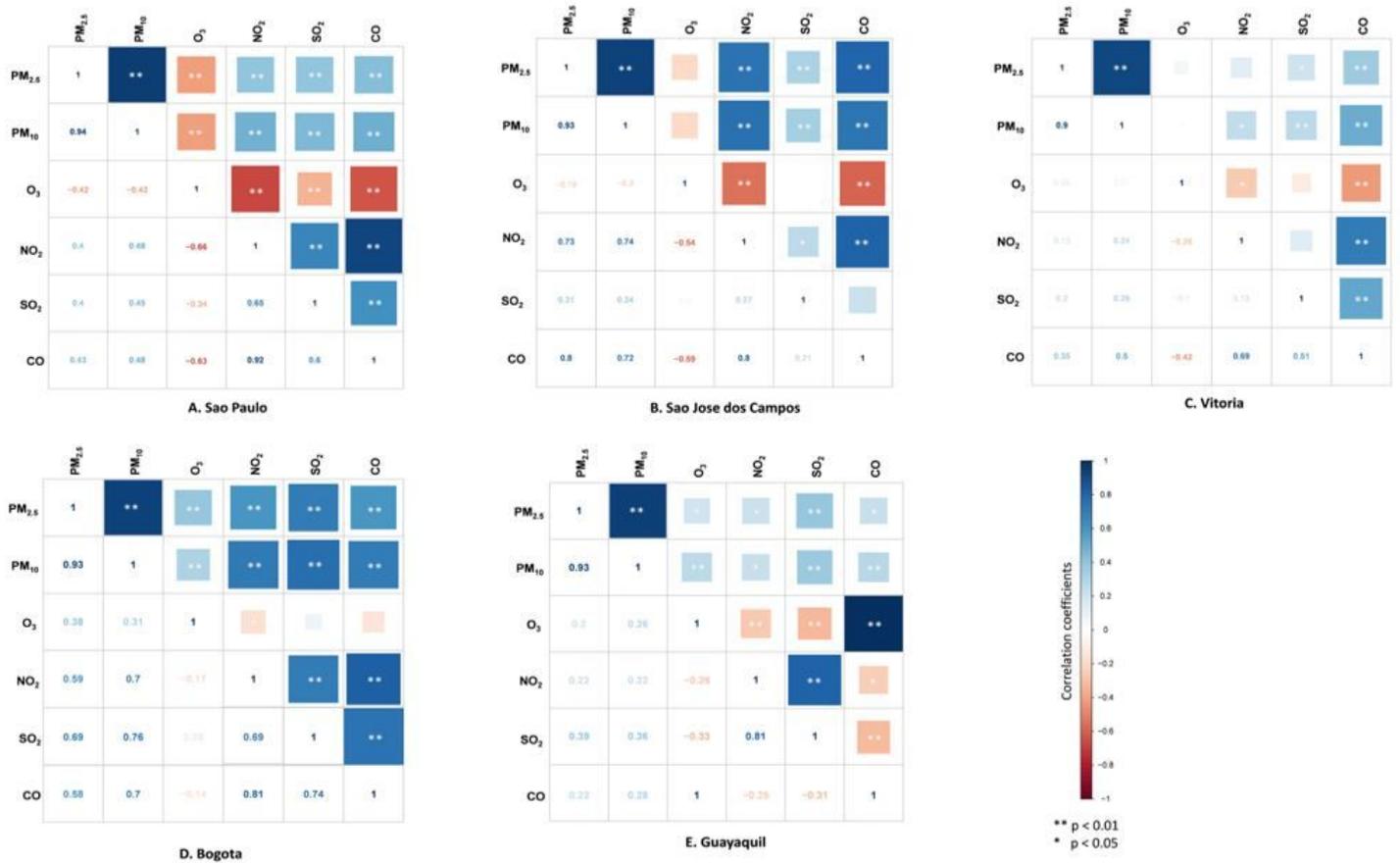
**Figure 3**

Spearman correlation between air pollution and Rt in the five regions.
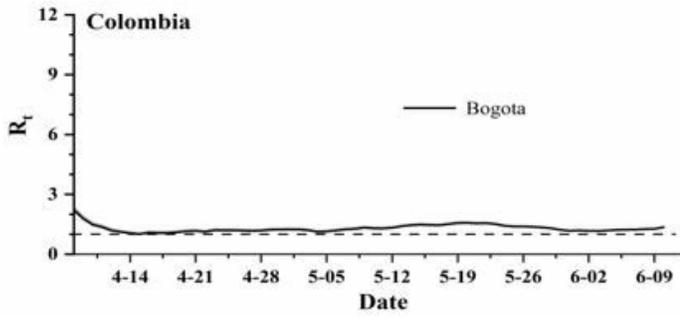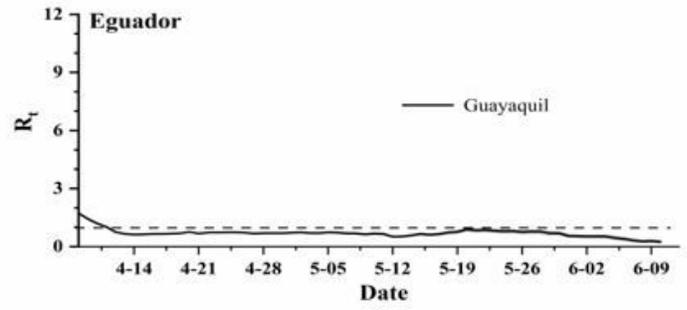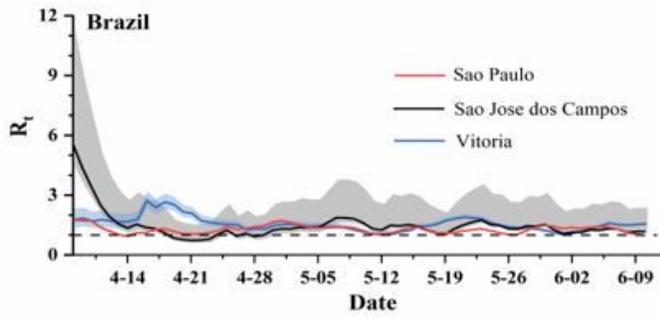
**Figure 4**

Daily estimated distributions of the effective reproduction number Rt.
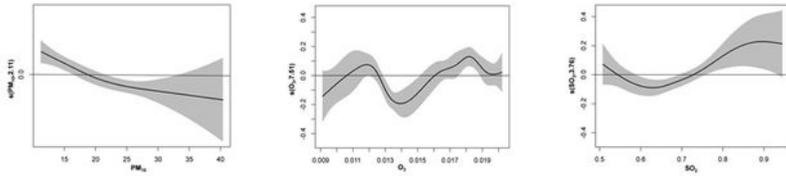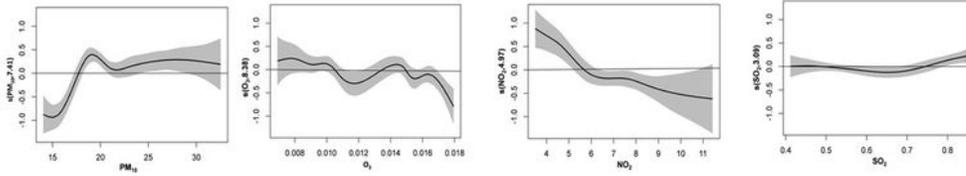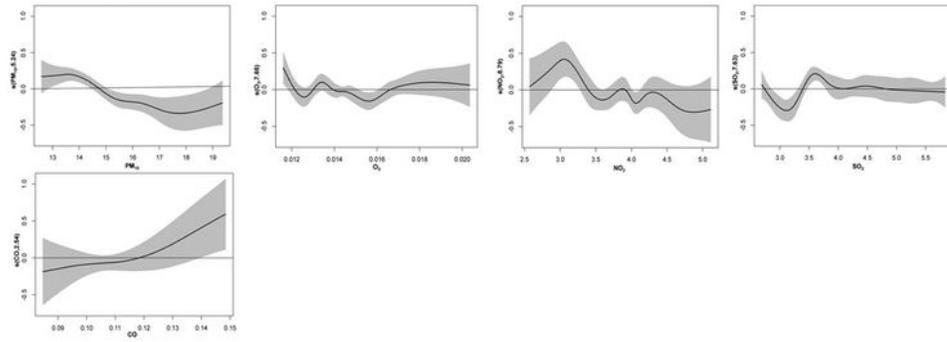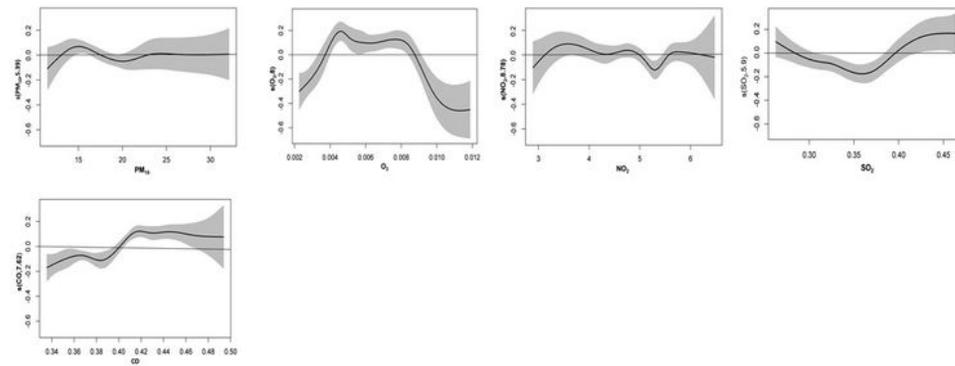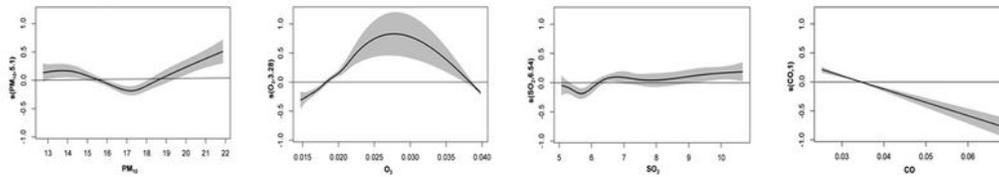
## Figure 5

The results of the GAM model for the effects of air pollutants on the variation of Rt.