

# Correlation between COVID-19 and air pollution: the effects of PM<sub>2.5</sub> and PM<sub>10</sub> on COVID-19 outcomes

E. KALLUÇI<sup>1</sup>, E. NOKA<sup>1</sup>, K. BANI<sup>1</sup>, X. DHAMO<sup>1</sup>, I. ALIMEHMETI<sup>2</sup>, K. DHULLI<sup>3</sup>, G. MADEO<sup>3</sup>, C. MICHELETTI<sup>3</sup>, G. BONETTI<sup>3</sup>, C. ZUCCATO<sup>4</sup>, F. BORGHETTI<sup>5</sup>, G. MARCEDDU<sup>5</sup>, M. BERTELLI<sup>3,5,6</sup>

<sup>1</sup>Department of Applied Mathematics, Faculty of Natural Sciences, University of Tirana, Tirana, Albania

<sup>2</sup>Faculty of Medicine, University of Medicine Tirana, Tirana, Albania

<sup>3</sup>MAGI LAB, Rovereto, Trento, Italy

<sup>4</sup>AERSAFE, Progetto Manifattura, Rovereto, Trento, Italy

<sup>5</sup>MAGI EUREGIO, Bolzano, Italy

<sup>6</sup>MAGISNAT, Atlanta Tech Park, Peachtree Corners, GA, USA

**Abstract. – OBJECTIVE:** Given its effects on long-term illnesses, like heart problems and diabetes, air pollution may be among the reasons that led COVID-19 to get worse and kill a larger number of people. Experiments have shown that breathing in polluted air weakens the immune system, making it easier for viruses to enter the air and grow. Viruses may be able to survive in the air by interacting in complex ways with particles and gases. These interactions depend on the particles' chemical makeup, the particles' electric charge, and environmental conditions like humidity, light, and temperature. Moreover, exposure to UV rays and air pollution may reduce the organism's production of antimicrobial molecules, thus supporting viral infections. More epidemiological studies are needed to determine whether air pollution has on COVID-19. **RESULTS:** This review discusses how air pollution, its such as PM<sub>2.5</sub> and PM<sub>10</sub>, contribute to the transmission of COVID-19.

**MATERIALS AND METHODS:** We used nine target cities in the Tuscany region to verify this correlation, and in these cases, the air pollution factors were found to be strongly correlated with COVID-19 cases. In each city, we applied multivariate analysis and found an appropriate model that better fits the data.

**RESULTS:** This review underlines that both short-term and long-term exposure to air pollution are crucial exacerbating factors for SARS-CoV-2 transmission and COVID-19 severity and lethality. Statistical analysis concludes that air pollution should be accounted for as a possible risk factor in future COVID-19 investigations and it should be avoided as much as possible in the general population.

**CONCLUSIONS:** Our research highlighted the correlation between COVID-19 and air pollution. Reducing air pollution exposure should be one of the first measures against COVID-19 spread.

**Key Words:**

COVID-19, Air Pollution, PM<sub>2.5</sub>, PM<sub>10</sub>, UV light, multivariate analysis

## Introduction

The COVID-19 pandemic has spread worldwide, with hundreds of millions of confirmed cases and millions of deaths. Several treatments have been proposed for people infected with the virus, such as antiviral drugs and monoclonal antibodies. Among many others, the development of the so-called “long COVID” syndrome is a crucial consequence of COVID-19 infection. People affected by this condition continue to have COVID-like symptoms (such as fatigue, brain fog, and shortness of breath) even after getting over the virus<sup>1</sup>.

COVID-19 transmission modalities have recently been identified<sup>2,3</sup> as direct and indirect. Direct pathways of SARS-CoV-2 bioaerosol transmission can be droplet nuclei and other physiological fluids floating in the interior atmosphere, as well as maternal-to-infant transmission. The indirect method is via fomites, contaminated surfaces on surrounding furniture, and fixtures that cause an infected person to get ill<sup>2</sup>. The nasal epithelial cells have been identified as the main entry for SARS-CoV-2, via the spike protein of the virus being cleaved by proteases. Then, SARS-CoV-2 spike protein attaches to the angiotensin-converting enzyme-2 (ACE2) receptors on the cellular membrane, thus gaining access to the host cells in the nasal and upper airway passages<sup>3</sup>.

Several studies<sup>4-8</sup> support the effects of air pollution in decreasing the antimicrobial defenses of the organism, increasing general inflammation and oxidation, and boosting the possibility of viral infections. Moreover, many viral infections, among which COVID-19, have been correlated to air pollution: for example, increased PM<sub>2.5</sub> concentrations have been associated with higher rates of respiratory virus transmission – including influenza, swine flu, and measles<sup>9</sup>. Moreover, it has been proved<sup>10</sup> that individuals living in air-polluted areas have an increased viral infection mortality risk. Exposure to polluted air also increases the prevalence of lower respiratory tract infections and also exacerbates respiratory virus symptoms<sup>10</sup>. Coal use, and thus fine and ultrafine particles, seem highly detrimental in increasing viral infection mortality<sup>11</sup>.

Among the different air pollutants, some specific ones have been correlated to viral infections, such as particulate matter (PM), with a 50% cut-off aerodynamic diameter of 10 µm (PM<sub>10</sub>), tiny particles (PM<sub>2.5</sub>) and ultrafine particles (0.1 µm in diameter). PM size substantially affects its ability to be transported and to reach its destination within the respiratory system and bloodstream. The composition of particulate matter may vary depending on its source<sup>12</sup>. Moreover, another typical air pollutant with widespread toxic effects is nitrogen dioxide (NO<sub>2</sub>). It is a significant air pollutant in cities, mainly due to traffic (especially from diesel automobiles), and has been linked to asthma, COPD, bronchiolitis, and cardiovascular disease.

## Material and Methods

This scoping review followed PRISMA guidelines<sup>14</sup> for reporting scoping reviews. This article starts with a review of existing literature that focuses on SARS-CoV-2 and the effects of air pollution, PM<sub>10</sub>, and PM<sub>2.5</sub>. To do this, we selected original and review articles from online databases such as PubMed and Scopus, using the following strings: (SARS-CoV-2 [Text Word]) AND (air pollution [Text Word] OR PM<sub>10</sub> [Text Word] OR PM<sub>2.5</sub> [Text Word]). Only articles published in English were included. In this study, we followed a pipeline of statistical methods in order to study the correlation between COVID-19 with air pollution and climate factors. In this study, four air pollution factors were taken into consideration: PM<sub>10</sub>, PM<sub>2.5</sub>, NO<sub>2</sub>, and sulfur dioxide (SO<sub>2</sub>). Additionally, five climate factors, namely maximum temperature (Max\_T), minimum temperature (Min\_T),

maximum temperature (Max\_T), dew point (DP), medium wind speed (Med\_WS), maximum wind speed (Max\_WS), humidity (H); there were 11 factors in total that are involved in the study. For the analysis, the open-access datasets were taken from the web (available at [https://www.arpat.toscana.it/temi-ambientali/aria/tema-aria/archivio\\_dati\\_orari](https://www.arpat.toscana.it/temi-ambientali/aria/tema-aria/archivio_dati_orari)). In a dataset with many variables, groups of variables often move together, and as we considered 11 factors, we applied Principal Component Analysis (PCA), which is a classical multivariate analysis technique to reduce the dimensions. PCA is one of the most widely used techniques where dimensionality reduction is required. The main purpose of PCA is to solve the problem of dimensionality reduction, and through it is possible to capture the 'information' contained in a dataset with a smaller set of variables compared to the original one. This method is used when there is a variable that is a function of other variables, and, in consequence, it contains redundant information; the other case is when the observed variables are correlated, and a small number of new variables could replace them without loss of information. The dimensionality reduction allows us to simplify posterior analysis and carry out graphical visualization in few dimensions. The PCA is the first step before performing a multivariate analysis.

We applied PCA for nine provinces in the region of Tuscany and chose 3 to 5 principal factors that better explain the original dataset. There are several methods to decide how many components to use; in this study, we used the percentage of explained variability – it is desirable to achieve a relatively high percentage of explained variability (i.e., 70-90%). We also used the Kaiser-Meyer-Olkin (KMO) test, which is a statistical measure to determine how suited data are for factor analysis. The higher the proportion, the higher the KMO value, and the more suited the data is to factor analysis. In the field of statistics, Bartlett's test, attributed to Maurice Stevenson Bartlett, is employed for assessing homoscedasticity. Specifically, it is used to determine whether multiple sets of data originate from populations characterized by comparable variances. Kaiser's criterion excludes those components whose eigenvalues are smaller than the average eigenvalue or others smaller than 1 if they are computed from the correlation matrix<sup>15</sup>. In this work, we used the high percentage of explained variability, Kaiser-Meyer-Olkin (KMO) test, Bartlett's test, and eigenvalues' test for the principal components

that we involved in the multivariate analysis. The detailed information and numerical calculation for our dataset are shown in [Supplementary File 1](#). With the new variables obtained from the PCA analysis, the multivariate analysis was performed using linear and nonlinear regression.

## Results

Multiple studies in literature have shown that increases in air pollutant concentrations relate to an increase in viral respiratory illnesses in children and adults, mainly when the viral infection occurs concurrently with a short-term surge in air pollution exposure<sup>4</sup>. These data prompted research on the potential relationship between pollution and COVID-19. According to several investigations<sup>4</sup>, long-term exposure to air pollution, which varies geographically and temporally, may increase the likelihood of COVID-19 causing severe consequences. COVID-19 cases have indeed been related to fine particle levels, showing that PM<sub>2.5</sub> has a greater impact than PM<sub>10</sub>. Indeed, PM<sub>2.5</sub> and PM<sub>10</sub> seem to have a positive relationship with SARS-CoV-2<sup>14,16,17</sup>, and recent research has shown that COVID-19 mortality has almost doubled in places with high PM<sub>2.5</sub> levels. Nitrogen oxides (NO<sub>x</sub>) and ozone (O<sub>3</sub>), two types of gaseous pollution, have also been linked to COVID-19 and other respiratory viruses. Indeed, NO<sub>2</sub> levels have been positively correlated<sup>16,17</sup> to the spread of COVID-19. Finally, air pollution may enhance ACE-2 (angiotensin-converting enzyme 2) synthesis in pulmonary endothelial cells, thus increasing SARS-CoV-2 infectivity<sup>2</sup>.

This study monitored the air pollution and climate factors with respect to the response of COVID-19 cases for a time interval of 44 days, the period 25.02.2020 – 08.03.2020. We decided to choose this period of time because it was the first month of the spread of the pandemic, and there were no vaccinations.

Table I shows the new variables performed from the PCA analysis and from which original variables they are composed, including 5 cities where the air pollution factors are in the first, fourth and fifth PC, in the other cases, the pollution factors are present in the first, second, and third PC.

The number of PCs presented in Table I was obtained from the high percentage of explained variability, Kaiser-Meyer-Olkin (KMO) test, Bartlett's test, and eigenvalues' test, while Table II shows the percentage of variance explained for each principal component. We noticed that for the five provinces, the total variance explained was over 80%. The complete information for the other provinces is given in [Supplementary File 2](#).

The first presented province is Florence, because it is the largest one with respect to population, the second one is Pistoia, and it is the only one with the specification that the four air pollution factors are present in the first and second principal components, the third province is Siena, because the composite factors of the first component are quite common with five cities.

In the following equation, we are giving the Linear Multiple Regression of the COVID-19 cases with respect to the first and second principal components, where the first principal component is related to the original variables NO<sub>2</sub>, O<sub>3</sub>, H, Med\_WS, Max\_WS, and the second principal

**Table I.** The principal components (PCs) of each city which explain the model. The factors are written in decreasing order for the percentage contribution to the respective PC.

City	First PC	Second PC	Third PC	Fourth PC	Fifth PC
<b>Florence</b>	NO <sub>2</sub> , O <sub>3</sub> , H, Med_WS, Max_WS	PM <sub>2.5</sub> , PM <sub>10</sub> , Med_T, Max_T, Med_WS.	Med_T, Min_T, DP.		
<b>Livorno</b>	PM <sub>2.5</sub> , PM <sub>10</sub> , Max_T, Med_WS.	Med_T, Min_T, DP.	NO <sub>2</sub> , O <sub>3</sub> , H.		
<b>Grosseto</b>	Med_WS, Max_WS	Min_T, DP, H.	Med_Tp., Max_Tp.,	PM <sub>2.5</sub> , NO <sub>2</sub> , O <sub>3</sub> , PM <sub>10</sub>	
<b>Massa Carrara</b>	Med_WS, Max_WS	Min_T, DP, H.	Med_T, Max_T,	PM <sub>10</sub> , PM <sub>2.5</sub>	
<b>Pistoia</b>	PM <sub>2.5</sub> , PM <sub>10</sub> , H, Med_WS, Max_WS	PM <sub>2.5</sub> , PM <sub>10</sub> , Med_T, Max_T, Max_WS.	Med_T, Min_T, DP, H.		
<b>Pisa</b>	PM <sub>10</sub> , PM <sub>2.5</sub> , Max_T, Med_WS, Med_WS	Med_T, Min_T, Dew point.	NO <sub>2</sub> , O <sub>3</sub> , H		
<b>Arezzo</b>	Med_WS, Max_WS,	PM <sub>10</sub> , PM <sub>2.5</sub> , Med_T, Max_T, Min_T, DP, H.	Med_T, Min_T, DP, H.		
<b>Prato</b>	NO <sub>2</sub> , Med_WS, Max_WS, H, NO <sub>2</sub> , H, Med_WS, Max_WS.	Med_T, Min_T, DP, H.	Med_T, Max_T,	PM <sub>10</sub> , PM <sub>2.5</sub> , O <sub>3</sub> , Max_T.	
<b>Reggio Emilia</b>		Med_T, Min_T, DP, H.	PM <sub>10</sub> , PM <sub>2.5</sub>		

component is related to the original variables  $PM_{2.5}$ ,  $PM_{10}$ ,  $Med\_T$ ,  $Max\_T$ ,  $Med\_WS$ .

$$y = 479.116 + 417.57x_1 + 145.74x_2$$

Figure 1 shows the graphical visualization of the plane that fits the data for Florence. In this model, we observed that the four considered air pollution factors among the climate factors were present, with humidity (H.), wind speed ( $Med\_WS$ ,  $Max\_WS$ ), and temperature ( $Med\_T$ ,  $Max\_T$ ) being the most important. For this model, the  $p$ -value corresponded to  $4.4517e^{-7}$ , meaning that it is statistically significant, giving a good approximation for the data.

The second model is constructed with respect to the second and third principal components. The second principal component is related to the original variables  $PM_{2.5}$ ,  $PM_{10}$ ,  $Med\_T$ ,  $Max\_T$ , and  $Med\_WS$ , and the third principal component is related to the original variables  $Med\_T$ ,  $Min\_T$ , and Dew Point (DP).

$$y = 531.02 + 151.11x_1 - 182.43x_2$$

From the visualization of the model, we see that the fitting is not good, meaning that adding more climate factors, such as the Dew Point, does not increase the accuracy of the approximation.

For the lack of accuracy, we find the nonlinear multiple regression of COVID-19 case with respect to the first and second principal components, shown in the right graph of Figure 2. This model has a statistical significance as  $p$ -value = 0.382, meaning a good approximation of the dataset.

$$y = 479.06 + 141.79x^1 + 51.11x^2$$

The linear multiple regression with three factors is given with the following equation, and the  $p$ -value is  $4.47e^{-8}$ , increasing the statistical significance compared with the previous nonlinear multiple regression with only two factors.

$$y = 477.11 + 116.96x^1 + 150.89x^2 - 181.12x^3$$

We could represent this model in a three-dimensional space, Figure 3 shows the addition with respect to the fitted line with a confidence interval of 95%.

The linear multiple regression with the first and second principal components for Pistoia is given with the following equation:

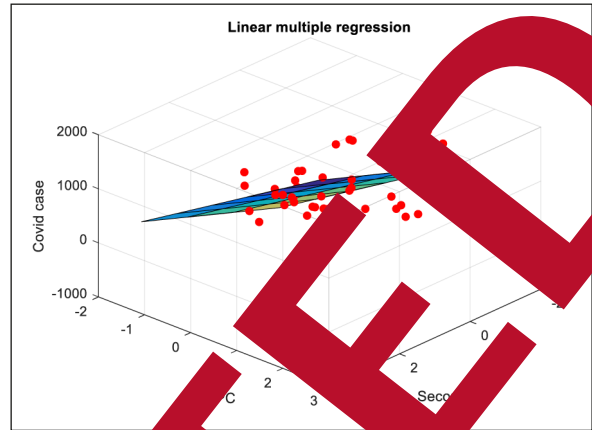


Figure 1. Linear multiple regression for Florence with the first and second PCs.

$$y = 531.02 + 151.11x_1 - 182.43x_2$$

Figure 4 shows the visualization of the linear multiple regression with respect to the COVID-19 cases. For the purpose of comparison,

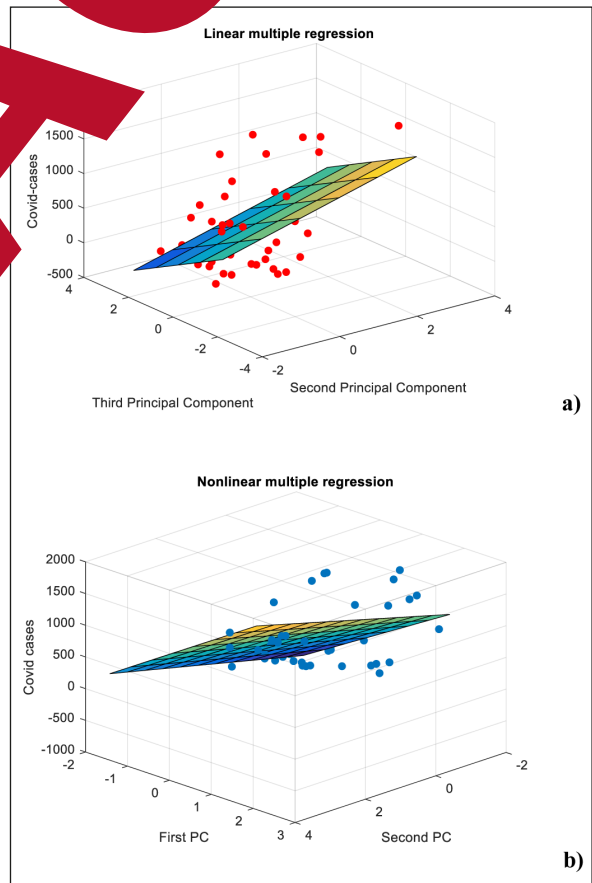


Figure 2. a, Linear multiple regression for Florence with the second and third PCs. b, Nonlinear multiple regression for Florence with the first and second PCs.

we constructed the nonlinear multiple regression with the first and second principal components.

$$y = 143.98 - 110.11x^1 + 41.84x^2 + 11.76x^1x^2$$

The accuracy for both models using the first and second principal components is very good, and the statistical significance of them is of the order  $p\text{-value} = e^{-9}$ .

Referring to the results of Table II, the original dataset for Pistoia is explained as 82% with three principal components. The following equation shows the linear multiple regression with all the principal components. The approximation is satisfactory, and the statistical significance is increased up to  $p\text{-value} = 6.34e^{-10}$ .

$$y = 143.42 - 113.64x^1 + 35.677x^2 - 40.503x^3$$

Figure 5 presents the visualization of nonlinear multiple regression for Pistoia. Siena is the third

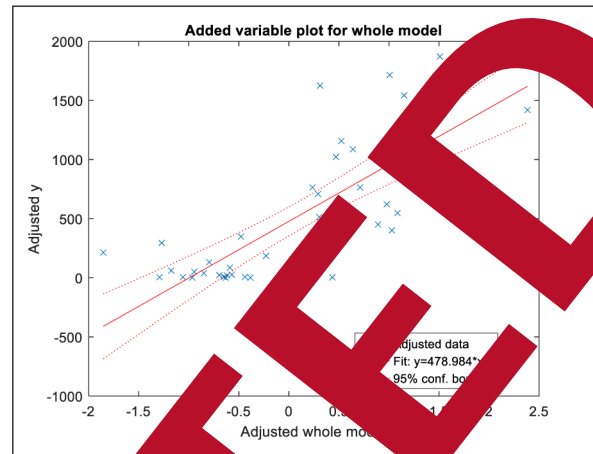


Figure 3. Linear multiple regression for Florence with three principal components.

principle, we have extracted to present in this work, and it models the linear multiple regression

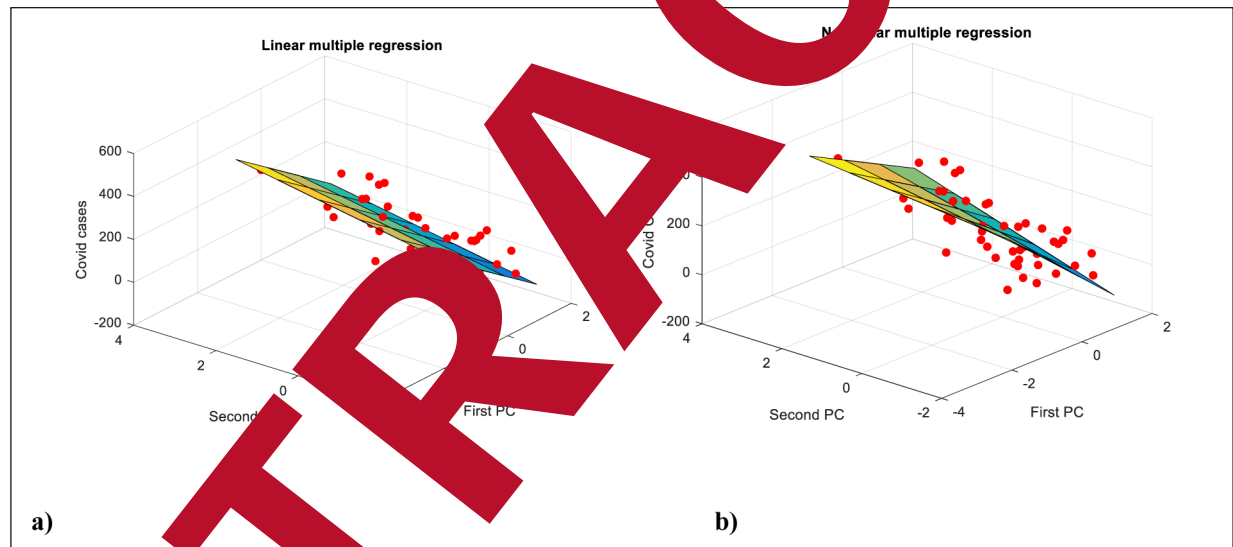
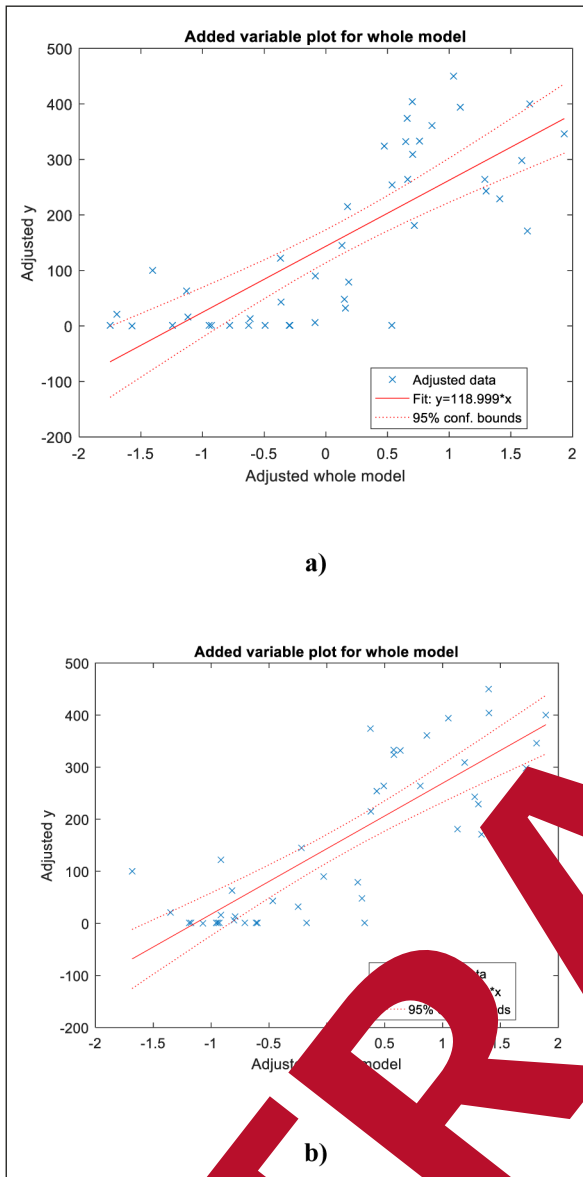


Figure 4. a) Linear multiple regression for Pistoria with the first and second PCs. b) Nonlinear multiple regression for Pistoria with the first and second PCs.

Table 1. The percentage of variance explained from each principal component (PC).

City	First PC	Second PC	Third PC	Fourth PC	Fifth PC	Total variance explained
Florence	37%	23%	18%			82%
Genova	39%	24%	14%			81%
Montecatini	35%	21%	15%	10%	5%	90%
Modena	37%	19%	18%	12%		86%
Pistoia	44%	22%	17%			82%
Prato	44%	25%	12%			81%
Siena	37%	24%	20%			82%
Verona	42%	23%	16%	10%		90%
Perugia	35%	25%	14%	11%		85%

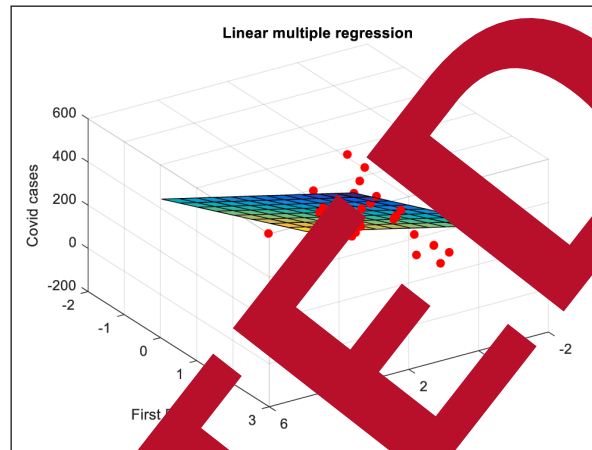


**Figure 5.** a), Nonlinear multiple regression for Pistoria with the first and second PCs. b), Nonlinear multiple regression for Pistoria with the first, the second, and the third PCs.

of the COVID-19 cases with respect to the first and second principal factors. The first principal component is related to the original variables  $NO_2$ ,  $Med\_WS$ ,  $Max\_WS$  and the second principal component is related to the original variables. The statistical significance is  $p\text{-value} = 0.0005654$  lower compared with the previous case but within the allowed limits.

$$y = 127.87 + 69.12x^1 + 37.97x^2$$

Figure 6 shows the visualization of the linear multiple regression with respect to Siena with the



**Figure 6.** Linear multiple regression for Siena with the first and second PCs.

first and second PCs. The linear model with three variables, according to the results given in Table II, explains that 83% of the total variance has statistical significance ( $p\text{-value} = 1.35e^{-6}$ ), which is much better than the model with two PCs.

$$y = 127.87 + 64.065x^1 + 39.449x^2 - 60.078x^3$$

Figure 7 shows the visualization of linear multiple regression for Siena. In order to find the best fit for the data, we have presented the linear and nonlinear multiple regression with the second and the third principal components presented with the following equations:

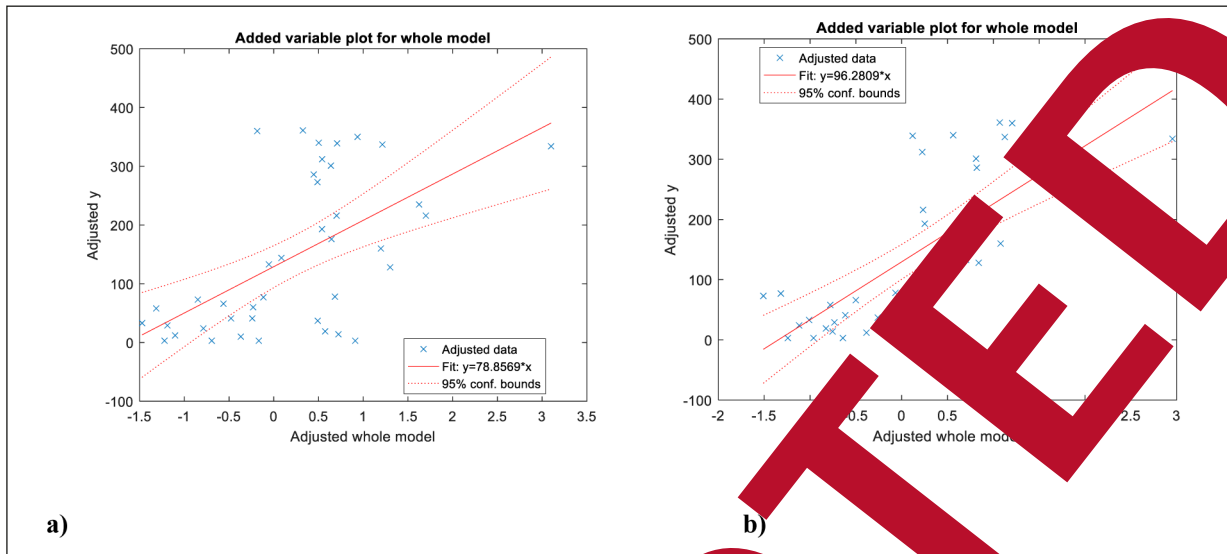
$$y = 145.86 + 39.32x^2 - 64.15x^3$$

$$y = 145.22 + 4645x^2 - 60.13x^3 + 20.72x^2x^3$$

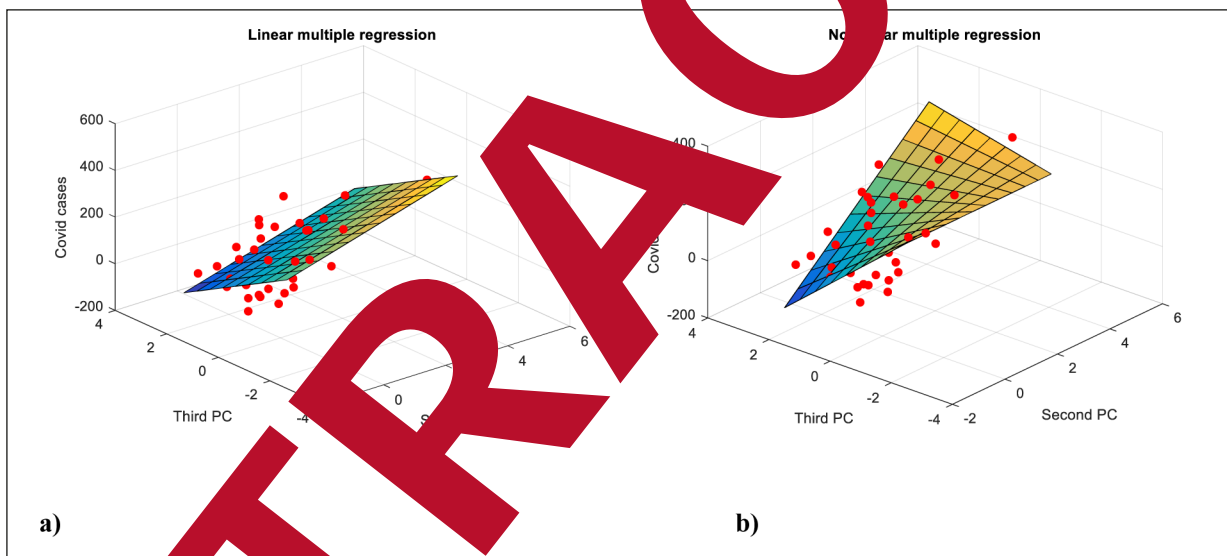
The visualization of the linear and nonlinear multiple regressions is given in Figure 8. Linear multiple regression for Siena with the second and third PCs has a statistical significance ( $p\text{-value} = 2.2575e^{-4}$ ), and the nonlinear multiple regression for Siena with the second and the third PCs has a statistical significance as  $p\text{-value} = 6.015e^{-4}$ . Comparing the accuracy, we conclude that it is more appropriate to use the linear model with the second and the third PC.

## Discussion

Both long-term and short-term/acute exposure to air pollution have adverse effects, contributing to a wide range of chronic disorders<sup>18,19</sup>. Epidemiological studies<sup>20,21</sup> have revealed that exposure to



**Figure 7.** a, Linear multiple regression for Siena with the first and the second PCs. b, Linear multiple regression for Siena with the first, the second, and the third PCs.



**Figure 8.** a, Linear multiple regression for Siena with the second and third PCs. b, Nonlinear multiple regression for Siena with the second and the third PCs.

air pollution may indirectly predispose people to severe and potentially fatal types of COVID-19. Indeed, the respiratory system, apart from being highly impacted by air pollution, is also the biological target that is affected by the symptoms of SARS-CoV-2, going from moderate upper airway sickness to severe pneumonia and abrupt respiratory distress syndrome (ARDS). Short-term and long-term impacts on obstructive airway disorders (like asthma and COPD) and restrictive lung pathologies (like fibrosis) are caused by the inflammation and oxidative stress air pollution

causes in the lungs. Children exposed to high  $NO_2$  concentrations are more likely to develop severe types of virus-induced asthma, suggesting that air pollution may exacerbate the severity of SARS-CoV-2 pneumonia by weakening the respiratory system<sup>22</sup>. Chronic rhinitis and rhinosinusitis, which have been linked to air pollution, may enhance airway mucosal permeability, thus making SARS-CoV-2 infections more likely<sup>3</sup>.

Meteorological conditions represent another factor influencing air pollution and viruses' vitality. Pollutants and respiratory viruses have

intricate interactions in the environment; for example, PM is known to contain microbes like viruses, and SARS-CoV-2 RNA was indeed discovered in PM. However, how long this virus stays infectious in ambient air and whether the tiny amount of virus in the aerosol is enough to cause infection are still open questions<sup>23</sup>. Weather elements, like ultraviolet light and relative humidity, all play a role in the complicated interactions between gases and viruses in the atmosphere. Air pollution may have a role in the immune response to viral infections by lowering vitamin D production and decreasing UV radiations (which have antiviral action), contributing to viral persistence in ambient air<sup>24</sup>.

This review underlines that both short-term and long-term exposure to air pollution may be crucial exasperating factors for SARS-CoV-2 transmission and COVID-19 severity and lethality through multiple mechanisms. Considering the numerical results obtained for nine provinces, we conclude that air pollution should be accounted for as a possible risk factor in future COVID-19 investigations, and it should be avoided as much as possible by the general population. Reducing outdoor and indoor air pollution in cities or nations may have immediate and significant health benefits, which may considerably exceed the costs; moreover, strict control of air pollutants could decrease the incidence of many disorders, among which COVID-19.

## Conclusions

Air pollution has been correlated with COVID-19 onset since it affects the organism by increasing inflammation and oxidative stress and decreasing the immune and microbial defenses of the organism. Indeed, many air pollutants, such as PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub>, have been correlated to high rates of SARS-CoV-2 infectivity and mortality. In the target provinces that we studied, air pollutants PM<sub>2.5</sub>, PM<sub>10</sub>, and NO<sub>2</sub> are present in the first and second principal components with a high percentage of variance explained. The models we constructed have a very good accuracy and show high statistical significance. The aim of this paper is to highlight the need to control air pollution combined with other risk factors on the spread of COVID-19 and, in general, in all respiratory diseases. Reducing air pollution exposure should be one of the first measures against COVID-19 spread.

## Informed Consent

The participants and their families provided informed consent.

## Ethics Approval

The Ethics Committee of the Civil Fraternity of Alcade Hospital approved the protocol with the number HCG/ CEI-2028/21. The protocol was performed in accordance with the Declaration of Helsinki.

## Availability of Data and Materials

All data associated with this paper are available from the corresponding author upon reasonable request.

## Funding

This research was funded by the Provincia Autonoma di Bolzano in the framework of the year 2006.

## Authors' Contributions

Conceptualization, E.K., and E.K.; Methodology, E.K.; Investigation, E.K., K.D., I.A., X.D., G.M., and M.B.; Writing original draft preparation, E.K., K.B., I.A., X.D., and G.B.; Reviewing and editing, K.D., G.M., C.M., G.B., C.Z., G.M., and M.B.; Project administration, E.K., and M.B.; Funding acquisition, E.K., and M.B. All authors have read and agreed to the published version of the manuscript.

## Conflicts of Interest

The authors declare no conflict of interest.

## References

- 1) Fronza R, Lusic M, Schmidt M, Lucic B. Spatial-Temporal Variations in Atmospheric Factors Contribute to SARS-CoV-2 Outbreak. *Viruses* 2020; 12: 588
- 2) Houghton C, Meskell P, Delaney H, Smalle M, Glenton C, Booth A, Chan XHS, Devane D, Biesity LM. Barriers and facilitators to healthcare workers' adherence with infection prevention and control (IPC) guidelines for respiratory infectious diseases: a rapid qualitative evidence synthesis. *Cochrane Database Syst Rev* 2020; 4: CD013582.
- 3) Larsson BM, Sehlstedt M, Grunewald J, Sköld CM, Lundin A, Blomberg A, Sandström T, Eklund A, Svartengren M. Road tunnel air pollution induces bronchoalveolar inflammation in healthy subjects. *Eur Respir J* 2007; 29: 699-705.
- 4) Bourdrel T, Annesi-Maesano I, Alahmad B, Maesano CN, Bind MA. The impact of outdoor air pollution on COVID-19: a review of evidence from in vitro, animal, and human studies. *Eur Respir Rev* 2021; 30: 200242.
- 5) Pennisi M, Lanza G, Falzone L, Fiscaro F, Ferri R, Bella R. SARS-CoV-2 and the Nervous System:



- From Clinical Features to Molecular Mechanisms. *Int J Mol Sci* 2020; 21: 5475.
- 6) Zielinska MA, Hamulka J. Protective Effect of Breastfeeding on the Adverse Health Effects Induced by Air Pollution: Current Evidence and Possible Mechanisms. *Int J Environ Res Public Health* 2019; 16: 4181.
  - 7) Wong SS, Webby RJ. Traditional and new influenza vaccines. *Clin Microbiol Rev* 2013; 26: 476-492.
  - 8) Zhang S, Huo X, Zhang Y, Huang Y, Zheng X, Xu X. Ambient fine particulate matter inhibits innate airway antimicrobial activity in preschool children in e-waste areas. *Environ Int* 2019; 123: 535-542.
  - 9) Wang B, Liu J, Li Y, Fu S, Xu X, Li L, Zhou J, Liu X, He X, Yan J, Shi Y, Niu J, Yang Y, Li Y, Luo B, Zhang K. Airborne particulate matter, population mobility and COVID-19: a multi-city study in China. *BMC Public Health* 2020; 20: 1585.
  - 10) Wilder-Smith A. COVID-19 in comparison with other emerging viral diseases: risk of geographic spread via travel. *Trop Dis Travel Med Vaccines* 2021; 7: 3.
  - 11) Mallah SI, Ghorab OK, Al-Salmi S, Abdellatif OS, Tharmaratnam T, Iskandar MA, Sefen JAN, Sidhu P, Atallah B, El-Lababidi R, Al-Qahtani M. COVID-19: breaking down a global health crisis. *Ann Clin Microbiol Antimicrob* 2021; 20: 35.
  - 12) T. Zhang. "Design and optimization of nanoparticles for drug delivery: a review". Available at: <https://mospace.umsystem.edu/xmlui/handle/10355/35313>.
  - 13) Marazziti D, Cianconi P, Mucci F, Foresi L, Arantini I, Della Vecchia A. Climate change, environment pollution, COVID-19 pandemic and mental health. *Sci Total Environ* 2021; 768: 145182.
  - 14) Tricco AC, Lillie E, Zarin W, O'Brien K, Colquhoun H, Levac D, Moher D, Peters MDJ, Horsley T, Weeks L, Hempel S, Aklonis C, Chang CL, McGeechan A, Diwan M, Freeman S, Godwin E, Hartling L, Alderson J, Stewart L, Hartling L, Aklonis C, Verrill C, Lewin S, Gagnon CJ, Moher D, McDonald MT, Langlois EV, Soares-Weiser K, Moher D, Clifford T, Tunçalp Ö, Straus SE. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med* 2021; 174: 169-177.
  - 15) A. Grane and A.Jach. "Applications of principal component analysis (PCA) in food science and technology", *Mathematical and Statistical Methods in Food Science and Technology*. John Wiley Sons 2014; 55-86.
  - 16) Coccia M. High health expenditures and low exposure of population to air pollution as critical factors can reduce fatality rate in COVID-19 pandemic: a global analysis. *Environ Res* 2021; 198: 111339.
  - 17) Rodriguez-Villamizar LA, Beltrán-Ceron LC, Fernández-Niño JA, Marín-González DM, Rojas-Sánchez OA, Acuña-Mercaderes M, Ramírez-García N, Mangones-Mateo SC, Vargas-Rodríguez JM, Herrera-Torres J, Cudelo-Castaño DM, Piñeros Jiménez J, Rojas-Roa NY, Rodríguez-Galindo VM. Air pollution, sociodemographic and health conditions effects on COVID-19 mortality in Colombia: a cross-sectional study. *Environ Int* 2021; 156: 106567.
  - 18) Meo SA, Shariq M. Effect of environmental air pollution on cardiovascular diseases. *Eur Rev Med Pharmacol Sci* 2015; 19: 489-497.
  - 19) Terzi C, De Gennaro F, Conti V, Graziani E, Petrolanni A. Air pollution ultrafine particles: toxicity beyond the lungs. *Eur Rev Med Pharmacol Sci* 2010; 14: 809-821.
  - 20) Roy MP. Air pollution and Covid-19: experience from India. *Eur Rev Med Pharmacol Sci* 2021; 25: 337-3376.
  - 21) Meo SA, Shariq M, Al-Masri AA, Al-Khlaiwi T, Al-Bahrani AM, Al-Jaz S, Alrassan LA, Yaqinuddin A. Air pollution in the Global South: effect of environmental pollution (PM<sub>2.5</sub>) on the incidence and mortality of SARS-CoV-2 in Karachi, Lahore, and Islamabad. *Eur Rev Med Pharmacol Sci* 2022; 26: 9054-9060.
  - 22) Gammeter G, Zmora P, Gierer S, Heurich A, Pöhlmann S. Proteolytic activation of the SARS-coronavirus spike protein: cutting enzymes at the cutting edge of antiviral research. *Antiviral Res* 2013; 100: 605-614.
  - 23) Kouhpayeh S, Shariati L, Boshtam M, Rahimmanesh I, Mirian M, Esmaeili Y, Najafu M, Khanahmad N, Zeinalian M, Trovato M, Tay FR, Khanahmad H, Makvandi P. The Molecular Basis of COVID-19 Pathogenesis, Conventional and Nanomedicine Therapy. *Int J Mol Sci* 2021; 22: 5438.
  - 24) Karković Marković A, Torić J, Barbarić M, Jakobušić Brala C. Hydroxytyrosol, Tyrosol and Derivatives and Their Potential Effects on Human Health. *Molecules* 2019; 24: 2001.
  - 25) Paital B, Agrawal PK. Air pollution by NO<sub>2</sub> and PM<sub>2.5</sub> explains COVID-19 infection severity by overexpression of angiotensin-converting enzyme 2 in respiratory cells: a review. *Environ Chem Lett* 2021; 19: 25-42.