Association between Air Pollutant and COVID-19 Confirmed Cases

Subjects: Public, Environmental & Occupational Health

Contributor: Chao-Tung Yang , Yu-Tse Tsan , Endah Kristiani , Po-Yu Liu , Wei-Min Chu

The COVID-19 pandemic raises awareness of how the fatal spreading of infectious disease impacts economic, political, and cultural sectors, which causes social implications. Across the world, strategies aimed at quickly recognizing risk factors have also helped shape public health guidelines and direct resources; however, they are challenging to analyze and predict since those events still happen.

COVID-19 AQI air pollutant correlation analysis deep learning LSTM lag times

1. Introduction

Although people remember and contemplate that during 26 January–3 October 2020, more than 300,000 people died in the United States, with two thirds of those deaths directly associated to COVID-19 [1], people might also assess what the newest science says about the pandemic. People know that those who live in places with severe levels of air pollution will face several hazards concerning their respiratory health throughout this outbreak. Currently, new research focuses on the correlations between air pollution and severe COVID-19 sickness, emphasizing the crucial need for everyone to breathe clean air. Research published in December 2020 attempted to assess the extent to which COVID-19 mortality is due to long-term exposure to fine particle pollution [2]. Using a combination of epidemiological data, satellite data, and other monitoring data worldwide, the researchers concluded that chronic air pollution might be responsible for 15% of COVID-19 fatalities globally [2]. The experts also distinguished air pollution generated by fossil fuels and pollution that is induced by other human activities. In the United States, fossil fuel-related air pollution is responsible for 15% of COVID-19 mortality, indicating that fossil fuel related air pollution contributes considerably to overall U.S. air quality [2].

2. Research on Association of Air Pollutant and COVID-19

Researchers conducted the research related to the association of air pollution and COVID-19 in various countries.

Zhu et al. [3] investigated the association between ambient air pollution and coronavirus infection. Between 23 January 2020 and 29 February 2020, in China, daily confirmed cases, air pollution concentrations, and climatic data were collected in 120 cities. They used a generalized additive model to examine the relationships between six air pollutants ($PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, and O_3) and verified instances of COVID-19.

Gupta et al. [4] estimated the increased risk of coronavirus disease (COVID-19), caused by severe acute respiratory syndrome coronavirus 2, by establishing a link between the mortality rate of infected individuals and air pollution, specifically Particulate Matters (PM) with aerodynamic diameters of 10 m and 2.5 m. Nine Asian cities' data are studied using statistical techniques such as analysis of variance and regression modeling.

Lolli et al. [5] quantified the relationship between COVID-19 transmission and meteorological and air quality indices in two significant urban regions in Northern Italy, Milan, and Florence, as well as the autonomous province of Trento. Milan, the capital of the Lombardy region, is often regarded as the heart of Italy's HIV epidemic.

Bashir et al. [6] investigated the relationship between COVID-19 and climatic indicators in New York City, United States of America. They analyzed secondary public data from the New York City Department of Health and the National Weather Service in the United States of America. The average temperature, lowest temperature, maximum temperature, rainfall, average humidity, wind speed, and air quality are all covered in the research. The Kendall and Spearman rank correlation tests were used to analyze the data.

Suhaimi et al. [7] investigated the relationships between air quality, climatic variables, and COVID-19 cases in Kuala Lumpur, Malaysia. The Department of Environment Malaysia provided air pollutants and meteorological data from 2018–2020, whereas the Ministry of Health Malaysia provided daily new COVID-19 case data in 2020.

Mehmood et al. [8] used geospatial tools to analyze the relationship between COVID-19 cases, air pollution, meteorological, and socioeconomic characteristics in three provincial capital cities and the federal capital city of Pakistan.

Hoang and Tran [9] investigated the temporal association in seven metropolitan centers and nine regions across Korea using the generalized additive model. The findings indicate a substantial nonlinear relationship between daily temperature and verified COVID-19 cases.

Travaglio et al. [10] matched current SARS-CoV-2 cases and fatalities from public databases to regional and subregional air pollution data collected across England.

In Singapore, Lorenzo et al. [11] examined the relationship between core air pollutant concentrations, climatic factors, and daily verified COVID-19 case numbers. The researchers here collected data on air pollutant concentrations (particulate matter [$PM_{2.5}$, PM_{10}], ozone [O_3], carbon monoxide [CO], nitrogen dioxide [NO_2], sulphur dioxide [SO_2], pollutant standards index [PSI]), and climatic variables (rainfall, humidity, and temperature). **Table 1** summarizes recent studies on the association between air pollutants and COVID-19.

Table 1. Recent research on Association of Air Pollutant and COVID-19.

Author (Year)	Objective	Location	Finding
Zhu et al. (2020)	Investigate the link between ambient air pollution and the new coronavirus infection.	One-hundred and twenty cities in China	$PM_{2.5}$, PM_{10}, NO_2, and O_3 levels were significantly higher in the previous two weeks in areas with newly confirmed COVID-19 cases.
Gupta et al. (2021)	Calculate the elevated incidence of coronavirus disease (COVID-19) induced by severe acute respiratory syndrome coronavirus 2 by demonstrating a correlation between the death rate of infected individuals and air pollution, especially Particulate Matters (PM).	Nine cities in Asia, Delhi India, Nagpur India, Kanpur India, Islamabad Pakistan, Lahore Pakistan, Jakarta Indonesia, Tianjin China, Guilin China, Hebei China	There is a positive association between a region's degree of air pollution and the mortality associated with COVID-19, demonstrating that air pollution is a significant and hidden factor exacerbating the worldwide burden of COVID-19-related mortality.
Lolli et al. (2020)	The correlation between meteorological and air quality indicators and COVID-19 transmission was quantified.	Northern Italy, Milan, and Florence	Although elements such as temperature and humidity are inversely connected with viral transmission, air pollution ($PM_{2.5}$) is positively correlated (to a lesser degree).
Bashir et al. (2020)	The connection between COVID-19 and climatic factors was analyzed.	New York City, USA	The COVID-19 pandemic was substantially related with average temperature, lowest temperature, and air quality.
Suhaimi et al. (2020)	Establish connections between air quality, climatic variables, and COVID-19 instances.	Kuala Lumpur, Malaysia	Spearman's correlation analysis revealed a positive connection between COVID-19 cases and PM_{10} ($r = 0.131$, $p < 0.001$), $PM_{2.5}$ ($r = 0.151$, $p < 0.001$), SO_2 ($r = 0.091$, $p = 0.003$), NO_2 ($r = 0.228$, $p < 0.001$), CO ($r = 0.269$, $p = 0.001$), and relative humidity (RH) ($r = 0.106$, $p = 0.001$).
Mehmood et al. (2021)	Using geospatial approaches to examine the connection between COVID-19 instances, air pollution, meteorological, and socioeconomic characteristics.	Three out of four provinces of Pakistan (Punjab, Sindh, Khyber Pakhtunkhwa)	The findings reveal that daily COVID-19 is positively linked with $PM_{2.5}$ and other meteorological variables, implying that climate has a significant role in determining the COVID-19 incidence rate in Pakistan.
Hoang and Tran	The generalized additive model was used to evaluate the temporal connection between ambient air pollution, weather, and COVID-19 infection.	Seven metropolitan cities and nine provinces across Korea	Daily temperature had a substantial nonlinear relationship with verified COVID-19 cases.

Author (Year)	Objective	Location	Finding
Travaglio et al. (2021)	Evaluated recent SARS-CoV-2 cases and fatalities from public databases to regional and subregional air pollution data collected at several locations.	England	There is a positive correlation between COVID-19 mortality and infectivity and air pollution concentrations, notably nitrogen oxides.
Lorenzo et al. (2021)	Determine the relationship between core air pollutant concentrations, climatic factors, and daily verified COVID-19 cases.	Singapore	There is a statistically significant positive correlation between NO_2, PSI, $PM_{2.5}$, and temperature and COVID-19 case numbers.
Mandalapu et al. (2022)	The link between air pollution and COVID-19 severity has been studied at the regional and metropolitan levels, but it is uncertain if this link holds true at the neighborhood level.	Los Angeles County, California	Eighteen of the twenty-three significant comparisons for the COVID-19 weekly death rate confirmed that NO_2 levels were higher in neighborhoods with higher COVID-19 weekly death rates. Similarly, 12 of the 19 comparisons confirmed the same relationship with CO levels, as 14 of the 23 comparisons confirmed the same relationship with ozone levels, and 6 of the 6 comparisons confirmed the same relationship with PM_{10}.
Sidell et al. (2022)	To examine at both long-term and short-term air pollution exposure, as well as COVID-19 occurrence, from 1 March 2020 to 28 February 2021.	Southern California	In all case peaks before February 2021, long-term $PM_{2.5}$ and NO_2 exposures were linked to an elevated probability of COVID-19 occurrence. Short-term exposures to $PM_{2.5}$ and NO_2 were also linked. Air pollution may have a role in raising the likelihood of COVID-19 infection.
Luo et al. (2022)	This study assessed the relationship between population movement and air quality in 332 Chinese cities from January to March (2019–2021), and the influence of three city factors (pollution level, city scale, and lockdown status) in this impact.	Three-hundred and thirty-two Chinese cities	Lower migration was linked to lower pollution levels (other than O_3). Susceptibility to pollution changes is more probable as NO_2 decreases and O_3 increases, whereas insusceptibility to pollution is more likely for CO and SO_2, and in cities with low migration. Cities with less air pollution and dense populations may benefit the most from lowering PM_{10} and $PM_{2.5}$. Those with rigorous traffic limits have higher links with population movement and air pollution than cities without limitations. The impacts of inter-city migration (ICM) and within city migration (WCM)

Author (Year)	Objective	Location	Finding
			on air pollution were found to be minor when city characteristics were considered.
Abdullah et al. (2022)	The connection between the Air Pollution Index (API) and COVID-19 infections is the objective of this research.	Malaysia	Each area has a positive connection between API and COVID-19: North 0.4% (R^2 = 0.004), Central 2.1% (R^2 = 0.021), South 0.04% (R^2 = 0.0004), East 1.6% (R^2 = 0.016), Sarawak 0.2% (R^2 = 0.002), whereas Sabah has a negative correlation of 4.3% (R^2 = 0.043).
Huang et al. (2022)	Data on air pollution and verified COVID-19 cases were collected from five severely affected cities in three South American nations. COVID-19's spread was measured using daily real-time population regeneration (Rt). The influence of environmental contaminants on the pandemic was investigated using two commonly used models: generalized additive models (GAM) and multiple linear regression.	South America	(1) In all five locations, Rt, which potentially represents COVID-19 dissemination, exhibited a progressive drop. (2) Rt had a substantial effect on PM_{10} and SO_2 in all of the locations studied. These two contaminants should be better monitored by regulators. (3) In cities with varying levels of air pollution, the link between air pollution and the spread of COVID-19 varied. The results indicate that there is a significant relationship between air pollution and COVID-19 infection.

...nts and [12][13][14][15][16]

[17] ... to predict ...remise is ...formance ...e training ...r, and the ...ultivariate ...e findings ...prediction

Al-Qaness et al. [18] presented an upgraded version of the adaptive neuro-fuzzy inference system (ANFIS) for forecasting the air quality index in Wuhan City, China. The PSOSMA is a hybrid optimization approach that uses a novel modified meta-heuristics (MH) algorithm, and a slime mold algorithm (SMA), which is enhanced by employing the particle swarm optimizer to increase ANFIS performance (PSO). The proposed PSOSMA-ANFIS was trained using three years of air quality index time series data and then used to forecast fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), carbon dioxide (CO_2), and nitrogen dioxide (NO_2) for a year. The suggested PSOSMA was also compared with various MH algorithms used to train ANFIS. The results discovered that the improved ANFIS incorporating PSOSMA outperformed the other methods.

Zhou et al. [19] discussed the COVID-19 forecasting, using the relevance of government initiatives in their suggested model, the Interpretable Temporal Attention Network (ITANet). Long short-term memory (LSTM) for temporal feature extraction and multi-head attention for the long-term dependency caption are used in the proposed model, which has an encoder–decoder architecture. The ITANet outperforms other models when it comes to anticipating COVID-19 new confirmed cases.

Saravanan et al. [20] described the impact of lockdown measures on air quality and rainwater accumulation in major cities. With respect to varying time length and climatic variables, the effects of COVID-19 on the environment during lockdown conditions were compared with those without lockdown conditions. During the lockdown, the concentrations of particulate pollution in Chennai, Bangalore, Delhi, and Melbourne were measured. The findings of this research indicate the effects of government actions and give a detailed perspective of the death rate in relation to air quality decrease.

Xu, et al. [21] created three deep learning models in their study to forecast the number of COVID-19 cases for Brazil, India, and Russia, including CNN, LSTM, and CNN-LSTM. The LSTM model, among the models constructed in this research, has the best forecasting performance, which indicates an improvement in prediction accuracy over certain current models.

Fu, et al. [22] used experimental public data sets from the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), the Air Quality Open Data Platform, the China Meteorological Data Network, and the WorldPop website. The Dual-link Bi-GRU Network predicts the epidemic scenario, and the Gauss–Newton iteration method quantifies the relationship between epidemic spread and other feature parameters. Among the selected characteristic elements, the reesarch discovered that population density had the most positive link with pandemic spread, followed by the number of landing planes.

Mumtaz, et al. [23] suggested an indoor air quality monitoring and prediction system based on the newest Internet of Things (IoT) sensors and machine learning capabilities, which can assess a variety of indoor pollutants. An IoT node including numerous sensors for eight pollutants, including NH_3, CO, NO_2, CH_4, CO_2, $PM_{2.5}$, as well as the ambient temperature and air humidity, has been designed for this purpose. With an accuracy of 99.37%, precision of 99%, recall of 98%, and F1-score of 99%, this model has showed promise in forecasting air pollutants' concentrations as well as overall air quality.

4. LSTM Network

In nonlinear sequence prediction issues, the LSTM network is a recurrent neural network (RNN) design that can learn order dependence. They have a habit of memorizing things for a long period. The memory cell, which substitutes classic neurons' hidden layers, is at the foundation of the LSTM network [24]. The LSTM networks, similarly to other RNNs, feature recurrent cells, but instead of a single NN gate, the recurring cell has an interactive input gate, output gate, and forget gate [25]. The cell remembers values for arbitrary time intervals, and these three gates control the flow of information into and out of the cell. Based on the past state, accessible memory, and current input, this structure guarantees that the LSTM can recognize which cells are stimulated and compressed. The LSTM networks were created to solve the problem of disappearing gradients that might occur when training traditional RNNs. As there may be unexpected delays between critical occurrences in a time series, LSTM networks are ideally suited for categorizing, processing, and generating predictions based on time series data. In many cases, LSTM has an advantage over RNNs, hidden Markov models, and other sequence learning approaches due to its relative insensitivity to gap length; therefore, the researchers selected LSTM as the model to predict the integration of COVID-19 and air pollutant data.

References

1. Rossen, L.M.; Branum, A.M.; Ahmad, F.B.; Sutton, P.; Anderson, R.N. Excess Deaths Associated with COVID-19, by Age and Race and Ethnicity—United States, 26 January–3 October 2020. MMWR Morb. Mortal. Wkly. Rep. 2020, 69, 1522–1527.
2. Pozzer, A.; Dominici, F.; Haines, A.; Witt, C.; Münzel, T.; Lelieveld, J. Regional and global contributions of air pollution to risk of death from COVID-19. Cardiovasc. Res. 2020, 116, 2247–2253.
3. Zhu, Y.; Xie, J.; Huang, F.; Cao, L. Association between short-term exposure to air pollution and COVID-19 infection: Evidence from China. Sci. Total Environ. 2020, 727, 138704.
4. Gupta, A.; Bherwani, H.; Gautam, S.; Anjum, S.; Musugu, K.; Kumar, N.; Anshul, A.; Kumar, R. Air pollution aggravating COVID-19 lethality? Exploration in Asian cities using statistical models. Environ. Dev. Sustain. 2021, 23, 6408–6417.
5. Lolli, S.; Chen, Y.-C.; Wang, S.-H.; Vivone, G. Impact of meteorological conditions and air pollution on COVID-19 pandemic transmission in Italy. Sci. Rep. 2020, 10, 16213.
6. Bashir, M.F.; Ma, B.; Komal, B.; Bashir, M.A.; Tan, D.; Bashir, M. Correlation between climate indicators and COVID-19 pandemic in New York, USA. Sci. Total Environ. 2020, 728, 138835.
7. Suhaimi, N.F.; Jalaludin, J.; Latif, M.T. Demystifying a Possible Relationship between COVID-19, Air Quality and Meteorological Factors: Evidence from Kuala Lumpur, Malaysia. Aerosol Air Qual. Res. 2020, 20, 1520–1529.
8. Mehmood, K.; Bao, Y.; Abrar, M.M.; Petropoulos, G.P.; Soban, A.; Saud, S.; Khan, Z.A.; Khan, S.M.; Fahad, S. Spatiotemporal variability of COVID-19 pandemic in relation to air pollution, climate and socioeconomic factors in Pakistan. Chemosphere 2021, 271, 129584.
9. Hoang, T.; Tran, T.T.A. Ambient air pollution, meteorology, and COVID-19 infection in Korea. J. Med. Virol. 2021, 93, 878–885.
10. Travaglio, M.; Yu, Y.; Popovic, R.; Selley, L.; Leal, N.S.; Martins, L.M. Links between air pollution and COVID-19 in England. Environ. Pollut. 2021, 268, 115859.
11. Lorenzo, J.S.L.; Tam, W.W.S.; Seow, W.J. Association between air quality, meteorological factors and COVID-19 infection case numbers. Environ. Res. 2021, 197, 111024.
12. Mandalapu, A.; Jiao, J.; Azimian, A. Exploring the Spatial Distribution of Air Pollutants and COVID-19 Death Rate: A Case Study for Los Angeles County, California. Int. J. Geospat. Environ. Res.

2022, 9, 4.

13. Sidell, M.A.; Chen, Z.; Huang, B.Z.; Chow, T.; Eckel, S.P.; Martinez, M.P.; Lurmann, F.; Thomas, D.C.; Gilliland, F.D.; Xiang, A.H. Ambient air pollution and COVID-19 incidence during four 2020–2021 case surges. Environ. Res. 2022, 208, 112758.
14. Luo, K.; Wang, Z.; Wu, J. Association of population migration with air quality: Role of city attributes in China during COVID-19 pandemic (2019–2021). Atmos. Pollut. Res. 2022, 13, 101419.
15. Abdullah, S.; Imran, M.A.; Mansor, A.A.; Yusof, K.M.K.K.; Dom, N.C.; Saijan, S.K.; Yatim, S.R.M.; Ahmed, A.N.; Ismail, M. Association of Air Pollutant Index (API) on SARS-CoV-2 of Coronavirus Disease 2019 (COVID-19) in Malaysia. Asian J. Atmos. Environ. 2022, 16, 2021094.
16. Huang, H.; Lin, C.; Liu, X.; Zhu, L.; Avellán-Llaguno, R.D.; Lazo, M.M.L.; Ai, X.; Huang, Q. The impact of air pollution on COVID-19 pandemic varied within different cities in South America using different models. Environ. Sci. Pollut. Res. 2022, 29, 543–552.
17. Aragão, D.P.; Oliveira, E.V.; Bezerra, A.A.; dos Santos, D.H.; Da Silva, A.G., Jr.; Pereira, I.G.; Piscitelli, P.; Miani, A.; Distante, C.; Cuno, J.S.; et al. Multivariate data driven prediction of COVID-19 dynamics: Towards new results with temperature, humidity and air quality data. Environ. Res. 2022, 204, 112348.
18. Al-Qaness, M.A.; Fan, H.; Ewees, A.A.; Yousri, D.; Elaziz, M.A. Improved ANFIS model for forecasting Wuhan City Air Quality and analysis COVID-19 lockdown impacts on air quality. Environ. Res. 2021, 194, 110607.
19. Zhou, B.; Yang, G.; Shi, Z.; Ma, S. Interpretable Temporal Attention Network for COVID-19 forecasting. Appl. Soft Comput. 2022, 120, 108691.
20. Saravanan, M.; Velmurugan, S.; Bhanupriya, P.; Booma Devi, P. Exploitation of artificial intelligence for predicting the change in air quality and rain fall accumulation during COVID-19. Energy Sources Part A Recover. Util. Environ. Eff. 2020, 1–10.
21. Xu, L.; Magar, R.; Farimani, A.B. Forecasting COVID-19 new cases using deep learning methods. Comput. Biol. Med. 2022, 144, 105342.
22. Fu, Y.; Lin, S.; Xu, Z. Research on Quantitative Analysis of Multiple Factors Affecting COVID-19 Spread. Int. J. Environ. Res. Public Health 2022, 19, 3187.
23. Mumtaz, R.; Zaidi, S.; Shakir, M.Z.; Shafi, U.; Malik, M.M.; Haque, A.; Mumtaz, S.; Zaidi, S. Internet of Things (IoT) Based Indoor Air Quality Sensing and Predictive Analytic—A COVID-19 Perspective. Electronics 2021, 10, 184.
24. Hochreiter, S.; Schmidhuber, J. Long short-term memory. Neural Comput. 1997, 9, 1735–1780.

25. Altan, A.; Karasu, S.; Bekiros, S. Digital currency forecasting with chaotic meta-heuristic bio-inspired signal processing tech-niques. Chaos Solit. Fractals 2019, 126, 325–336.