

Article

Assessing the Impacts of Human Activities on Air Quality during the COVID-19 Pandemic through Case Analysis

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Abstract: COVID-19 is the latest of many pandemic affecting the world in the past few decades, and it has had a significant impact on the global environment. Some research has analysed the effects of the pandemic on air quality; however, very few studies have employed relationship analytics. In order to analyse the potential relationship between pandemic-related information and air quality data from a more holistic and detailed point of view, we propose a methodology based on pure data analysis. Three types of data were collected, namely air quality index, pandemic-related events, and number of COVID cases. Data were collected from five cities—Wuhan, New York, Seoul, Melbourne, and Singapore—to further analyse the response of air quality index to COVID events, thus revealing how human activity influences air quality from a pandemic perspective. The results show that a potential connection does exist in most cases and provide more evidence showing that air pollution declined during the pandemic. However, the strength of this relationship may also be related to other factors, such as geography, politics, population density, and measures imposed by local authorities, etc. This study provides another perspective to assist stakeholders in improving environmental decision making.

Keywords: COVID-19; visual analysis; relationship analytics; graph visualisation; air quality index; *PM2.5*



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1. Introduction

Coronavirus disease (COVID-19) has become a worldwide pandemic since it first appeared in Wuhan, China in December 2019 [1]. As of 3 December 2021, 263,563,622 confirmed coronavirus cases had been reported worldwide, including 5,232,562 deaths [2]. The global outbreak and spread of COVID-19 have posed a severe threat to public health and caused significant interference in worldwide economic activities [3]. The COVID-19 pandemic forced most countries to take preventive measures to stop its disease spread, with local lockdowns being one of the main preventive measures employed [4]. Air quality is also thought to strongly interact with the mortality rate of COVID-19 [5]. A study showed that when *PM2.5* (fine particulate matter defined as particles with diameters ≤ 2.5 microns) increased by one $\mu\text{g}/\text{m}^3$, the COVID mortality rate increased by 8% in the United States [6]. Ironically, one of the few positive effects during a pandemic may be the health “benefits” of reduced air pollution [7], and there were significant reductions in air-pollutant levels in areas in which lockdowns were imposed [8].

Some studies have explored the interaction between COVID and air quality across the globe during the pandemic [9,10]. In China, studies have been conducted to evaluate changes in air quality by analysing the concentrations of major air pollutants, such as *NO2*, *SO2*, *C.O.*, *O3* (ozone), and *PM2.5*, etc. before and during the pandemic [11,12] and to quantify the effects of reduced human activities on air quality [13]. In central China, where the novel coronavirus first broke out, atmospheric concentrations of *PM2.5*, *PM10*

(particulate matter with diameters ≤ 10), NO_2 , $C.O.$, and SO_2 (sulphur dioxide) decreased significantly in 2020 (as compared with the past three years) [14]. According to air quality data monitored from 2017 to 2020, in the U.S., $PM_{2.5}$ and NO_2 levels decreased by 11% and 26%, respectively, during the pandemic [6,15]. Similar research has been carried out in Milan, Italy [16]; Baghdad, Iraq [17]; Canada [18]; Brazil [19–21]; and South Korea [14]. Overall, during the pandemic, air quality may have improved to a certain extent due to the indirect impact of reduced traffic, tourism [22], and economic activity [23].

Relevant information and communications technologies (ICT), such as machine learning, big data, and data visualisation, have been applied to analyse COVID data in order to glean decision-making insights. The capability of generating visually appealing raw data representations is valuable in COVID data analysis [24], and such visual representations can be utilised to analyse pandemic risk [25], such as severe acute respiratory syndrome (SARS) outbreak data [26]. At this stage, improved visualisation of infection rates analysis is required to rapidly detect patients with the disease [27]. Big-data visualisations and visual analytics tools were introduced in COVID data analytics to assist users in obtaining a better understanding of information concerning confirmed cases [28]. Additionally, some research has been conducted from a visualisation point of view in order to analyse air pollution and COVID data. An online questionnaire was circulated to look into the pandemic situation and air quality data through related visualisation techniques [29]; a visual application was established based on an assessment of air quality and air pollution by evaluating various relevant parameters [30]. A multi-source dataset was imported to examine the epidemic data using visualisation and machine learning methods [31]. Some studies have implemented descriptive statistics and outlier analysis of air quality datasets [15], while others have used time-series [1] and chemical analysis [4]. An augmented-reality application, AiR, was proposed that can assist users in visualising pollutants in the air and create an immersive user experience on Android devices [31].

In our study, to investigate air quality trends worldwide during the pandemic, we collected air quality data from five representative cities in Western and Asian countries for experiments. In particular, the $PM_{2.5}$ index was imported to represent air quality, covering the first six months of 2019 and the whole year of 2020. It is important to note that Melbourne's changes in air quality seem to be acting alone. We collected $PM_{2.5}$ data from Wuhan, New York, Seoul, Melbourne, and Singapore before and during the outbreak as input for experiments. The reasons for choosing these cities are: Wuhan is the city in which the pandemic began; as one of the cities with the worst outbreaks, New York has a high population density, did not pay enough attention to the epidemic [32], and had multiple protests during the outbreak [33,34]; Seoul was severely affected at the beginning of the pandemic but managed to control the situation without an official lockdown [35]; Melbourne has been closed for the longest time of all cities worldwide [36] and also had mass demonstrations [37,38]; Singapore is a country with a small land area but a high population density, which might accelerate disease spread during the pandemic, and was also one of a few counties that maintained opened borders in 2020 [39].

Actual air-pollution reduction varies [40], and lockdown mandates were not strictly implemented in many cities around the world [41,42].

To the best of our knowledge, most of the existing studies on air quality data were conducted through relevant raw data analysis, mainly focusing on air quality in a single period or area. Few studies have been conducted from the perspective of multiple periods or combined with relevant social events. The purpose of this work is to analyse the relationship between the COVID-19 pandemic-related events and air quality from a more holistic and detailed point of view and to analyse the potential relationship, mainly through visualisation technology, such as line chart, bar chart, stack area chart, etc., combined with $PM_{2.5}$ and COVID-related data, for a comprehensive analysis. We also explored whether new cases during the pandemic affected the volatility of $PM_{2.5}$, linking the three sets of data and extracting deeper insights from the dataset. Our hypotheses are as follows.

Hypothesis 1 (H1). *The reduction in human activity during the outbreak may positively improve air quality.*

Hypothesis 2 (H2). *During the pandemic lockdown, air-quality improvement may be more significant.*

Hypothesis 3 (H3). *During the outbreak, changes in new cases may affect human social activities, thus indirectly affecting shifts in air quality.*

Hypothesis 4 (H4). *The improvement of air quality in cities that imposed lockdowns may be more significant than in cities without restrictions.*

Hypothesis 5 (H5). *The degree of variability in air quality may vary due to cultural diversity and the implementation strength of prevention measures.*

Hypothesis 6 (H6). *During the epidemic, city-closure policies may have an impact on air quality.*

The rest of this article is organised into several parts. In Section 2, relevant data and details of analysis are given; we also introduce related methods and features involved in experiments. In Section 3, we offer visual results, as well as some descriptions, we also summarise statistical data and discuss issues here. In Section 4, the conclusion of this work and a discussion of future research are given.

2. Materials and Methods

We downloaded and collected three types of raw data [43] for analysis, ranging from 1 January 2019 to 30 June 2021; data from 1 July to 31 December 2019 were excluded. The weeks used in this experiment refer to the sequential weeks of the year. For example, week1 represents 1–7 January.

(1) Air quality index data

Air quality index data mainly refer to $PM_{2.5}$ index data, including the daily average $PM_{2.5}$ value from Wuhan, New York, Seoul, Melbourne, and Singapore. Original data were downloaded from aqicn.org [44], with a total of 1074 data entries finalised.

(2) COVID-19 new-case data

The raw data covering five cities worldwide reflect daily new cases during the pandemic, involving 2020 and 2021. The data were downloaded and collected from several official government websites: Hubei Provincial Health Commission [45], NYC Open Data [46], Korea Centers for Disease Control and Prevention [47], Ministry of Health of Victoria [48], and the Ministry of Health of Singapore [49]. A total of 890 data entries were imported.

(3) COVID-19-related event data

These raw data include the lockdown period of cities involved and significant protests. Details and sources can be found in [43]. Event data were included as supplementary evidence, in addition to COVID new-case data, in order to complete the analysis.

2.1. Data Processing

All collected raw data were cleaned and formatted. The processes are as follows.

(1) $PM_{2.5}$ weekly value process

In experiments, data were processed on a weekly basis. Specifically, collected raw data were transformed from daily to weekly format. For each week, the median value of $PM_{2.5}$ during the week is selected as the present week's $PM_{2.5}$ data. Please refer to Table 1 for details (data for the other four cities can be found in [50]). Since not all $PM_{2.5}$ values are available, there are invalid data for some weeks. In this case, we assume that pm_w is the present week's $PM_{2.5}$ value yet has no valid value, pm_{w-1} is the $PM_{2.5}$ value of the previous week, pm_{w+1} is the value of the next week. Then, the average value of week $w - 1$

and $w + 1$ is applied to fill in missing data. Weekly new cases is the sum of case numbers for each week, cn_i is the value of new cases on the i th day in a week, an week w 's case number is cn_w (each week starts on Monday and ends on Sunday in this study).

$$pm_w = \frac{pm_{w-1} + pm_{w+1}}{2} \tag{1}$$

$$cn_w = \sum_{i=1}^7 cn_i \tag{2}$$

Table 1. Median $PM_{2.5}$ value for each week and weekly new COVID cases in Wuhan.

Date	$PM_{2.5}$ (2019)	$PM_{2.5}$ (2020)	$PM_{2.5}$ (2021)	New Cases (2020)	New Cases (2021)
week1	165	165	162	59	0
week2	172	119	126	0	0
week3	187	177	157	241	1
week4	191	137	176	1472	0
week5	165	160	156	6446	0
week6	165	122	151	12,119	0
week7	149	101	156	25,767	1
week8	142	128	128	2971	0
week9	126	111	83	2099	0
week10	153	128	132	438	0
week11	149	142	128	27	0
week12	134	139	134	1	1
week13	160	63	122	1	0
week14	133	119	128	1	0
week15	129	111	134	0	1
week16	122	116	146	0	2
week17	136	109	108	0	1
week18	123	132	104	0	0
week19	128	99	82.5	6	0
week20	142	105	61	0	0
week21	143	119	67.5	0	0
week22	100	112	74	0	0
week23	121	85	67.5	0	0
week24	125	85	61	0	1
week25	86	85	73	0	0
week26	127	85	110.5	0	2

(2) $PM_{2.5}$ weekly changing-rate process

The changing rate of the $PM_{2.5}$ index was determined based on data from the same week in 2019, 2020, and 2021. For details, please refer to Table 2 (data for the other four cities can be found in [50]). pm_{wy} is the value of the $PM_{2.5}$ on week w of the year, y ; and pm_{wy+1} is the value of the $PM_{2.5}$ on week w of the year $y + 1$; and pmc_w represents the corresponding rate of change of the $PM_{2.5}$ index on week w between those two years.

$$pmc_w = \frac{pm_{wy+1} - pm_{wy}}{pm_{wy}} * 100\% \tag{3}$$

Table 2. Weekly *PM2.5* changing rate in Wuhan.

Date	Changing Rate (%) (2019–2020)	Changing Rate (%) (2020–2021)	Changing Rate (%) (2019–2021)
week1	0.00	−1.82	−1.82
week2	−30.81	5.88	−26.74
week3	−5.35	−11.30	−16.04
week4	−28.27	28.47	−7.85
week5	−3.03	−2.50	−5.45
week6	−26.06	23.77	−8.48
week7	−32.21	54.46	4.70
week8	−9.86	0.00	−9.86
week9	−11.90	−25.23	−34.13
week10	−16.34	3.13	−13.73
week11	−4.70	−9.86	−14.09
week12	3.73	−3.60	0.00
week13	−60.63	93.65	−23.75
week14	−10.53	7.56	−3.76
week15	−13.95	20.72	3.88
week16	−4.92	25.86	19.67
week17	−19.85	−0.92	−20.59
week18	7.32	−21.21	−15.45
week19	−22.66	−16.67	−35.55
week20	−26.06	−41.90	−57.04
week21	−16.78	−43.28	−52.80
week22	12.00	−33.93	−26.00
week23	−29.75	−20.59	−44.21
week24	−32.00	−28.24	−51.20
week25	−1.16	−14.12	−15.12
Week26	−33.07	30.00	−12.99

(3) *PM2.5* yearly changing-rate process

The average changing rate of *PM2.5* was calculated between every two years of 2019, 2020 and 2021. pmc_y represents the corresponding rate of change of the *PM2.5* index between two years. For more information, please refer to Table 3. Table 4 gives details of the relevant changing rates of four cities during lockdowns (Seoul excluded).

$$pmc_y = \sum_{i=1}^n pmc_{wi} / n \tag{4}$$

Table 3. Yearly (the first 26 weeks only) *PM2.5* changing rate in five cities.

City	Changing Rate (%) (2019–2020)	Changing Rate (%) (2020–2021)	Changing Rate (%) (2019–2021)
Wuhan	−16.03	0.71	−18.02
New York	−8.48	19.90	6.02
Seoul	−13.85	0.11	−17.87
Melbourne	15.76	7.25	10.11
Singapore	−9.56	12.57	−0.91

Table 4. Yearly (the first 26 weeks only) *PM2.5* changing rates in four cities during lockdowns.

City	Changing Rate (%) (2019–2020)	Changing Rate (%) (2020–2021)	Changing Rate (%) (2019–2021)
Wuhan	−17.81	15.88	−9.37
New York	−11.72	35.71	17.20
Melbourne	15.88	16.24	24.91
Singapore	−15.17	32.33	9.43

To discover the connection between COVID pandemic data and the $PM_{2.5}$ index, we generated visual plots corresponding to the outbreak and $PM_{2.5}$, as well as changes in new cases, based on the final data produced from the above processes [50]. Here, we use dates to bridge the related contact. Then, we integrated the three data types in Section 2. These include the changing trend of $PM_{2.5}$ and new cases in Wuhan, New York, Seoul, Melbourne, and Singapore in 2019, 2020, and 2021. Ultimately, 260 records were retained for analysis.

2.2. Methods

This section introduces the relevant methods, including visualisation methods and study procedures.

2.2.1. Feature Selection

The raw data involved can be found in Section 2. $PM_{2.5}$ refers to the particles in the ambient air with an aerodynamic equivalent diameter ≤ 2.5 microns, which is the main characteristic of smoke. $PM_{2.5}$ can be suspended in the air for a long time, and the higher its concentration in the air, the more serious the air pollution. $PM_{2.5}$ particles are also a dangerous form of pollution because they are so small that they can bypass the nose and throat, enter the lungs, and possibly enter the circulatory system [51]. Therefore, the $PM_{2.5}$ index is suitable to measure air-quality performance. Wuhan, New York, Seoul, Melbourne, and Singapore are representative cities for which $PM_{2.5}$ and COVID new-case data were available from public sources. Therefore, in this study, $PM_{2.5}$ data of those five cities were processed to reflect the air quality of cities. Additionally, we collected data concerning newly confirmed cases of COVID-19 in the five representative cities during the pandemic, along with data concerning other events, to measure impacts on air quality.

2.2.2. Graph Visualisation Method

In this study, line chart, bar chart, and stack area charts were applied to present the experimental results. The broken-line/bar-chart component can display multiple series of data on the chart and can be used to show details of each city's $PM_{2.5}$ data. The stacking area map, on the other hand, is capable of delivering the trend lines of the $PM_{2.5}$ index and changing rate of each city over time and can highlight relevant intersections between $PM_{2.5}$ and the numerical values on the series axes, which makes it appropriate to assist in analysis of the variances in air-quality changes in different cities. In addition, Tableau, a powerful tool widely used in the data-analytics field, is also used for visualisation, owing to its capability of visualising complex datasets [52,53].

2.2.3. Cross-Sectional and Time-Series Analysis

In this study, two types of evaluation were carried out, namely cross-sectional and time-series analysis. We compared behaviours from week 1 to 26 in 2019, 2020, and 2021, respectively, in order to look into the differences during the same period across three years. In addition, relevant data were analysed following the time series of 2020, which is not the worst pandemic year but the first year that COVID spread worldwide; 2020 also might be the year in which people panicked the most due to the fear of an unknown virus.

2.2.4. Procedure

The collected raw data were imported as input for processing, and five factors were taken into account: date, $PM_{2.5}$ index, weekly changing rate of $PM_{2.5}$, yearly changing rate of $PM_{2.5}$, and weekly new cases of COVID. Then, the response results of the five cities, combined with relevant social events, were compared to examine the relationships among them, i.e., whether the epidemic impacted air quality, as well as other research questions mentioned in Section 1. The workflow is as follows.

- (a) Collecting relevant raw data from multiple sources.
- (b) Data filtering and formatting to process all collected data, deal with invalid values, etc., and then format and import the data file for graph generation.
- (c) Comparing visual results via observation and statistics.
- (d) Discussion of findings according to the hypotheses.

3. Results and Discussion

In the experiments, five factors were compared across five cities based on data for first six months of 2019, 2020, and 2021 for cross-sectional analysis. Time-series analysis was performed by importing relevant social events from the five representative cities in 2020. Figures 1–5 show the weekly median values of the *PM2.5* index for the five cities from January to June in 2019, 2020, and 2021. Some statistics regarding *PM2.5* values are presented below.

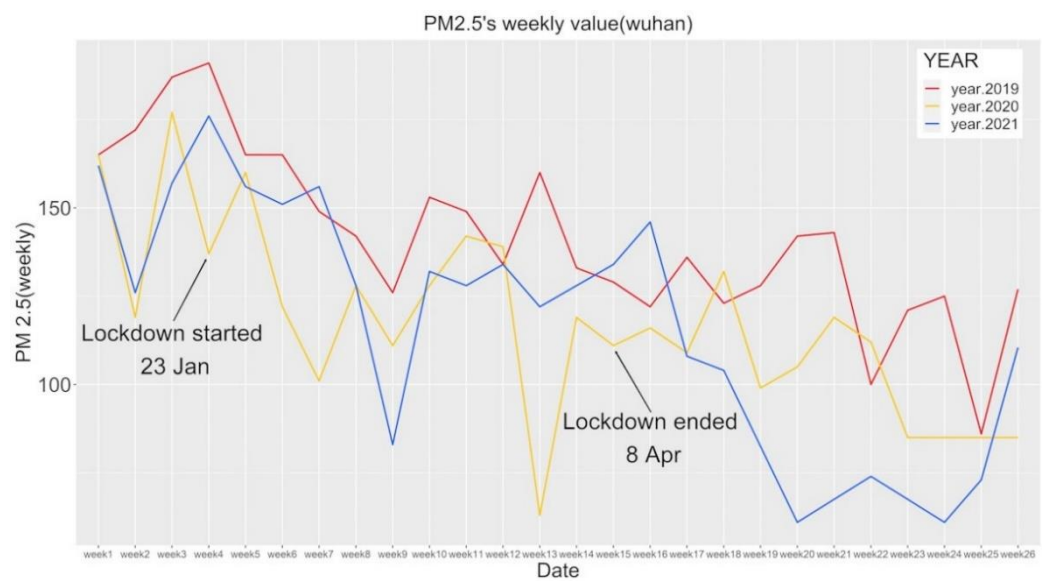


Figure 1. Weekly *PM2.5* value (Wuhan).

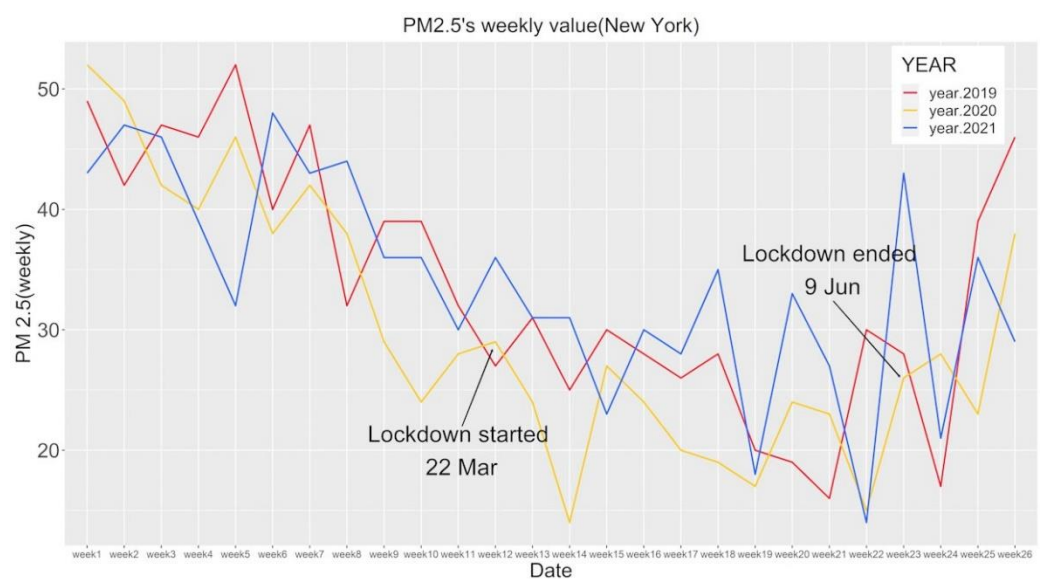


Figure 2. Weekly *PM2.5* value (New York).

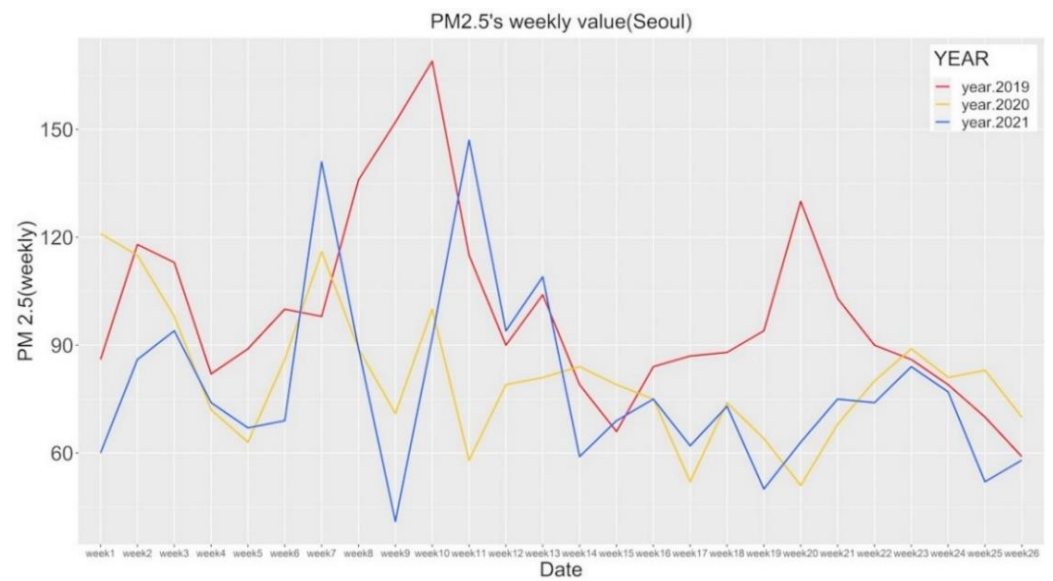


Figure 3. Weekly *PM2.5* value (Seoul).

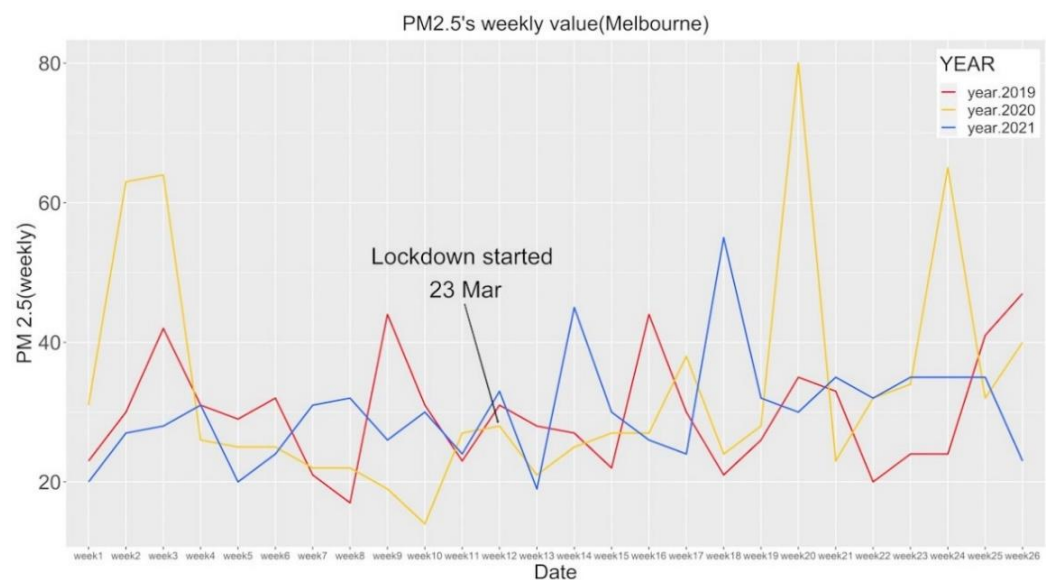


Figure 4. Weekly *PM2.5* value (Melbourne).

As seen in Figure 1, Wuhan’s *PM2.5* levels in 2020 was significantly lower than in 2019; only weeks 12, 18, and 22 out of 26 weeks had higher *PM2.5* values in 2020 than in 2019, with lower values than in 2019 for all other weeks. During the same period, compared with 2019 *PM2.5* values, in 2020, the proportion of weeks with declining *PM2.5* values was 88.5%, and that of increasing week was 11.5%. Additionally, compared with same period in 2019, in 2021, the proportion of weeks with declining and increasing *PM2.5* values was 84.6% and 11.5%, respectively. Comparing 2020 and 2021 data, the proportion of weeks with declining and increasing *PM2.5* values was 57.7% and 38.5%, respectively. Furthermore, the yearly *PM2.5* value dropped by 16.03% between 2019 and 2020 and decreased by 18.02% between 2019 and 2021.

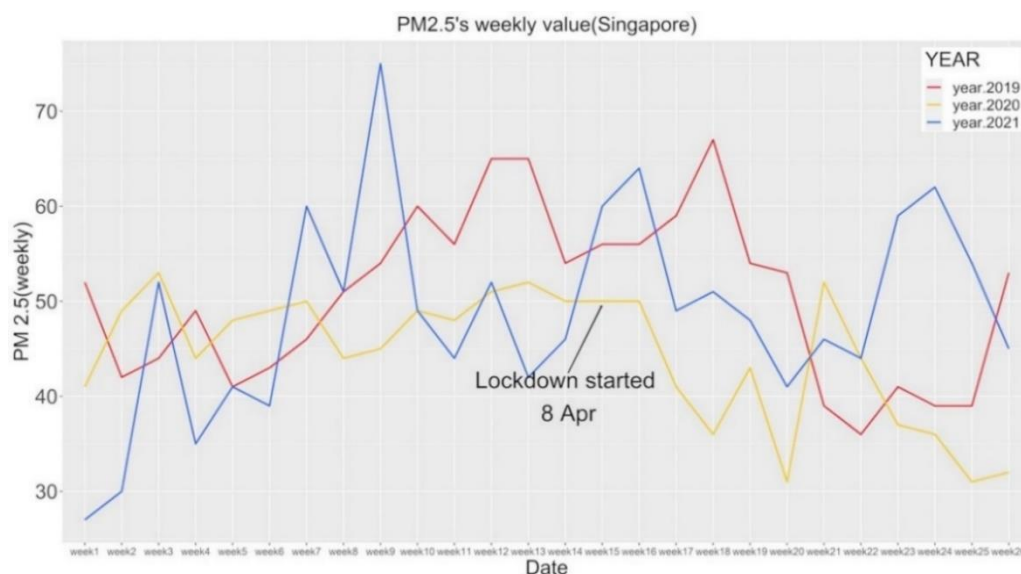


Figure 5. Weekly $PM_{2.5}$ value (Singapore).

Figures 2–5 show that from the perspective of weekly $PM_{2.5}$ values, compared to the values of each week in the first 26 weeks in 2019, for the first 26 weeks in 2020: $PM_{2.5}$ values fell in 73% of weeks and rose in 27% of weeks in New York; the proportion of weeks with declining and increasing $PM_{2.5}$ values was 69.2% and 30.8%, respectively, in Seoul; in Melbourne, the proportion of weeks with declining and increasing $PM_{2.5}$ values was 46.2% and 53.8%, respectively; and in Singapore, the proportion of weeks with declining and increasing $PM_{2.5}$ values was 73% 27%, respectively.

Regarding the yearly $PM_{2.5}$ value, it was found that the $PM_{2.5}$ level in 2020 was significantly lower than that in 2019 during the same period, with reductions ranging from 8.48% to 13.85%, except for Melbourne (its data shows that $PM_{2.5}$ levels in 2020 were higher than those in 2019 during the same period for most weeks). However, between 2019 and 2021, $PM_{2.5}$ values declined only in Asian cities (Wuhan, Seoul, and Singapore; there was a slight drop in Singapore); and between 2020 and 2021, although $PM_{2.5}$ yearly values rose in all five cities, the values for Wuhan and Seoul remained relatively at the same levels. Details can be referred to in Table 3. The $PM_{2.5}$ indices of Wuhan, New York, Singapore, and Seoul all exhibited similar trend during the pandemic. When the outbreak was severe or the number of new cases increased, the $PM_{2.5}$ index decreased, especially during periods of city closures. In addition, in most cases, after the pandemic situation had been improved or lockdowns were lifted, the $PM_{2.5}$ index increased. Although Seoul did not implement a lockdown during studied period, increasing case number had a similar impact, sometimes (weeks 2–6, 8–13, and 16–22) even more significant than in Wuhan and Singapore.

Interestingly, the $PM_{2.5}$ index in Melbourne seems either not to be affected by outbreak conditions or to be correlated with the outbreak negatively. When a pandemic is severe, $PM_{2.5}$ values may rise; when the pandemic improves or before it gets worse, $PM_{2.5}$ values may fall. For example, after Melbourne was locked down in 2020, the $PM_{2.5}$ index rose to relatively high levels. $PM_{2.5}$ levels even increased compared to the previous year during the same weeks and showed a downward trend before the outbreak began and before lockdown was imposed.

The weekly changing rate is employed to indicate the magnitude of change in $PM_{2.5}$. For example, Figure 6 shows the weekly changing rate in Wuhan. The green line indicates the changing rate from 2019 to 2020. It can be seen that 23 out of 26 weeks reflect reduced $PM_{2.5}$ levels in Wuhan, which means that $PM_{2.5}$ levels in Wuhan were lower 88.5% of the time in the first six months of 2020 compared to the same period in 2019; in other cities, the proportion of weeks with improved air pollution was 73% in New York, 69.2%

in Seoul, 46.2% in Melbourne, and 73% in Singapore. In general, the changing rates were predominantly negative in all cities, except for Melbourne, from 2019 to 2020.

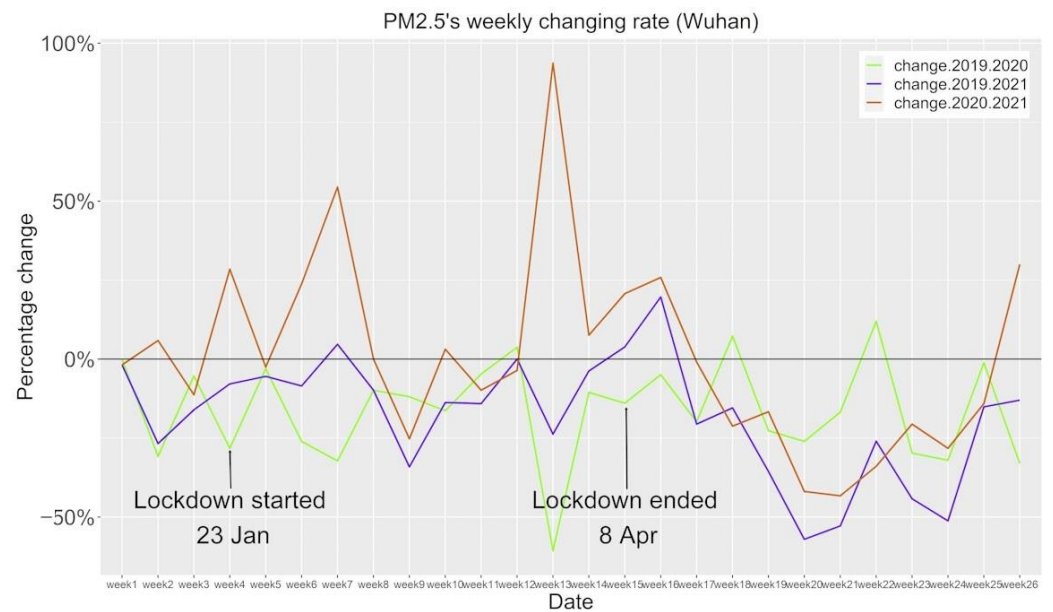


Figure 6. Weekly *PM2.5* changing rate (Wuhan).

Figures 7 and 8 show weekly new COVID cases and weekly *PM2.5* values in Wuhan and New York for the first six months of 2020. It can be observed that in Wuhan, when weekly cases reached their peak in week 7, the *PM2.5* level dropped to the lowest relative level during this period (Wuhan’s lockdown), which was 14% lower than the average and 42.9% lower than the maximum, i.e., the air quality was relatively better during the period of lockdown. In Figure 8, New York is seen to act similarly; the lowest *PM2.5* value appeared in week 14, corresponding with the greatest number of new cases, which was 53.3% lower than the average and 73% lower than the peak. Similar results can be found in Melbourne, whereas Seoul and Singapore did not exhibit a clear pattern but maintained a relatively stable decrease *PM2.5* values.

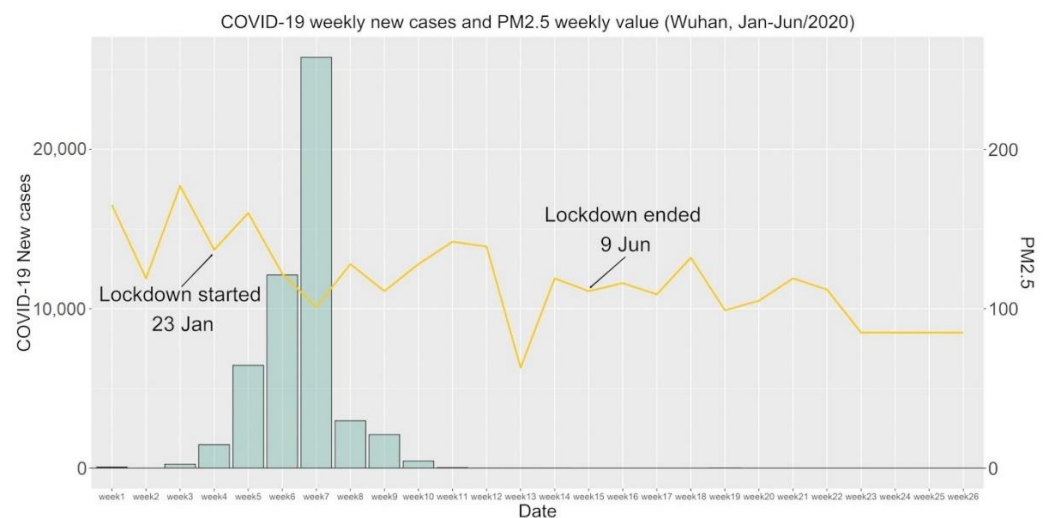


Figure 7. Weekly new COVID-19 cases and weekly *PM2.5* values (Wuhan, Jan–Jun/2020).

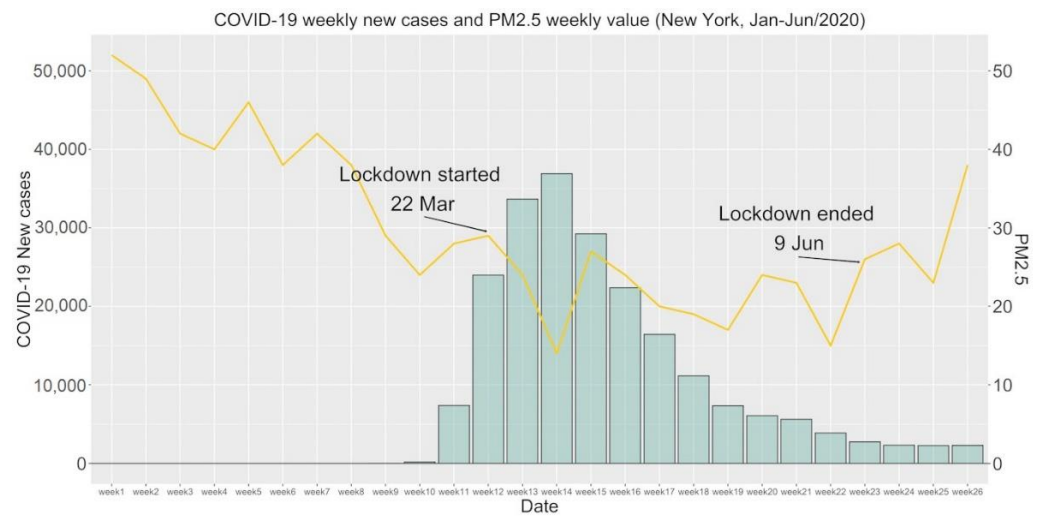


Figure 8. Weekly new COVID-19 cases and weekly *PM2.5* values (New York, Jan-Jun/2020).

It can be seen from Figures 9 and 10 that *PM2.5* dropped in all cities from 2019 to 2020, except for Melbourne. Wuhan had the most significant drops (negative values). In Figure 9, the blue columns representing the change from 2020 to 2021 are all positive; from 2019 to 2021, Wuhan, Seoul, and Singapore are negative, and New York and Melbourne are positive. Figure 10 is a subset of Figure 9, and it shows only four cities during lockdown periods (there was no lockdown in Seoul). Comparing data from Figures 9 and 10, the yearly changing rates from 2019 to 2020 were -17.81% and -16.03% in Wuhan, -11.72% and -8.47% in New York, and -15.17% and -9.56% in Singapore. For details, please refer to Tables 3 and 4. Cities that implemented closures tended to have greater yearly *PM2.5* changing rates than those without lockdowns, with the exception of Melbourne.

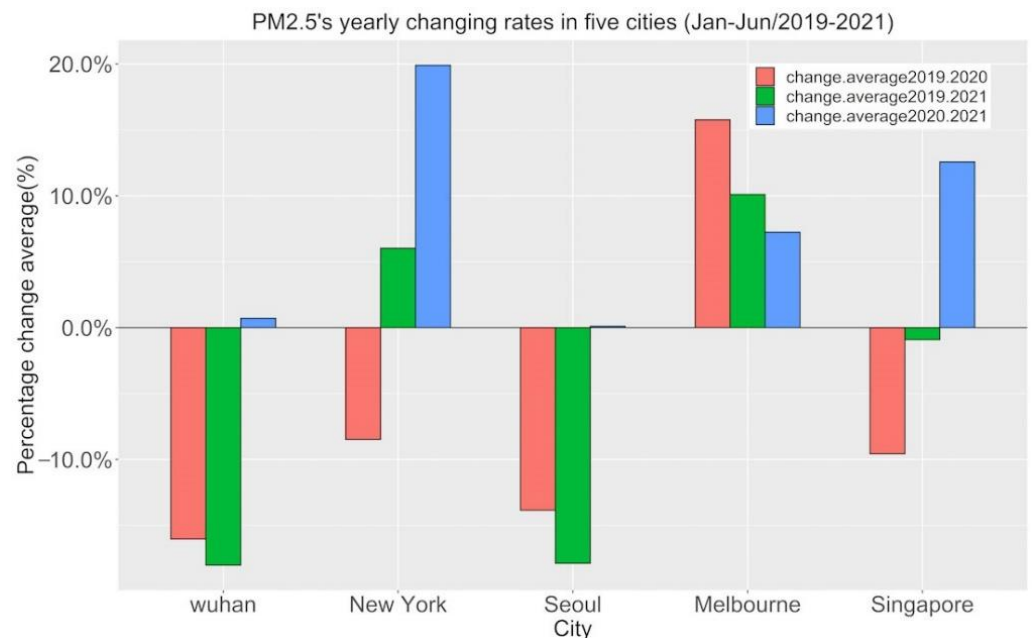


Figure 9. Yearly *PM2.5* yearly changing rates in five cities (Jan-Jun/2019–2021).



Figure 10. Yearly $PM_{2.5}$ changing rates in four cities during lockdowns (Jan–Jun/2019–2021).

Regarding Melbourne, even when it was in lockdown, that city still showed an extreme opposite reaction in comparison to other cities; its air quality was worse during the closure period than during the open period. Its “individual” behaviour may be related to the mass demonstrations and protests that occurred in response to its six lockdowns, as well as government policies and, of course, repeatedly being affected by the pandemic [37]. However, relevant data have not yet been collected, and the specific influencing factors are not within the scope of the current study. We plan to introduce relevant major events and policies in the next phase of our research to reveal how air quality was affected by the outbreak in this particular city.

As shown in Figure 11, Wuhan was in lockdown or partial lockdown for the first six months of 2020, and its $PM_{2.5}$ levels changed substantially; in the second half of the year, due to the improvement of the pandemic situation, the closure did not continue, and $PM_{2.5}$ levels increased. Singapore imposed two closures in 2020. $PM_{2.5}$ levels dropped slightly after lockdowns and remained stable, not changing significantly. During the first six months in 2020 in Seoul, $PM_{2.5}$ was been stable, at around 80, with slight fluctuations. Melbourne and New York implemented secondary and additional lockdowns in 2020. Melbourne was closed for the longest time of all cities in the world during this period but did not experience any significant changes in $PM_{2.5}$ levels.

In Figure 12, it can be observed that: In Wuhan, the number of new cases reached its peak 3 weeks after the lockdown and went back to being under control within 4 weeks. $PM_{2.5}$ reached its new low 3 weeks after the closure and reached its minimum 9 weeks after the lockdown. In New York, the number of new cases reached its peak 2 weeks after the lockdown and went back to being under control within 4 weeks. $PM_{2.5}$ reached its new low 2 weeks after the lockdown and has remained stable since. In Melbourne, there were not many cases during the studied period (the first 26 weeks in 2020), and $PM_{2.5}$ levels increased following lockdowns. In Singapore, the number of new cases reached its peak 1 week after the lockdown and went back to being under control within 8 weeks. $PM_{2.5}$ reached its new low 5 weeks after the lockdown. In Seoul, no lockdown was imposed, and there were not many cases during the studied period. $PM_{2.5}$ in all cities tended to decrease during the first 26 weeks in 2020, except for Melbourne. Additionally, for the two cities with the most cases among the five representative cities, Wuhan and New York, they both took 2–3 weeks to reach the peak number of cases and 4 weeks to get the outbreak under

control after lockdown; *PM2.5* levels in these two cities reached relative low points within 2–3 weeks following lockdowns.

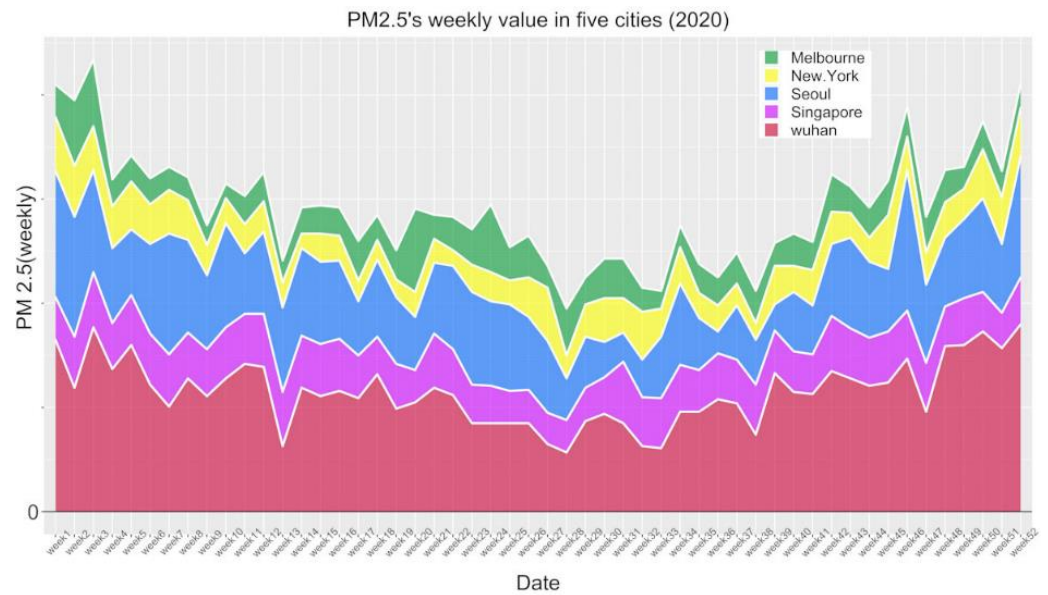


Figure 11. Weekly *PM2.5* values in five cities in 2020 (area of each colour indicates the present week’s *PM2.5* values).

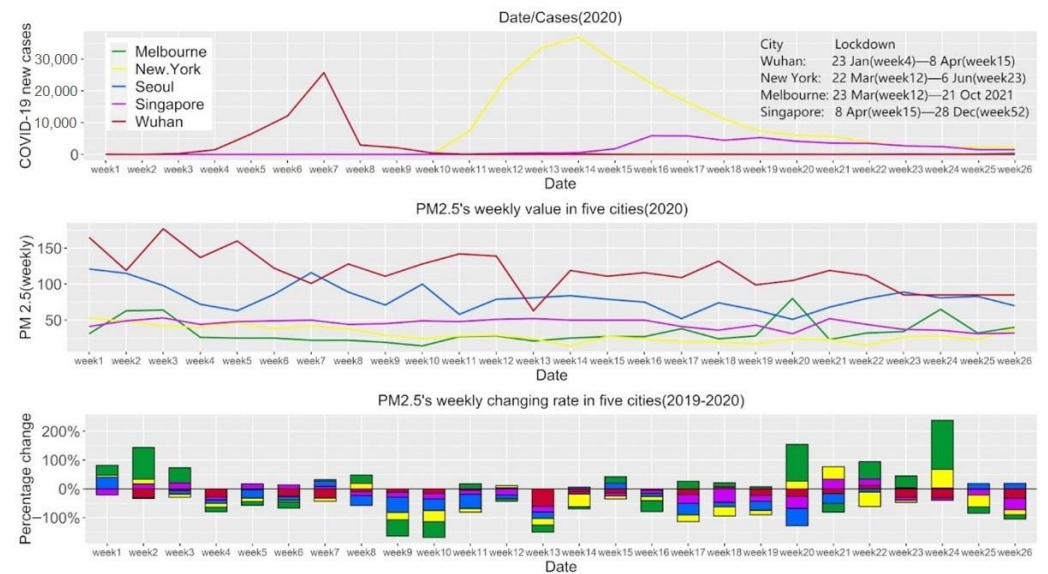


Figure 12. The relationship between *PM2.5*, new cases, and lockdowns in five cities during weeks 1 to 26 of 2020.

As seen in Figure 13, we compared Seoul with four other representative cities. In the top-left chart, it can be seen that the blue area with negative values is larger than the red area with negative values, which implies that *PM2.5* dropped more noticeably in Seoul than in Wuhan during the studied period (weeks 1–26 in 2020). Furthermore, based on the three other charts, Seoul’s *PM2.5* levels decreased more evidently than those of Singapore but less intensely than those of New York. The reduction in *PM2.5* levels in Seoul were similar to in Melbourne during this period.

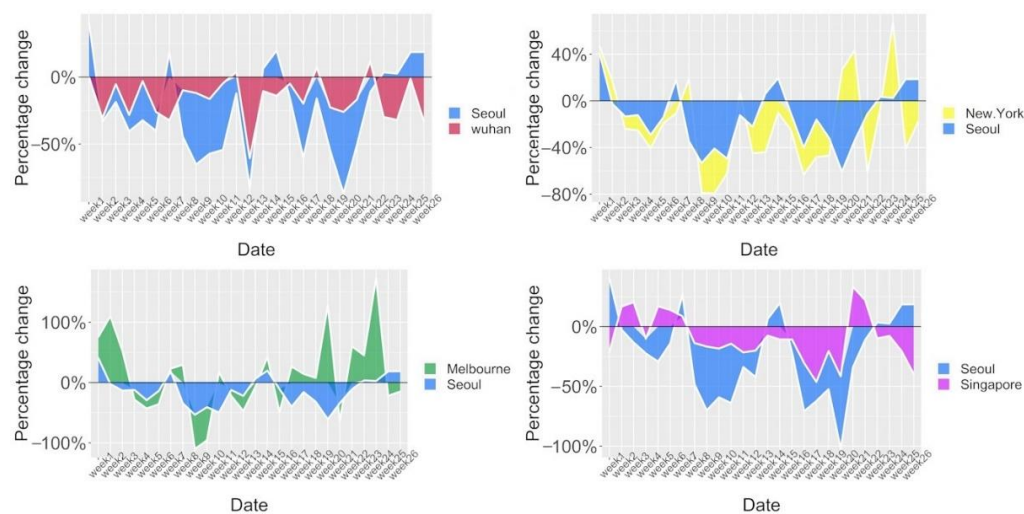


Figure 13. Weekly $PM_{2.5}$ changing rate comparing Seoul and other cities in 2020.

During 2020, except for Seoul, all four other representative cities implemented city closures. The combination of graphs and statistics shows that $PM_{2.5}$ levels remained in the range of $\pm 15.7\%$ of 127 from week 39 to 46 in Wuhan, and $\pm 11.6\%$ of 43 from week 32 to 41 in Singapore. This suggests that $PM_{2.5}$ levels in Wuhan and Singapore were essentially stable during the second half of 2020. In contrast, $PM_{2.5}$ levels in New York and Melbourne fluctuated during the same period. Air quality may be affected by the implementation of lockdown policies by local governments, though this effect has not yet been studied.

With regards to our hypotheses, based on the generated graphs, observation, and statistics, the following can be concluded:

For H1, except for Melbourne, there were significant changes in air quality in all cities during the outbreak, following a similar trend. During the pandemic, various restrictions led to a reduction in human industrial activity and traffic movement, which may improve air quality [17]. Similar trends may enhance air quality, but in our experiments, this held true for four cities, excluding Melbourne. Melbourne's $PM_{2.5}$ changing rate was the opposite affected in many ways. Furthermore, this represents only a general outcome of the reduction in human activity, as actual impact varies.

For H2, based on analysis of the relevant values and changing rates, the magnitude of $PM_{2.5}$ change in cities in which lockdowns were imposed was greater than in cities without closures. Based on our experiments, it can be concluded that during the outbreak, air quality improved to a greater extent (more than 10%) during lockdown in most cases; it can be noticed that lockdowns caused an improvement in air quality in all cities compared to 2019 (Seoul excluded), as seen in Table 4. The reason for this outcome might be that 2020 was the year that people panicked the most due to fear of an unknown virus. Hence, lockdowns are not likely the main contributing factor to improved air quality, which could be dependent on the strictness of enforcement instead. This finding does not apply to Melbourne, which may be affected by factors such as mass demonstrations [37], although such factors remain uncertain at this stage.

For H3, when weekly new cases reached their highest points in New York, Wuhan, and Melbourne in week 14, week 7, and week 13, $PM_{2.5}$ values were 53.3%, 14%, and 36.7% lower than the average, and 73%, 42.9%, and 73.8% lower than the peak, respectively. Overall, $PM_{2.5}$ levels fell to relative lows when the number of new cases highest was peaking; however, a similar trend was not observed in Seoul and Singapore. Therefore, it can be concluded that changes in the number of new cases could potentially affect social activities, thus indirectly inducing changes in air quality; however, the significance of this correlation remains unknown.

For H4, although no lockdowns were implemented in Seoul, the city exhibited similar patterns in air-quality change to other cities, with significant air-quality improvements

compared to 2019 ($PM_{2.5}$ dropped 13.85% from 2019 to 2020). Therefore, it cannot be confirmed that air quality improves more in cities with lockdowns than those without. Many factors may be involved, and there is no solid evidence showing that cities with lockdowns have less human activity than cities without closures. Therefore, implementation strength of prevention measures may play a role, although we have not yet been able to take such factors into account, so this assumption has not yet been confirmed.

For H5, as did not discover consistent patterns among Asian cities and Western cities, it cannot be inferred whether cultural diversity and the implementation strength of prevention measures impact air pollution. Thus, this hypothesis cannot be confirmed. However, three Asian cities, particularly Wuhan and Seoul, did show greater improvements $PM_{2.5}$ when comparing data between 2019 and 2020, as well as 2019 and 2021 (see Table 3), and Singapore was one of few counties that maintained opened borders in 2020 [39].

For H6, the implementation of lockdowns in Wuhan and Singapore was relatively strong, and their $PM_{2.5}$ levels exhibited a steady downward trend in 2020. City closures in New York and Melbourne were relatively weak due to multiple protests. There were 17 COVID-related demonstrations in New York and 18 in Melbourne from 2020 to 2021, all for anti-lockdown and anti-mandate purposes [33,34,38]. There was also one protest over the student COVID-19 vaccine pass mandate in Seoul in 2021 [54]; however, only 70 people were involved. There were no COVID related demonstrations in Singapore and Wuhan. $PM_{2.5}$ levels fluctuated in all five cities during the studied period. Among them, Melbourne was closed for the longest time [55], although $PM_{2.5}$ levels for that city sometimes showed an upward trend. However, considering its many protests, Melbourne's closures might not have been as strict as in other cities. It is a well-known fact that lockdown mandates were not strictly implemented in many cities around the world [41,42]. Therefore, it can be concluded that the implementation strength of city-closure policies has an impact on air quality in most cases.

Overall, with Melbourne excluded, H4, H5, and H3 (the peak of new cases affected human activity and thus indirectly influenced air quality in New York, Wuhan, Singapore, and Seoul) cannot be proven. Other hypotheses have been confirmed in this work. The outlying behaviour of air-quality changes in Melbourne during the outbreak may have been caused by multiple factors, such as geographical, political, population density, and economic reasons, that lie beyond the scope of the current study.

4. Conclusions

Frequent air-quality fluctuations were reflected in changing $PM_{2.5}$ values in 2020. The fear of unknown viruses may have led to a significant reduction in human activity in the early stages of the pandemic, resulting in a decrease in air pollution and, ultimately, improved air quality [13]. This study generated graphs and statistics to analyse the potential connections between COVID pandemic data and air quality. $PM_{2.5}$ fluctuations were found to be more evident before and after lockdowns. $PM_{2.5}$ levels were greatly affected by the outbreak in Wuhan, Seoul, and Singapore; its impact in New York was mediocre; and it was tangential in Melbourne, showing an opposite effect as compared to the four other representative cities. Our hypotheses have been partially verified, and an outbreak is likely to reduce human activity (though not in all cases) and therefore affect air quality. According to the experimental results, in most cases, worse epidemic situations, such as a greater number of infections, leads to less human activity (owing to lockdowns, etc.), resulting in air-quality improvement. In contrast, improved epidemic situations cause city closures to lifted, resulting in more human activity, leading to air-quality deterioration to some extent. However, due to many other factors, such as government prevention measurements and their implementation strength, a city's geographical location, cultural diversity, etc. that have not been investigated at this stage, the detailed indirect impact of the outbreak on air quality is uncertain, and actual reduction in air pollution varies. To the best of our knowledge, a study involving multiple cities and periods has not been carried out before. This work may be helpful for the analysis of air quality data from another perspective—the

relationship between air pollution and pandemic data. Additionally, this research could potentially assist stakeholders in understanding interactions among various factors (major social events and outbreak data, etc.), offering more comprehensive evidence from which to deduce the effects of human activities on air quality.

This work is the first step in analysing the relationship between the outbreak data and air quality. The limitations of this work include several aspects. Regarding the complexity of air quality data, *PM2.5* was the only imported for analysis in this study, which may be an essential element, although additional factors could also contribute to the study of air quality during the pandemic. Additionally, we only collected data from five cities in Asia, North America, and Oceania, and our study lacked data from other continents (especially Europe, for which relevant open datasets are available). This study also lacks air quality data from other months/years. Political, economic, and population density factors are also important, as they relate to research on air pollution during the epidemic and have not been taken into account. Furthermore, from a visualisation perspective, this study could import spatial and temporal settings to present a better dashboard for further analytics.

We will address the above limitations in our future work, collect more air pollution factors, and import those factors into our research. We will also introduce a novel interactive visualisation method to show the relationship between COVID-19 data and air quality index data, diving deeper into the relationship and eventually providing a more comprehensive understanding of this topic based on pure data analytics.

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