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From COVID-19 Pandemic of Five Selected East Asian Cities to Assessment of Data Openness and Integration for Future City Development

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About JLFC and the JLFC Report Series

The Joint Laboratory on Future Cities (JLFC) was set up jointly by the Faculty of Engineering and the Faculty of Social Sciences at the University of Hong Kong in July, 2019. It was founded by Dr. Keumseok (Peter) Koh, Mr Tong Leung, Professor Becky P.Y. Loo (Founding Co-Director), Professor Thomas S.T. Ng, Dr. Hayden So (Founding Co-Director), Ms. Rosana Wong, and Professor S.C. Wong. The main aim of JLFC is to establish a platform that facilitates studies on future cities: the people that live in them; the natural environment that they must coexist with; and the technologies that will enable these activities.

As urbanization sets to become a global trend in the coming century, an increasing portion of the Earth's population are going to be migrating into cities on a global scale. Such massive increase in urban population not only put significantly stress on the existing infrastructure but also challenge every aspect of the human-environment relationship. To ensure the sustainability and resilience of future cities, there is a genuine imminent need to develop fundamentally innovative approaches of constructing and conceiving the ways in which future cities will operate. It is clear that any solutions to the challenges faced by future cities are going to require talents from a wide range of disciplines to innovate in an interdisciplinary environment.

The JLFC incubates such environment through a series of interdisciplinary projects, symposiums and workshops that involve academics, the industry, as well as the government. JLFC was made possible by the generous support by the Prosit Philosophiae Foundation. We also work in partnership with the Global Future Cities AI Lab.

The JLFC Report Series aim to provide state-of-the art reviews of key urban theories/concepts and real-life experiences. A particular focus is placed on the experience of Hong Kong as a high-density and compact city, and its relevancy to other metropolitan cities around the world. All reports in the JLFC Report Series are free for download by the general public. Comments and suggestions either on specific reports or the series may be directed to jlfc@hku.hk.

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1. Introduction and Background

1.1. Challenges of the COVID-19 Pandemic

After the confirmation of the first coronavirus caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in Wuhan, Hubei, China, a new strain of cases has been detected in various cities of China since early 2020. Since then, the disease COVID-19 [1] has spread to other countries in the world upon human-based interactions and travelling. The World Health Organization (WHO) has declared it a global pandemic from March 2020 onwards. The connection of these cases gradually became harder and harder to be tracked, despite earliest cases were mostly connected to people being infected in the Huanan Seafood Wholesale Market situated in Wuhan [2]. There are several major factors that imposed challenges for virus tracking, as outlined in Lewis (2020) [3]: (1) The transmission of disease is extremely fast. Even after a person has got infected, he/she might not be aware of it due to the lack of immediate symptoms. Thus, this group of infected people are likely to maintain normal daily and human-to-human activities, and exacerbate the spread of COVID-19; (2) Early testing of COVID-19 often got delayed, especially for developing cities, due to the insufficiency of medical support and technologies. Hence, it took several days to confirm both positive and negative results, and the once-again verification was needed for all positive cases; (3) The people who were being requested to isolate did not actually follow the rules strictly, according to a survey conducted in the United Kingdom in May 2020. In particular, 61% of people actually left the isolated venue or camp site [4]; (4) There are wide spatial discrepancies with regard to citizens' attitude in providing information about their whereabouts, and their willingness to isolate themselves when suffering from COVID symptoms. For places like France, Germany, and the United States, 25%, 21% and 21% of citizens were not willing to assist the national contact-tracing campaigns; while in Vietnam, 96% of citizens were willing to participate in the data collection process [5]; (5) Some countries like South Korea, Vietnam, Russia, Ecuador etc. have attempted to gather national efforts in tracking mobility of all citizens via advanced technologies, newly established platforms, and apps on mobile phones. However, such practice was being banned in some countries like Slovakia. The lack of confidence of local citizens towards the way of how governments and respective organizations handle collected data could be a major privacy concern. As a whole, all aforementioned environmental and human factors hugely affected and slowed down the progress of tracking and preventing the occurrence of the COVID-19 pandemic. Thus, future city development must seek an active way of facilitating data collection, smart utilization and integration processes, while protecting personal privacy and interests of participants and local citizens who are willing to provide personal information for overcoming the medical challenges ahead.

During the period of 31 December 2019 to 3 January 2020, the Chinese government has reported totally 44 cases to WHO, but the Huanan Seafood Wholesale Market was still operating until mid-January 2020. People being infected during that several weeks might not be aware of the severity of the disease [6]. The sudden deterioration of the pandemic was not only caused by human activities, but also the lack of proactive security awareness. From late January 2020, the number of reported cases in China's neighboring countries like Iran, Japan and South Korea increased sharply. As the affected countries were tripled, the number of cases in these countries also increased by 13 times [6, 7]. During these two years, the outbreak of the COVID-19 pandemic has hindered normal livelihood, and brought huge health burdens and medical challenges to the entire world at all spatial scales from country to city and even county levels [8-11]. Further, it has induced extensive economic loss and potential social challenges in both short and long terms through, for example, the reduction of manufacturing outputs, the collapse of supply chains and selected industries like aviation and catering service, as well as threats towards financial and business industries worldwide [12-14]. Take the case of the postponement of the Olympic and Paralympic Games 2020 in Tokyo. The lack of spectators at stadiums and contest venues could possibly lead to ¥2.4 trillion (US $23.1 billion) economic loss for Japan [15].

1.2. Temporal Trends and Spatial Dynamics of COVID-19 Pandemic and Insights

In terms of health burdens and worldwide COVID-19 trends after the first reported death in Wuhan, China on 11 January 2020, most countries have reported respective first death figure during March to April 2020. As of 15 July 2021, it was confirmed that more than 4.07 million deaths were attributed to COVID-19, and around 189 million infection cases were detected worldwide [16]. The long-lasting pandemic can be categorized into different stages, which we call "waves of COVID-19". Starting from 20 May 2020, the number of daily new confirmed COVID-19 cases has exceeded 100,000. For most of the period from 21 October 2020 onwards till 5 February 2021, there were more than 400,000 new cases every day. Moreover, there was a sudden and continuous spike during the November 2020 to January 2021 period. After a partial reduction of COVID-19 cases during early February to mid-March 2021, another obvious COVID-wave was then detected during April 2021. As shown in Figure 1 (based on [16]), the worldwide trend from October 2020 to now can be roughly approximated by a sine curve.

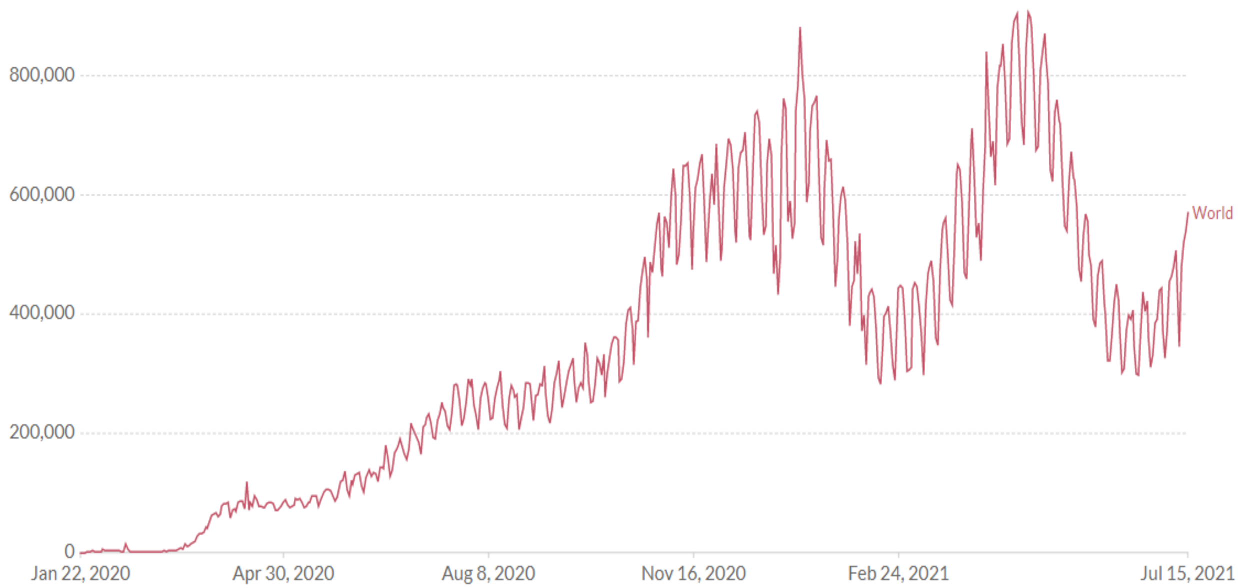


Figure 1. Daily worldwide new confirmed COVID-19 cases from 22 January 2020 to 15 July 2021. Source: Johns Hopkins University CSSE COVID-19 Data (with reference to [16])

In terms of spatial distribution, COVID-19 cases were first reported and transmitted within China in early 2020. It then spread to other East Asian countries, European and American countries. Figures 2 and 3 (based on [16]) illustrated the number of confirmed COVID-19 cases detected at the national level, as well as the total number of deaths in respective countries. As at 22 January 2020, 548 cases were detected in China, as compared to several (less than 5) cases in Thailand (4 cases), Vietnam (2 cases), Japan (2 cases), South Korea (1 case), Taiwan (1 case), and the United States (1 case). The spatial distribution pattern was similar (i.e., most cases were detected in China) until 26 March 2020, when the number of cases detected in the United States (86,693 cases) first exceeded China (81,329 cases), followed by Iran (29,406 cases) and France (29,252 cases) thereafter. In mid- to late April 2020, the pandemic in Russia suddenly became more serious, and its number of confirmed cases also exceeded China from 27 April 2020 onwards. By that time, there were already one million confirmed cases in the United States. Afterwards, Iran and Brazil became the hotspots of COVID-19 in May 2020, while India and several European countries had sudden increases in COVID-19 cases from summer 2020 onwards. On the other hand, the pandemic in China was gradually becoming steady due to strict precautionary measures and policies imposed, for example, the maintenance of social distancing, introduction of lockdown policies at different spatial scales, and the transformation of working and education activities from face-to-face to online (or mixed-mode) modes. From early 2021, the United States, India and Russia have become obvious hotspots of COVID-19, while European countries like Turkey, France, Germany and Poland reached several millions of infected cases from May 2021.

As for the number of deaths, the spatial trends were generally similar, being the most serious in China and the United States during the first few months of 2020. Then, Brazil, France and Spain experienced a growing trend in terms of death figures from mid-

April 2020 onwards. The observed phenomenon could be attributed to the maturity and development of medical tools for combating the pandemic, citizens' positive attitude and self-preventive measures towards COVID-19, as well as the pace and mode of delivery and updates of health information to the public. India and Iran got gradually more death cases during summer 2020. These governments were struggling not only with the COVID-19 pandemic, but also other popular diseases like dengue, seasonal influenza, and malaria, which shared similar symptoms [17, 18]. Further, the reporting of deaths in these places were generally incomplete, and infected people died before receiving a test on COVID-19. Thus, the lack of well-established clinic protocols and formal mortality surveillance, as well as the relatively low technological levels and less comprehensive medical systems in these countries, were indirect causes of deaths resulted from SARS-Co-V-2 [17, 19].

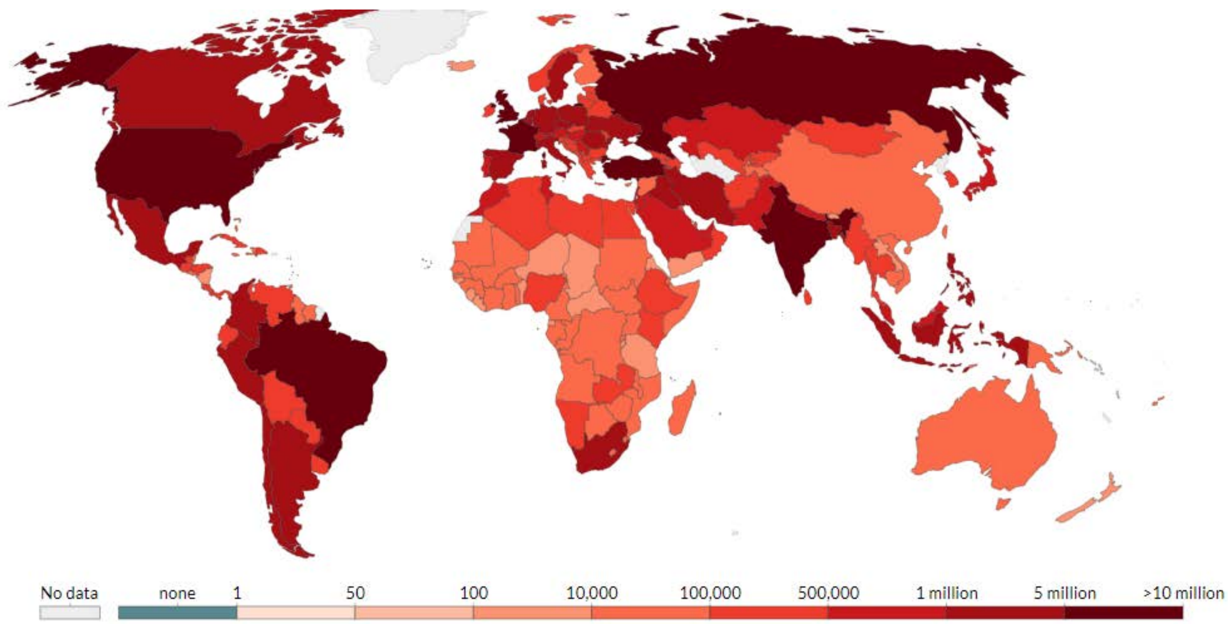


Figure 2. Spatial Distribution of worldwide confirmed COVID-19 cases from 22 January 2020 to 15 July 2021. Source: Johns Hopkins University CSSE COVID-19 Data (with reference to [16])

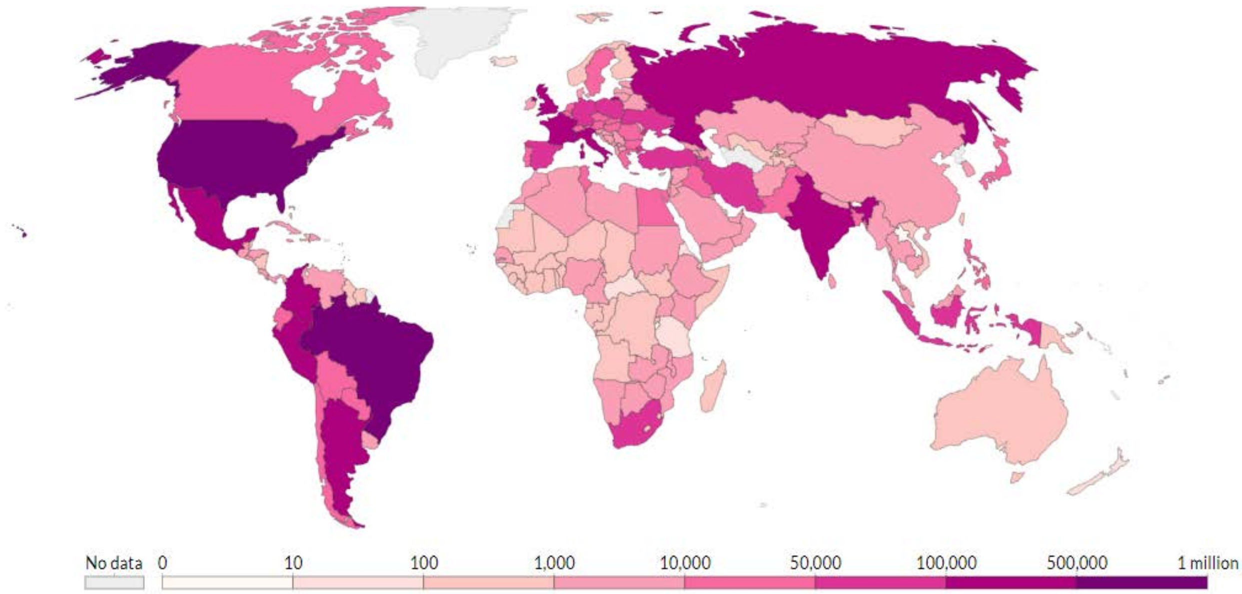


Figure 3. Spatial Distribution of worldwide death cases due to COVID-19 from 22 January 2020 to 15 July 2021. Source: Johns Hopkins University CSSE COVID-19 Data (with reference to [16])

Similar as the number of confirmed cases, more deaths were found in European countries like Russia, the United Kingdom, Italy, France and Turkey from early 2021. However, the process of vector transmission of COVID-19 was still an unsolvable global problem, while the mobility of citizens among countries and cities cannot be completely controlled or monitored. Furthermore, the limited testing, technological challenges, lack of public awareness, and even the hindering of data openness in some less developed countries have led to the underestimation of the actual number of COVID-19 cases or death rates [16]. Therefore, it is necessary to sort out means for conducting fair spatial and temporal medical assessments, monitoring the latest country-wise pandemic situations, and releasing the latest health information and advice to public, for better prevention and self-protection.

1.3. Overall Association between Lockdown Policies and Pollution Attributes

Despite the above challenges and the devastating impacts caused by the COVID-19 pandemic, different levels and stages of lockdown policies during critical moments have actually led to short-term improvements of air quality in most well-developed countries, especially for cities with heavy traffic and industrial activities. Based on the assessment via satellite retrieval and more than 100,000 air quality monitoring stations, Venter et al. (2020) have shown that after accounting for weather conditions and meteorological factors, 34 countries that have undergone an average of 62 days of lockdown had an average of 60% decrease $(11\ \mu\mathrm{g\ m^{-3}}\ \text{in average})$ in ground level NO_2 concentrations, accompanied by the decline of $PM_{2.5}$ by an average of 31% $(12\ \mu\mathrm{g\ m^{-3}}\ \text{in average})$. Due to the effect of NO_x titration, the averaged O_3 concentrations of these 34 countries have slightly increased by 4% ($4\ \mu g\, m^{-3}$ in average) [20]. As compared to NO_2, the spatial variability of air quality during the COVID-19 pandemic was more obvious for $PM_{2.5}$ and O_3 concentrations because of two major reasons. First, some countries emphasized more on industrial production. For these countries, the resulting pollution emission sources from industries decreased sharply during the COVID-19 pandemic. However, this may not be the case for other more developed countries, which specialise on financial and commercial industries. Second, the chemistrcal interaction of ambient air pollutants is complicated and determined by numerous meteorological quantities. A slight change of one meteorological quantity could hugely alter the pollution concentrations from time to time. Further, a reduction of NO_2 during the COVID-19 pandemic could be observed in almost all countries because of the decline in the surface transport sector. The lockdown of cities and towns restricted human mobility and thus minimized road traffic. Such phenomenon could be observed and found in both European and Asian countries. And the temporary control of NO_x could potentially further reduce the $PM_{2.5}$ concentrations on ground [21-24].

Yet, the reduction of major pollutants was temporary, and could not last for a long period of time. Once the lockdown policies were eased at a specific country, the concentrations of these pollutants, especially for NO_2 and $PM_{2.5}$, would rebound and return to higher levels. As remarked in Venter et al (2020) [20], lockdown policies were relaxed in Wuhan Province since 8 April 2020, and in the entire China since early April 2020. The partial resumption of normal daily life activities has led to abrupt fluctuations of pollutant concentrations. For instance, the sudden increase of NO_2 concentrations in many European countries like Italy, Spain and the United Kingdom from April to May 2020 was caused by an increase of economic activities and the relaxation of lockdown policies in major cities of these countries [20, 25]. These sudden changes in environmental and climatic conditions could bring potential harm to local citizens, especially the highly susceptible groups, like the elderly and people suffering from long-term diseases like asthma and respiratory diseases [26, 27]. There can be huge stress to local healthcare systems and environmental monitoring platforms for coping with these abrupt changes.

Hence, there is a genuine need to assess changes of major pollutants during the COVID-19 pandemic from early 2020 to July 2021, and then associate such changes with respective socio-economic factors, like policies imposed, human practice and habits, and the timeline of the prevention of pandemic. In this report, we focus on analyzing the temporal trends of COVID-19 cases, city-wise or national policies, and the temporal changes of pollutants like $PM_{2.5}$, NO_2 and O_3 in major East Asian cities. Five cities, namely Beijing, Hong Kong, Taipei, Tokyo and Seoul, were selected for discussion in Section 2. Then, respective data collection approaches for monitoring air quality conditions, and the manner of delivering and updating environmental and pandemic information and attributes were assessed with reference to the approach and framework developed by Mak and Lam (2021) [28]. Based on these quantitative and qualitative assessments, insights of acquiring, handling, releasing and integrating relevant datasets via the data analytic framework were outlined. The aim is to combat health epidemics and associated spatial challenges in the future, and maintain the resilience of these East Asian cities. The ideas can also be generalized and applied to other countries of the world.

2. COVID-19 Pandemic and Air Quality Conditions of Selected East Asian Cities

2.1. Cumulative Confirmed COVID-19 Cases over Time

Figure 4 shows the cumulative confirmed COVID-19 cases of each continent from Jan 2020 to 15 July 2021. As observed, the number of infected cases in Asia, Europe, and America far exceeded Africa and Oceania during any time period. Steady and consistent increase in COVID-19 confirmed cases were detected in both North America and South America, unlike Asia and Europe, where sudden spikes were detected from time to time.

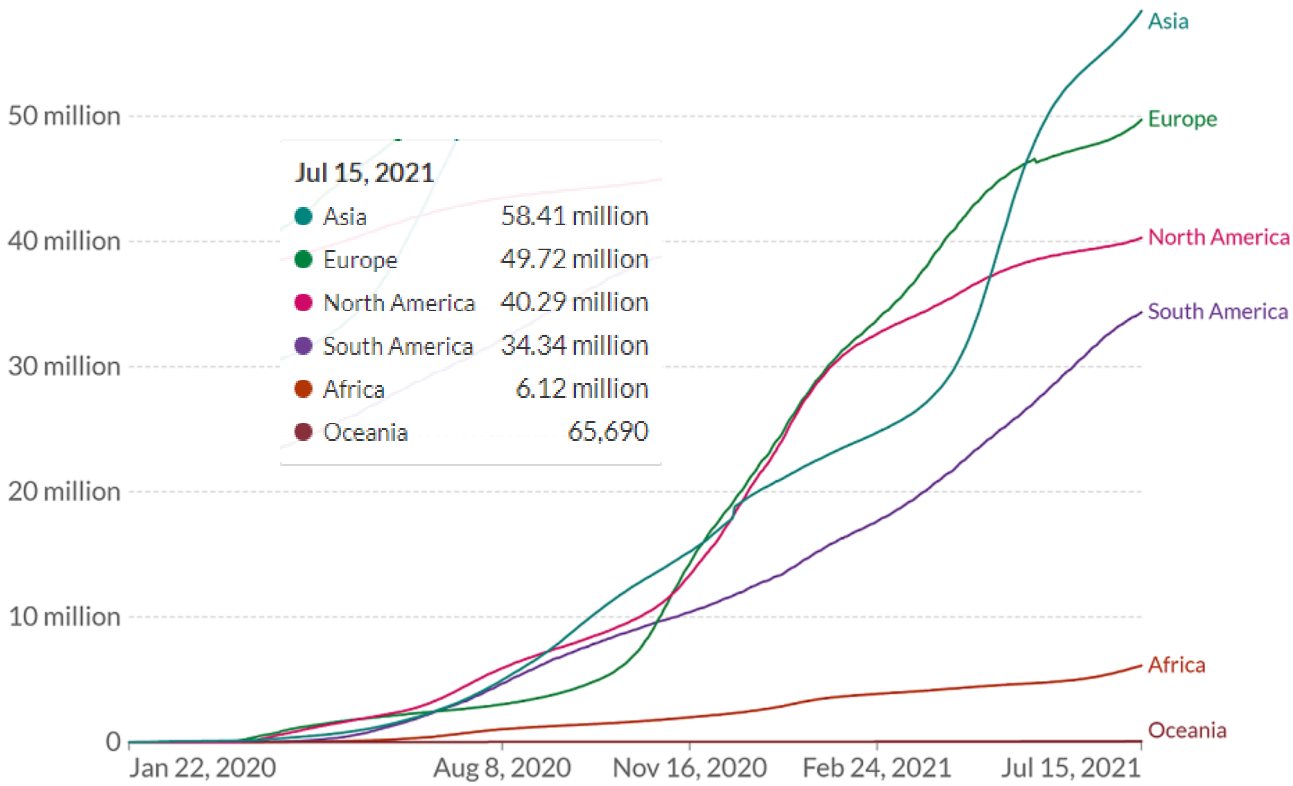


Figure 4. Cumulative confirmed COVID-19 cases of each continent from 22 January 2020 to 15 July 2021. Source: Johns Hopkins University CSSE COVID-19 Data (with reference to [16])

For Europe, the pandemic was particularly serious from March to May 2020, while the situation became better and steadier from late June to November 2020. However, from November 2020 onwards, the occurrence of a pandemic spike has brought Europe into the leading position in terms of cumulative confirmed COVID-19 cases. Overall, the temporal trend of Asian countries is quite similar to that of Europe, where the two curves nearly overlapped during the November 2020 to late February 2021 period. Despite the gradual recovery from the COVID-19 pandemic with a steady number of confirmed cases around 20-27 million in total during December 2020 to mid-March 2021, the situation became devastating again from late March 2021 till now. In particular, the cumulative figure of Asia returned to a leading position from 14 May 2021 onwards. So far, more than 58 million people from Asia have got infected, followed by around 49 million in Europe and 40 million in North America respectively. From Figure 4, the temporal trend and most critical periods of each continent can be found.

Next, we look more closely into the temporal patterns and changes of daily confirmed COVID-19 cases in selected major East Asian cities, and identify different pandemic waves that have taken place in these regions. Figures 5(a)-(e) show the time series of COVID-19 cases in Beijing, Hong Kong, Taiwan, Tokyo, and South Korea respectively. The data of Beijing, Hong Kong, Taiwan and South Korea were acquired from [16], while the respective data of Tokyo was obtained from its city-based COVID-19 website (https://stopcovid19.metro.tokyo.lg.jp/). Cases specifically about Taipei and Seoul are not directly available from other sources. Although these five East Asian cities are situated next to each other geographically, their temporal trends of COVID-19 are different from each other. In particular, after the outbreak in Wuhan in early 2020, the pandemic in Beijing and other Chinese cities was much more serious than neighboring countries like Japan and South Korea. In particular, the 1st wave of Beijing and Hong Kong happened in January and February 2020 respectively, as compared to the outbreak in South Korea in mid-late February, and mid-late March for Taiwan and Tokyo respectively. As visualized in Figure 5(a), after the 2nd wave of pandemic in summer 2020, the number of daily confirmed cases in Beijing was maintained at low levels, despite a minor peak during winter 2020 to early 2021. The reduction of confirmed cases can be attributed to the strict national and provincial prevention and control measures imposed at different spatial scales, especially the restriction of large population movements from one province (or city) to another [29]. After the UK virus variant was confirmed in January 2021, partial lockdown was immediately applied in Beijing [30], where 5 neighborhoods of Beijing stopped people from leaving and entering the city [31].

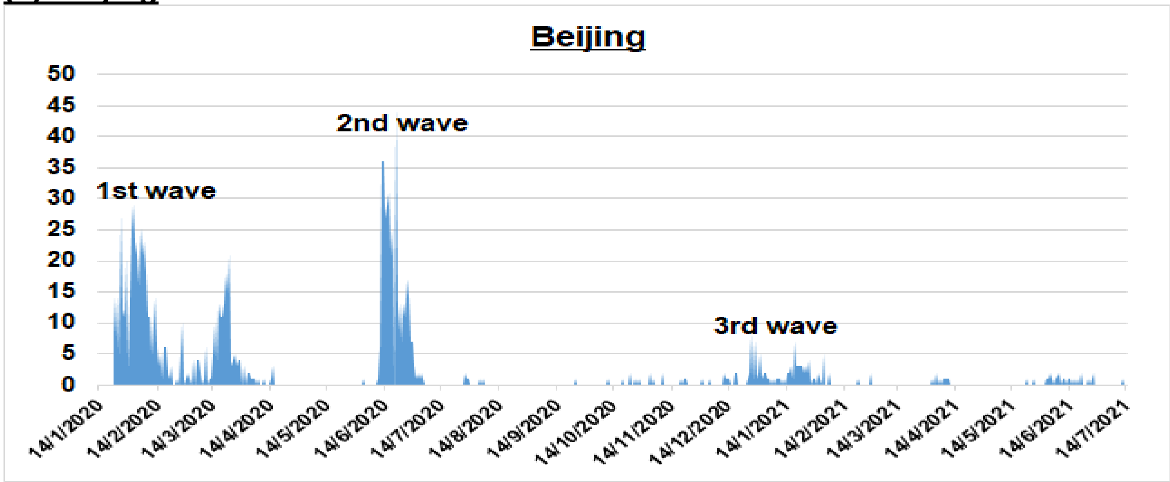
For Hong Kong, the first case of COVID-19 was confirmed on 22 January 2020, in which the infected person came from Shenzhen via the high-speed rail. The HKSAR government then immediately imposed enhanced measures to mitigate the spread of the pandemic, but the situation continued and became even more serious. Many people criticized that if all boundary control points were shut down immediately, the 2nd wave would not take place, while others suspected the capabilities of medical service providers in defeating the new wave of pandemic ahead [32]. The number of confirmed cases dropped and became steady from late April to early July 2020. However, to maintain the provision of daily necessities and service, “loopholes” and exemptions of quarantines existed for selected occupation groups entering Hong Kong, thus leading to the outbreak of the 3rd COVID wave during summer 2020 [33]. Since then, social distancing measures have been very strict to all groups of people, in terms of dining, quarantine, social gathering, and events.

Unlike most Chinese provinces, Taiwan has its first COVID case being confirmed on 21 January 2020, but there were no spikes immediately afterwards; and the impact of the pandemic was far less than many other industrial cities [34]. The concerted efforts of the Taiwanese government and local community in tracing of human trajectories, and provision of COVID-19 and healthcare information to public, have assisted the identification of patients, and minimized the health risks at the neighborhood level [35]. The situation was extremely steady until late April 2021, when several China Airlines crew members got infected without being detected. This has caused a sudden sharp peak from mid-May 2021, as visualized in Figure 5(c). Since then, the borders of Taiwan were shut down to non-citizens, and teaching mode has shifted from face-to-face to online learning [36].

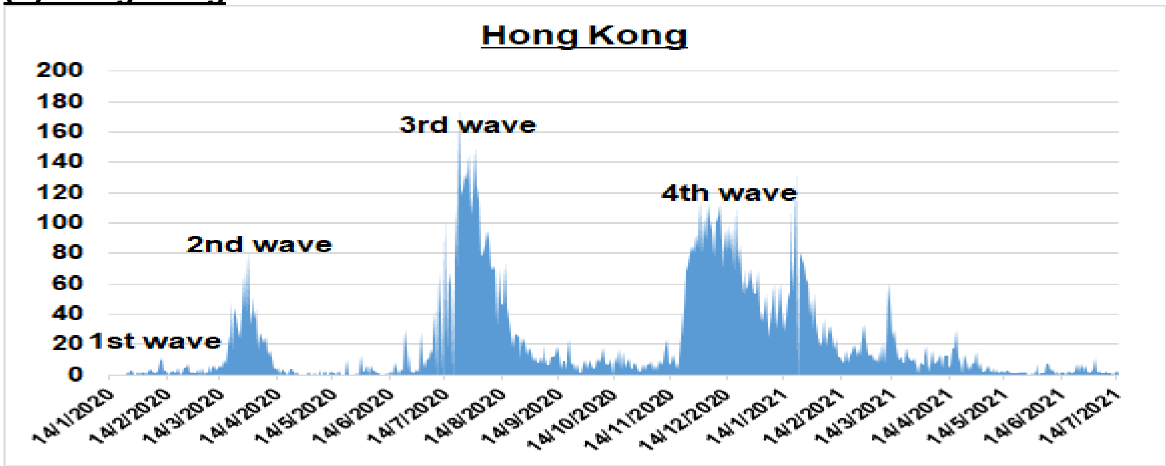
As for Japan and South Korea, the temporal trends look quite similar (as shown in Figures 5(d) and (e)), with different waves occurring during similar time periods. Japan and South Korea were the first few countries to have confirmed COVID-19 cases outside China. Nevertheless, by considering all five waves in these two countries, although the 1st wave of South Korea during early 2020 was relatively more serious than that in Tokyo, these relatively high numerical figures were only about 10% of the number of COVID-19 cases during the first wave of the United States [37]. Japan and South Korea were capable of controlling the pandemic and flattening the epidemic curve in an efficient manner, through different processes like testing, tracing, and isolating concerned groups of people during quarantine. According to Scott et al (2021) [37], more than 10,000 tests have been performed in South Korea on a daily basis, as compared to less than 100 in the United States. This has highlighted the importance and applicability of enhanced medical systems and technologies in South Korea after the outbreak of MERS virus several years ago. Regarding data collection processes related to COVID-19, despite the efficiency and technological advancement, public officials of South Korea have accidentally leaked personal information collected from patients [37], which has aroused public concerns regarding the tracking of personal mobility and travel paths. Thus, the openness of medical and human trajectory data was seen as a potential concern in South Korea, despite the benefits and opportunities behind. From Figure 5(e), it can also be observed that the 3rd wave (from December 2020 onwards) has persisted much longer than the 2nd wave (August-September 2020). This could mainly be attributed to the immediate strengthening of social distancing policies during summer 2020 [38]. Again, this observation has underlined the importance of early public health intervention and related national policies to effectively prevent the widespread of pandemic, and enhance the cooperation of different medical stakeholders within society.

Tokyo, the host of 2020 Summer Olympics, has undergone 5 COVID-19 waves during the past 1.5 years. Its pandemic was the most serious during the December 2020 to February 2021 period (as observed in Figure 5(d)). On 30 January 2020, soon after the first COVID case was confirmed in Japan, the Japan Anti-Coronavirus National Task Force was set up [39], then all schools in Japan were closed from late February 2020 until early April 2020. The one-month state of emergency policies and practice were implemented in many cities and prefectures [40]. Most of these waves were related to tourists, returnees and travelers from European countries and the United States [41], and the number of confirmed cases in Tokyo continued to increase until today.

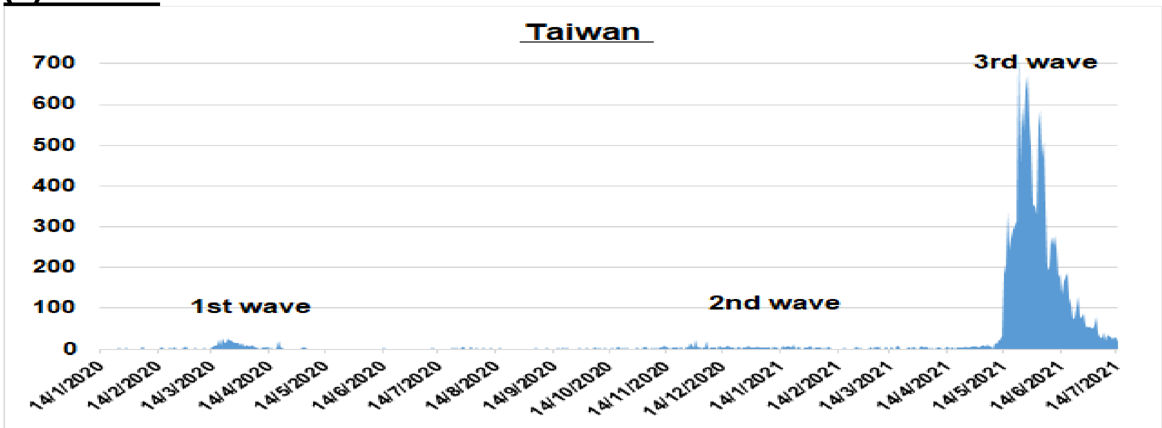
(a) Beijing



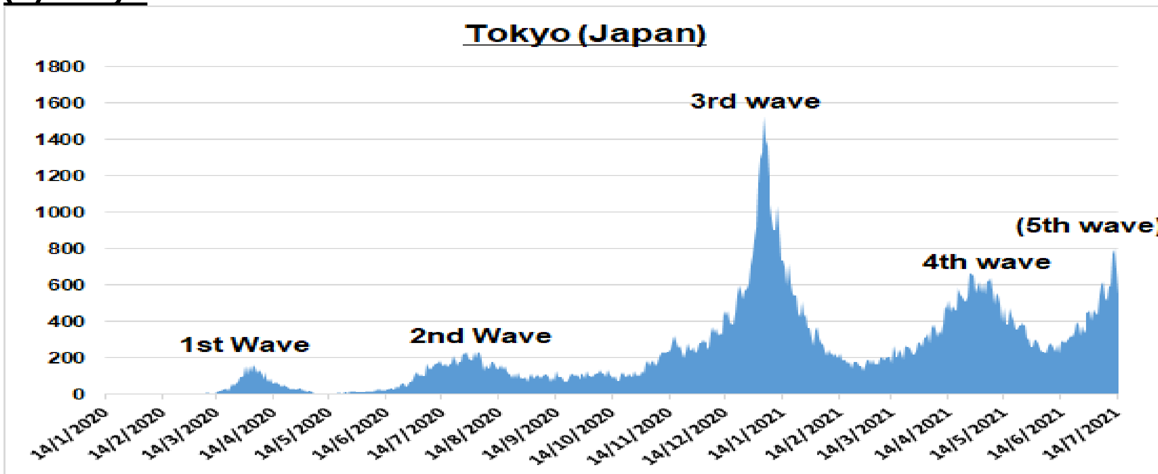
(b) Hong Kong



(c) Taiwan



(d) Tokyo



(e) South Korea

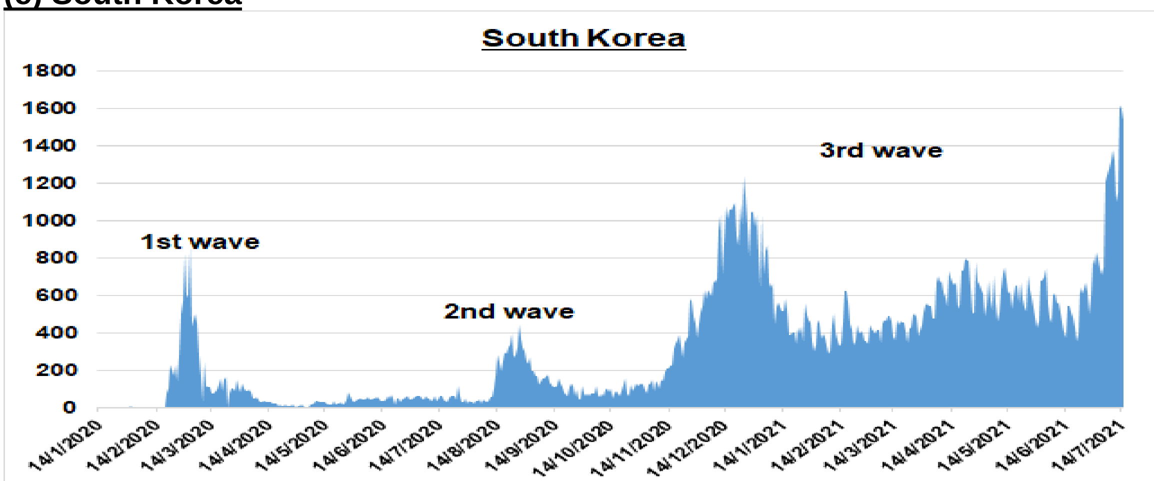


Figure 5. Time series of COVID-19 pandemic and different highlighted waves (as indicated) in selected countries/cities of East Asia, from late January 2020 to 15 July 2021.

Based on Figures 5(a) – (e), Table 1 provides a summary of the occurrence of the first confirmed COVID-19 case, and the exact period of different waves from January 2020 to now.

Table 1. A summary of the COVID-19 situation in five East Asian countries/cities

Name of Country/City	Date of the first confirmed COVID-19 case (Details)	Period of different COVID-19 waves (based on officially announced details)
Beijing	20 January 2020 (the case has visited Wuhan, China) [42]	1st wave: January – February 2020 [47] 2nd wave: Mid-June – July 2020 [48] 3rd wave: December 2020 – February 2021

Hong Kong	22 January 2020 (the case has visited Shenzhen, China, and has taken high speed rail) [43]	1st wave: February 2020 [49] 2nd wave: Late March-April 2020 [50] 3rd wave: July-August 2020 [49] 4th wave: late November 2020 – February 2021 [49]
Taiwan	21 January 2020 (the case has been to Taoyuan International Airport, and is serving as a teacher) [44]	1st wave: February 2020 (for 54 consecutive days) [51] 2nd wave: Early January– 9 February 2021 [51] 3rd wave: 20 April 2021 – now [51]
Tokyo	15 January 2020 (the case is actually a resident of Kanagawa Prefecture returning from Wuhan) [45]	1st wave: March – April 2020 2nd wave: June – August 2020 3rd wave: December 2020 – February 2021 [52] 4th wave: April – May 2021 Potential 5th wave: July 2021 onwards
South Korea	20 January 2020 (the case is a worker in Wuhan with flu symptoms during return) [46]	1st wave: 29 February-late March 2020 [53] 2nd wave: 13 August-18 September 2020 [38] 3rd wave: 4 November 2020 – now [38]

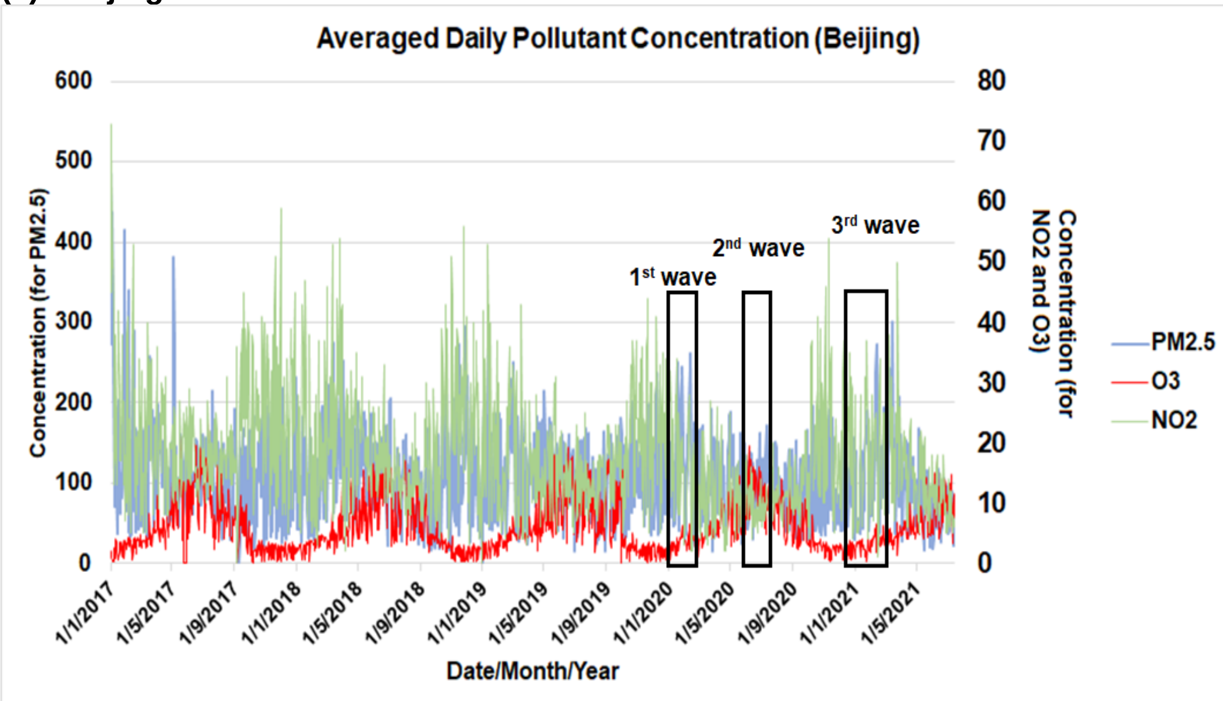
2.2. Pollution Figures Before and During the Pandemic

In this report, we would like to investigate the impacts of COVID-19 on air pollution levels of selected East Asian cities, as compared to similar time periods in previous few years. The implementation of a series of social distancing measures and lockdowns of major cities in East Asia have restricted mobility, thus leading to reduced travelling and transportation service required for transiting. It was verified that changes in traffic emissions could result in a substantial short-term reduction of NO_2, and reduced $PM_{2.5}$ concentrations, despite the occurrence of heavy pollution episodes from other sources [54]. Further, due to the NO_x titration effects, the reduction of NO_2 could result in a short-term increase of tropospheric O_3 concentrations [54]. Overall, the air quality conditions of many cities during the COVID-19 pandemic generally improved [55]. The improvement could be attributed to reduced domestic consumption of fuels, as well as the decrease in pollutant emissions from urban vehicles [56]. In particular, the air quality of Wuhan during 2020 has improved by 17.6%-20.1% when compared to previous three years [57]. For countries with consecutive COVID-19 waves (e.g., Canada), the air quality was maintained at a safe level for a longer period [56]. However, for cities having a long time gap in between two consecutive COVID-19 waves, fluctuations of pollutant concentrations could be large. In particular, the air quality could deterioriate again, or become even worse once the lockdown policies were eased [54]. Moreover, control measures of air pollution may not lead to immediate response and improvements in local air quality. Due to complicated meteorological effects, the improvement of air quality may take place few months after relevant pandemic policies were imposed, i.e., it may be observed at the end of a respective COVID-19 wave within the city. Thus, huge seasonal variations in pollutant concentrations during and after COVID-19 could be expected [58].

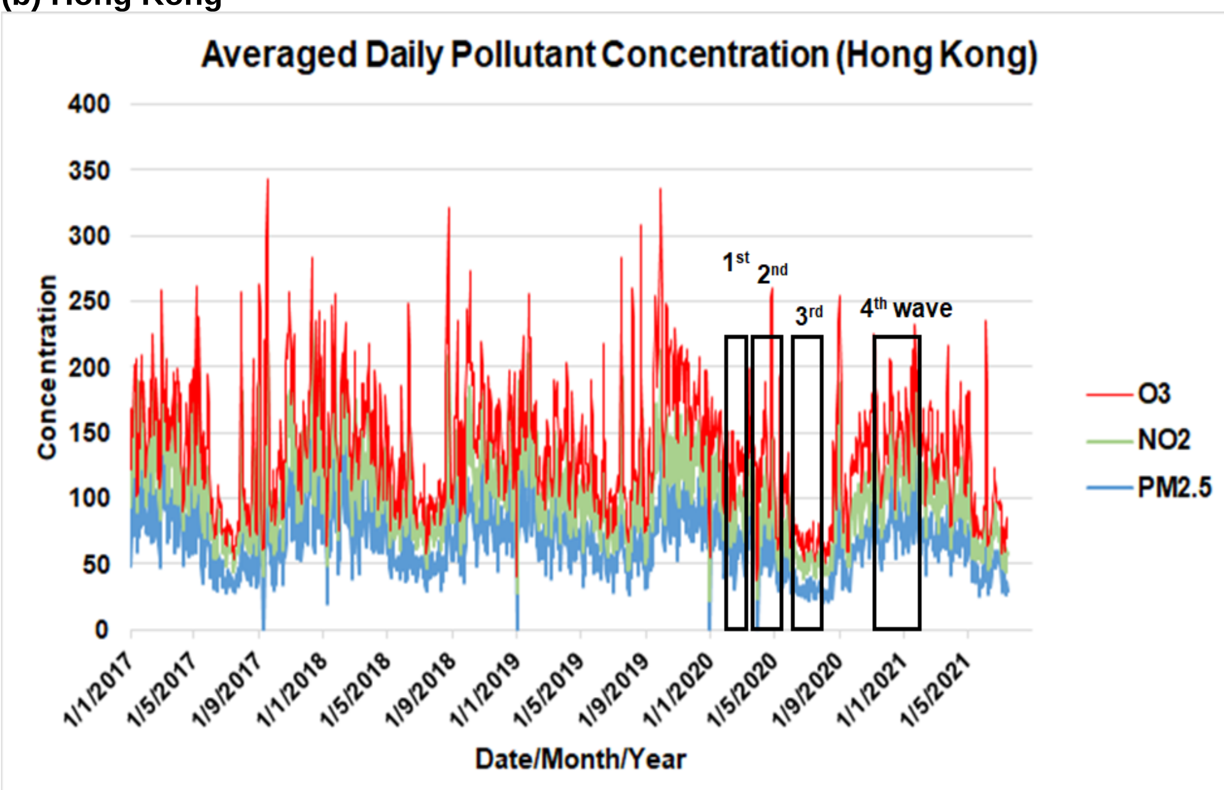
To quantify changes of air quality during and after individual COVID-19 waves in the aforementioned five East Asian cities, the average daily pollutant concentrations, including $PM_{2.5}$, NO_2 and O_3 are utilized to obtain corresponding time series. Potential temporal changes, as compared to the normal or past pollutant concentrations during that month or season, can be traced. Here, it is implicitly assumed that the meteorological quantities like temperature, atmospheric pressure, and relative humidity did not vary much during the pandemic. Thus, the effects of lockdown policies and COVID-19 towards changing air quality conditions can be investigated. To obtain a fair analysis, the time series of pollutant concentrations starting from 1 January 2017 to 15 July 2021 in respective city were obtained to minimize the uncertainty induced due to abrupt changes that may happen in one of the previous years. In particular, the Spring Festival of China of each year was at different months of the Calendarium Gregorianum; some in January, while some in February. Around two weeks before the Spring Festival, Chinese workers would normally start to return to their hometowns from large cities (i.e., their workplace). Thus, huge traffic burden ems would easily pop up, and lead to different environmental and public health concerns [59]. Further, it was also found that the display of firework during the Chinese Spring Festival could cause short-time but sharp increments of local particulate concentrations (including both $PM_{2.5}$ and PM_{10}) [60] becaue the coarse- and fine-mode particles of firework could accumulate within the concerned spatial domain for several days [61]. Thus, all these social effects must be considered if we would like to assess how COVID-19 and relevant lockdown and precautionary policies could affect city-wise air pollution.

Figures 6(a)-(d) show the time series of $PM_{2.5}$, NO_2 and O_3 concentrations of Beijing, Hong Kong, Tokyo and Seoul from 2017 to now, covering the period of the COVID-19 pandemic (i.e., from early 2020 to now). These data were acquired from aqicn.org [62], which provides daily average concentrations of six key types of pollutants, namely $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2 and CO. Based on the numerical figures obtained, the website also uses different colors to indicate the number of days within each month having different air pollution levels, from “good” to “hazardous”. As for Taiwan, since sensors of many monitoring stations have only operated starting from recent few years, air pollution datasets of these stations are available only from late 2019. As COVID-19 began in early 2020, it will be hard to assess any changes in its air quality conditions. As a result, we extracted the historical air quality records of four monitoring stations in Taiwan, namely Hualien, Xianxi, Qianzhen, and Wanli, from 2014 onwards and observed for any changes during or after different waves of pandemic, by coinciding the time period of air quality changes historically. The three figures in Figure 7 show the changes of each concerned pollutant detected within these four monitoring stations of Taiwan, which can also serve as good references to look for potential spatial variabilities. Here, we refer to the timeline of COVID-19 in the five cities, based on the prescribed pandemic waves as outlined in Table 1.

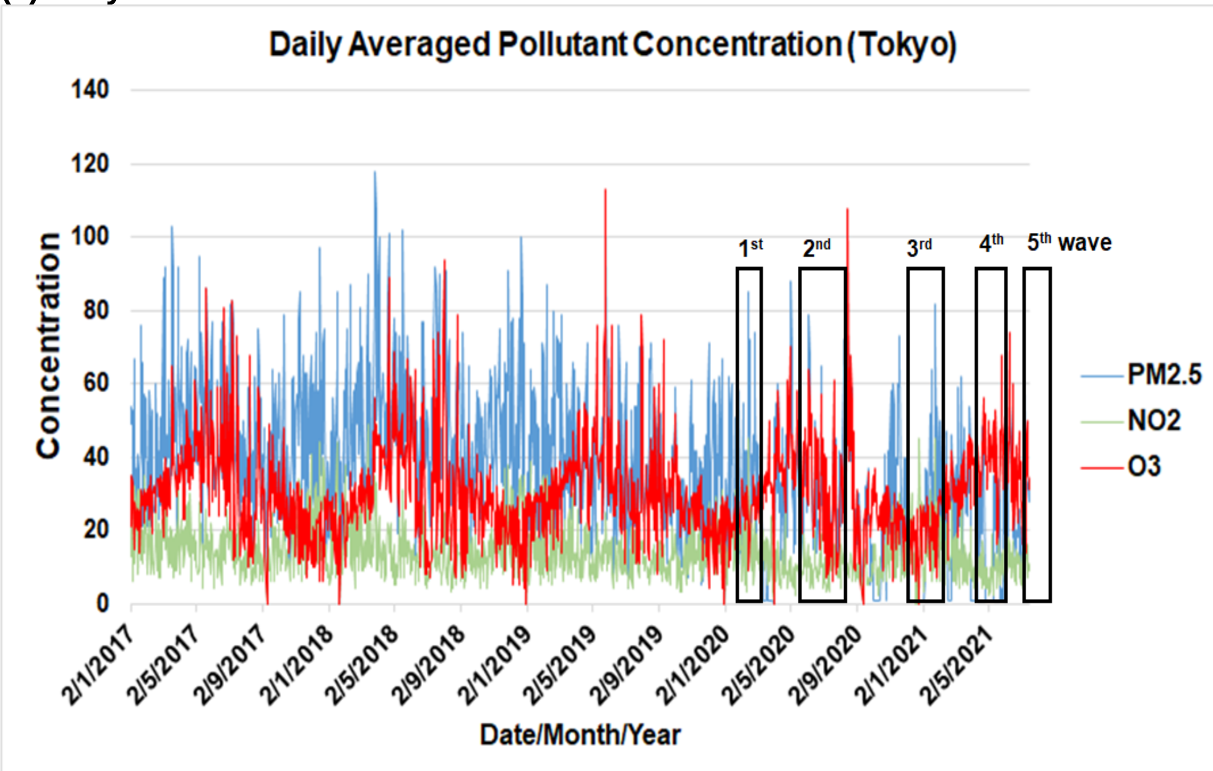
(a) Beijing



(b) Hong Kong



(c) Tokyo



(d) Seoul

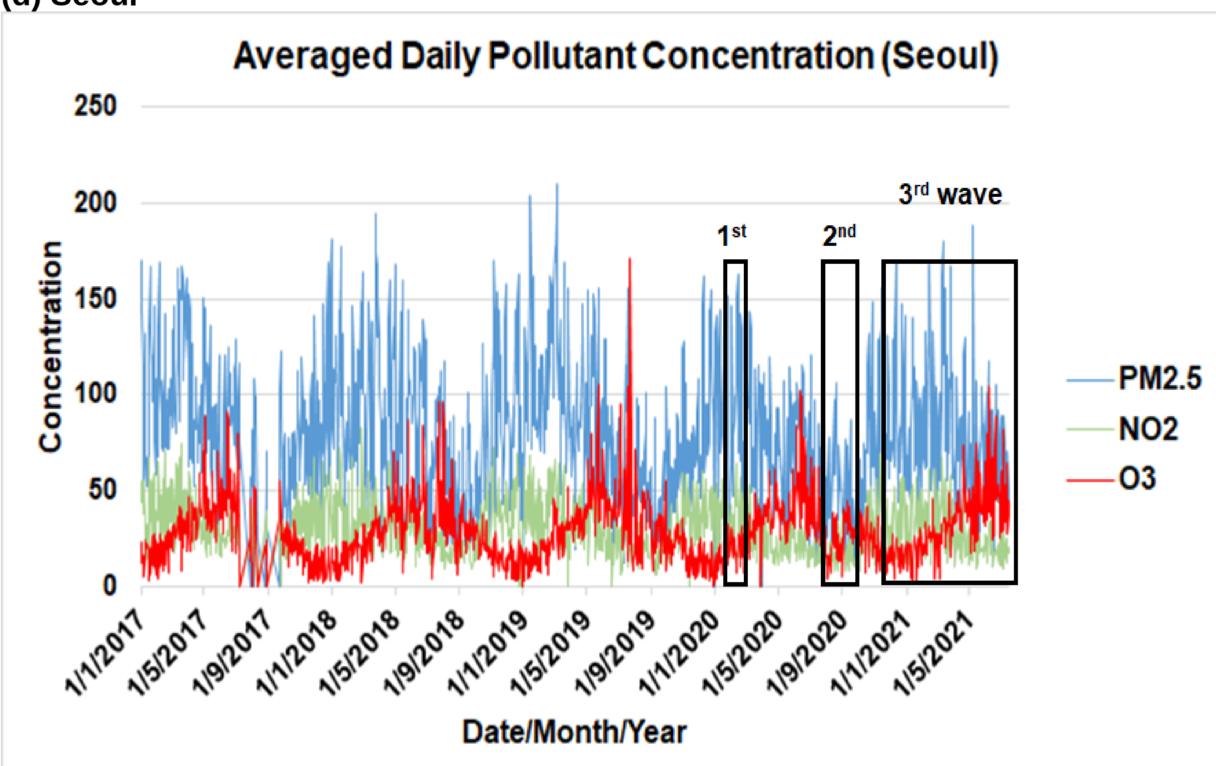
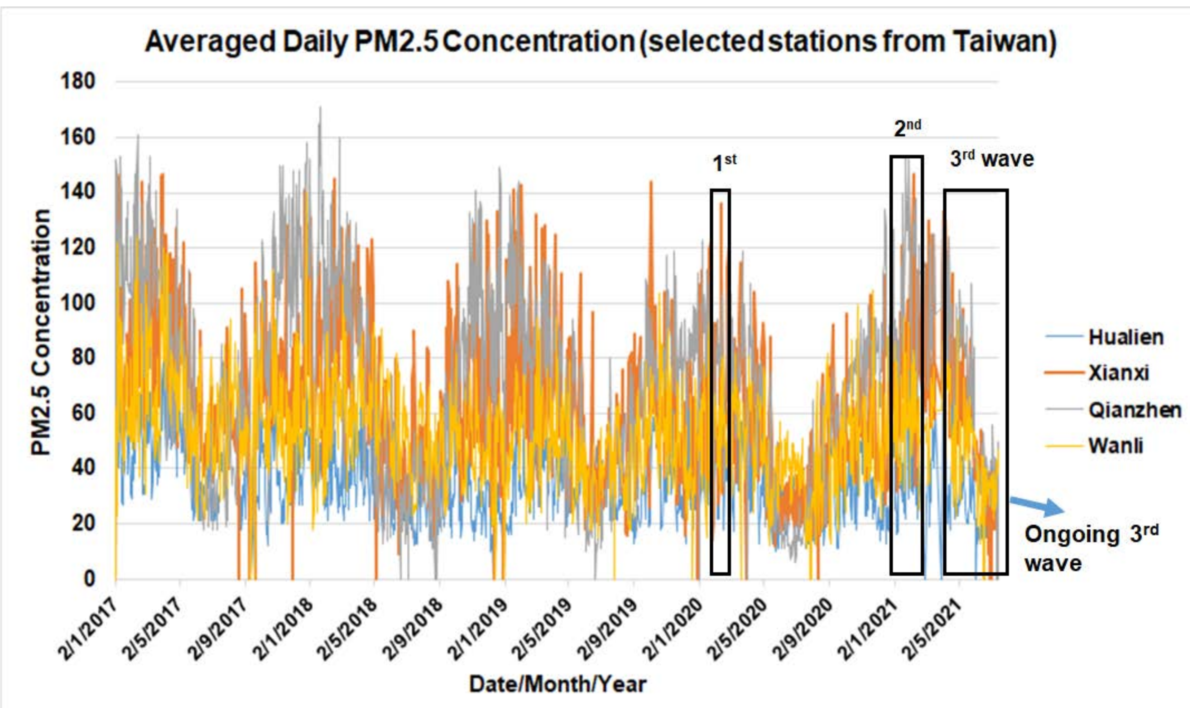


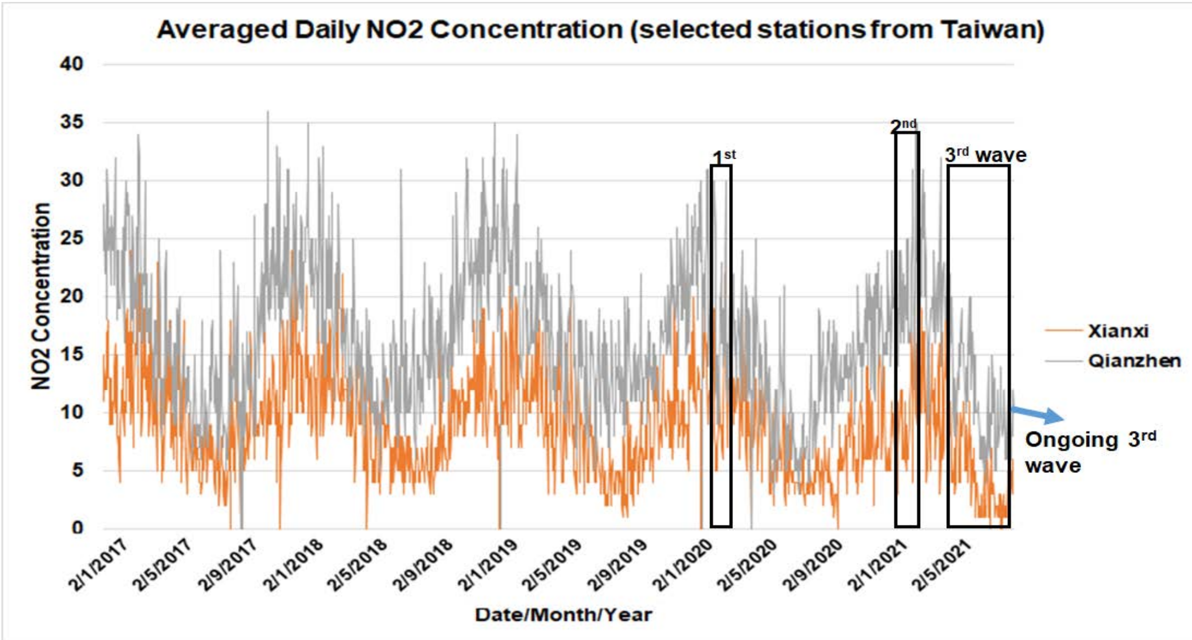
Figure 6. Time series of major air pollutants ($PM_{2.5}$, NO_2 and O_3) within (a) Beijing; (b) Hong Kong; (c) Tokyo; and (d) Seoul, from 1 January 2017 to now. COVID-19 pandemic: from January 2020 to now. The boxes indicate the pandemic waves in respective cities, with reference to Table 1. The concentrations are all in $\mu g\ m^{-3}$.

By observing all these temporal series, it was observed that the $PM_{2.5}$ (indicate as blue) and NO_2 (indicate as green) concentrations among all cities decreased during the pandemic. Yet, there were some quick rebounds after each COVID-19 wave. Also, the reduction of these two pollutants had a relatively more obvious effect in 2020, as compared to 2021. The reduction of NO_2 is of a greater magnitude than $PM_{2.5}$ mainly because of much less traffic in these areas due to lockdown and the implementation of work-from-home policies. For O_3 (as indicated by the red curves), different temporal trends appeared at these five cities during COVID-19. In particular, the average O_3 concentration in Beijing increased in 2020, while the corresponding concentration of Hong Kong has an obvious decrease during the same period. For Tokyo and Seoul, the average O_3 concentrations remained almost the same in 2020, but experienced a slight increase during 2021. The peak observed in Seoul in 2019 was not found in 2020 nor 2021 so far.

(a) $PM_{2.5}$



(b) NO_2



(c) O_3

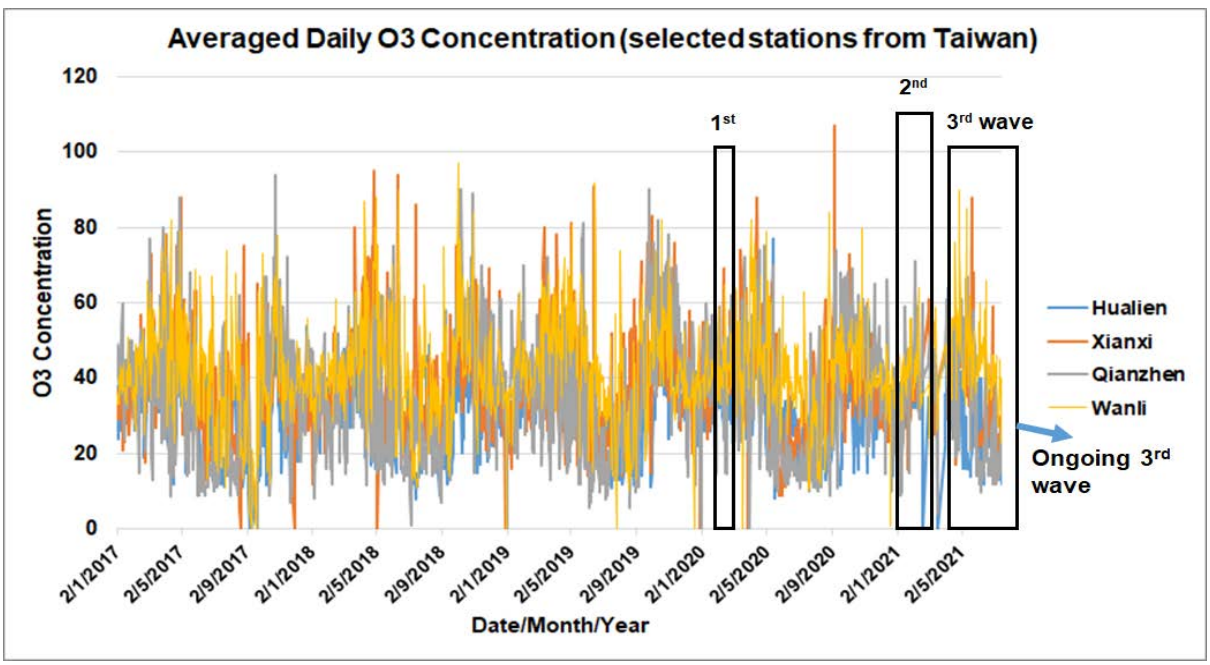


Figure 7. Time series of average Daily (a) $PM_{2.5}$; (b) NO_2; and (c) O_3 concentrations in four selected stations of Taiwan (i.e., those with long-term air pollution datasets) – Hualien, Xianxi, Qianzhen, and Wanli, from 1 January 2017 to now. The boxes indicated the pandemic waves of Taiwan, with reference to Table 1. The concentrations are all in $\mu g\ m^{-3}$.

For Taiwan, it is observed that the $PM_{2.5}$ and NO_2 concentrations within all four stations had an obvious decrease during 2020, especially during its 1st wave of pandemic. Then, during its 2nd and 3rd wave of pandemics, $PM_{2.5}$ concentrations detected in Wanli were at low levels when compared with previous several years. However, the effect of reduced pollution could not be observed at Xianxi and Qianzhen stations (Figure 7(a)). For NO_2, as shown in Figure 7(b), both stations have detected reduced NO_2 concentrations during and in between the three waves of pandemic, especially from April 2021 onwards, which could be attributed to the tightened coronavirus-induced restrictions imposed at different places. For example, within the four-tier system of Taiwan, the nationwide level-three alert (i.e., warning) was valid from 19 May 2021 to 12 July 2021 [63]. In other words, non-essential travels were generally not allowed, and visitors or residents returning to Taiwan should follow self-quarantine rules for 14 days upon arrival [64]. On top, all face-to-face classes were suspended during different wavs of pandemic in Taiwan. Human mobility and interaction were effectively restricted. Finally, no obvious changes in O_3 concentrations could be observed from Figure 7(c). Therefore, to conduct in-depth statistical assessments, we refer to the exact numerical figures of pollutant concentrations, and see whether these concentration levels would bring any health implications, and whether any cautionary measures are needed.

According to the rubrics on aqicn.org [62], the daily Air Quality Index (AQI) can be calculated simply by the 24-hr averaged hourly readings of each pollutant concentration detected by sensors. Figure 8 shows the air pollution level, health implications, and cautionary statement (for $PM_{2.5}$) of different AQI ranges. Whenever the pollutant concentration exceeds 100 $\mu g\ m^{-3}$, it will be considered as “unhealthy”. For the purpose of conducting temporal assessments, we refer to the concerned periods of different waves of pandemic during 2020 and/or 2021 (as shown in Table 1), calculate the average $PM_{2.5}$, NO_2 and O_3 concentrations during these periods, and compare with corresponding figures in previous few years (i.e., 2017, 2018 and 2019 in our study). For Beijing, Hong Kong and Taiwan, if the Spring Festival is within certain COVID-19 pandemic wave period, we take into account the pollutant concentrations one month before and after the Spring Festival as well, to obtain a fair comparison, and to minimize the impacts of enhanced traffic and reduced industrial emissions during the Festival. Table 2 shows the corresponding numerical figures and summaries of changes of pollutant concentrations during individual wave of the pandemic.

AQI	Air Pollution Level	Health Implications	Cautionary Statement (for PM2.5)
0 - 50	Good	Air quality is considered satisfactory, and air pollution poses little or no risk	None
51 -100	Moderate	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.	Active children and adults, and people with respiratory disease, such as asthma, should limit prolonged outdoor exertion.
101-150	Unhealthy for Sensitive Groups	Members of sensitive groups may experience health effects. The general public is not likely to be affected.	Active children and adults, and people with respiratory disease, such as asthma, should limit prolonged outdoor exertion.
151-200	Unhealthy	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects	Active children and adults, and people with respiratory disease, such as asthma, should avoid prolonged outdoor exertion; everyone else, especially children, should limit prolonged outdoor exertion
201-300	Very Unhealthy	Health warnings of emergency conditions. The entire population is more likely to be affected.	Active children and adults, and people with respiratory disease, such as asthma, should avoid all outdoor exertion; everyone else, especially children, should limit outdoor exertion.
300+	Hazardous	Health alert: everyone may experience more serious health effects	Everyone should avoid all outdoor exertion

Figure 8. The categorization of Air Pollution Levels based on respective daily AQIs (calculated from the average of hourly average pollutant concentrations), potential health implications and cautionary statement (for $PM_{2.5}$), with reference to [62].

Table 2. Comparison of average $PM_{2.5}$, NO_2, and O_3 concentrations during each pandemic wave in 2020 and/or 2021, with the pollutant concentrations obtained in 2017, 2018 and 2019 respectively.

Country/City	Periods of pandemic waves	Average Pollutant Concentrations (during the pandemic) (in $\mu g\ m^{-3}$)*				Average Pollutant Concentrations (within past years) (in $\mu g\ m^{-3}$)*			
Beijing	1st wave: Jan-Feb 2020		***$PM_{2.5}$***	***NO_2***	***O_3***		***$PM_{2.5}$***	***NO_2***	***O_3***
		1st	123.7	16.2	26.1	*2017*	153.8	25.5	20.7
		2nd	108.1	9.9	82.4	*2018*	91.7	19.0	23.9
		3rd	104.9	17.6	22.7	*2019*	118.8	21.2	23.7
	2nd wave: Mid Jun-Jul 2020						***$PM_{2.5}$***	***NO_2***	***O_3***
						2017	116.0	16.9	90.1
						2018	107.3	15.7	82.3
						2019	105.9	13.0	87.7
	3rd wave: Dec 2020-Feb 2021						***$PM_{2.5}$***	***NO_2***	***O_3***
						2017	93.1	20.6	21.3
						2018	109.9	20.9	20.8
						2019	118.3	18.7	22.4

Hong Kong	1st wave: Feb 2020		***$PM_{2.5}$***	***NO_2***	***O_3***		***$PM_{2.5}$***	***NO_2***	***O_3***
		1st	65.9	31.0	28.8	*2017*	90.8	41.1	31.0
		2nd	66.2	32.5	37.5	*2018*	95.2	42.8	28.4
		3rd	36.7	23.4	23.0	*2019*	74.4	31.1	24.8
		4th	82.0	37.1	33.1				
							$PM_{2.5}$	***NO_2***	***O_3***
	2nd wave: Late Mar-Apr 2020					*2017*	83.3	38.8	33.2
						2018	85.2	33.8	33.0
						2019	68.5	31.9	31.9
							$PM_{2.5}$	***NO_2***	***O_3***
	3rd wave: Jul-Aug 2020					*2017*	49.5	28.6	23.2
						2018	56.1	32.2	25.9
						2019	39.7	30.9	30.9
							$PM_{2.5}$	***NO_2***	***O_3***
	4th wave: Late Nov 2020-Feb 2021					*2017*	93.6	41.6	30.3
						2018	86.3	37.0	26.0
						2019	76.4	36.9	32.6
Tokyo**	1st wave: Mar-Apr 2020		***$PM_{2.5}$***	***NO_2***	***O_3***		***$PM_{2.5}$***	***NO_2***	***O_3***
		1st	23.2	11.0	36.2	*2017*	53.2	17.1	37.0
		2nd	34.6	9.7	32.2	*2018*	57.2	16.4	39.1
		3rd	31.8	17.2	22.7	*2019*	42.0	14.3	36.8
		4th	25.6	8.7	40.0				
		5th	25.2	11.2	31.2		***$PM_{2.5}$***	***NO_2***	***O_3***
	2nd wave: Jun-Aug 2020					*2017*	47.3	13.2	34.3
						2018	52.2	11.7	33.3
						2019	38.0	12.1	31.1
							$PM_{2.5}$	***NO_2***	***O_3***
	3rd wave: Dec 2020-Feb 2021					*2017*	43.9	20.2	22.4
						2018	43.6	18.2	23.9
						2019	36.5	17.5	22.2
							$PM_{2.5}$	***NO_2***	***O_3***
	4th wave: Apr-May 2021					*2018*	58.3	14.1	43.2
						2019	40.5	13.4	43.5
						2020	34.0	9.4	39.8
							$PM_{2.5}$	***NO_2***	***O_3***
	5th wave: Jul 2021 onwards (data here are until 22 Jul 2021)					*2018*	56.2	11.5	32.3
						2019	35.5	12.6	28.4
						2020	25.1	8.9	21.7
Taiwan***	1st wave: Feb 2020		***$PM_{2.5}$***	***NO_2***	***O_3***		***$PM_{2.5}$***	***NO_2***	***O_3***
		1st	59.4	25.8	43.4	*2017*	80.6	28.4	36.4
		2nd	69.4	26.9	35.0	*2018*	75.4	27.6	35.0
		3rd	38.5	20.5	21.9	*2019*	60.3	25.7	33.2

	2nd wave: Early Jan-Feb 2021						***$PM_{2.5}$***	***NO_2***	***O_3***
						2018	71.0	26.8	32.3
						2019	63.8	27.2	33.2
						2020	59.3	25.8	32.3
	3rd wave: 20 Apr 2021 – now						***$PM_{2.5}$***	***NO_2***	***O_3***
						2018	44.5	22.5	31.1
						2019	40.7	23.4	26.7
						2020	33.5	21.3	22.3
Seoul	1st wave: 29 Feb-late Mar 2020		***$PM_{2.5}$***	***NO_2***	***O_3***		***$PM_{2.5}$***	***NO_2***	***O_3***
		1st	84.1	28.5	31.1	*2017*	123.9	43.4	29.8
		2nd	53.4	18.6	27.2	*2018*	104.0	36.5	26.6
		3rd	80.7	29.4	30.6	*2019*	121.5	38.1	30.5
	2nd wave: 13 Aug-18 Sep 2020 #						***$PM_{2.5}$***	***NO_2***	***O_3***
						2018	49.0	18.5	30.6
						2019	47.5	17.5	33.4
	3rd wave: 4 Nov 2020 – now						***$PM_{2.5}$***	***NO_2***	***O_3***
						2017	89.6	33.1	24.7
						2018	96.3	35.0	28.5
						2019	80.4	29.7	28.8

*All numerical figures are corrected to 1 decimal place, and are averaged numerical figures during the concerned period. The effect of Spring Festival has been considered for Beijing, Hong Kong, and Taiwan.

** Obtained from Naitomadi, Shinjuku, Tokyo, Japan.

*** The numerical figures of Taiwan are the spatial average of the 4 stations with historical record.

The corresponding pollution figures during most dates of the same period in 2017 were missing, therefore only 2018 and 2019 datasets have been adopted for comparison purposes.

Based on the numerical figures obtained from Table 2, the trends of different pollutants are different, even within the pandemic waves of the same city. For instance, during the 1st and the 2nd COVID-19 waves of Beijing, $PM_{2.5}$ concentrations detected in 2020 were lower than that in 2017, but were roughly equal to the average concentrations in 2018 and 2019. However, the average $PM_{2.5}$ concentration during the 3rd pandemic wave (i.e., Dec 2020 – Feb 2021) was obviously lower than that in 2018 and 2019. This can be attributed to a combination of different social activities, like Spring Festival, social gathering bans, and restricted mobility in some places of Beijing. In particular, the Spring Festival of 2018 and 2019 were on 16 February and 5 February, thus high $PM_{2.5}$ and NO_2 concentrations were expected due to human movement and increased traffic activities. For NO_2, a consistent decreasing trend was attained within different pandemic waves, with a decrease of 26.0%, 34.9% and 12.3% when compared to the average NO_2 concentrations of Beijing from 2017-2019. As for O_3, different trends could be observed. There was an increase of 14.6% during the 1st COVID-19 wave, but a slight increase during the 3rd pandemic wave. The O_3 concentrations during the 2nd wave were lower than that in 2017 and 2019, but roughly equal to that attained within the same period of 2018. This also shows that meteorological impacts and complex photochemical reactions within atmosphere could determine how O_3 concentration changes, even within the same period of different years.

For Hong Kong, the $PM_{2.5}$ concentrations of most "pandemic periods" peaked in 2018. Due to concerted governmental efforts and the installment of extra sensors for monitoring, $PM_{2.5}$ concentrations had a sharp reduction in 2019 before the outbreak of COVID-19. A slight reduction was again found when compared with the average $PM_{2.5}$ concentrations in 2019 and 2020. Overall, the average $PM_{2.5}$ concentrations during each COVID-19 wave have decreased by 24.1%, 16.2%, 24.2% and 4.02%, when compared with the temporal-averaged data from 2017 to 2019. Such obserations derived from the "aqicn.org" data source have also been supported by the analysis of the Environmental Protection Department (2019) [65], which verified that the concentrations of $PM_{2.5}$, PM_{10}, NO_2 and SO_2 in ambient air and roadside pollution monitoring network have actually decreased by 34-80% and 34-82% from the highest level from 1999 to 2019 [65]. A significant reduction from peak values by around 70% was also found for visibility [65]. For NO_2 concentrations, a general decreasing trend was found in all four pandemic periods of Hong Kong, though the exact timing of attaining decreased NO_2 differs. In particular, for February, the majority of NO_2 reduction was attained during 2018-2019, while the average NO_2 concentration in 2020 was similar to that in 2019. For March-April and late November, the corresponding concentrations in 2020 were quite similar to that in 2018 and 2019, and these magnitudes were much lower than that in 2017. As for the summer, NO_2 concentration has decreased by a total of 23.4% overall among recent years. For O_3, the trend is quite complicated, with a slight decrease in most seasons, then followed by a rebound in terms of average O_3 concentrations. It is interesting to see that both NO_2 and O_3 concentrations during Jul to Aug 2020 decreased simultaneously, as compared to the average concentrations during the same period of past years.

For Tokyo, a commonly observed decreasing trend of $PM_{2.5}$ concentrations could be found in recent years. As reviewed in Table 2, the obvious decrement in many pandemic periods were first detected during 2018-2019, while another round of major reduction could be found during 2019-2020, too. By comparing the figures in 2020 with the temporal average of $PM_{2.5}$ concentrations in previous three years, the percentage decrease in $PM_{2.5}$ concentrations ranged from 23.1% (3rd wave: Dec 2020-Jan 2021) to 54.3% (1st wave: Mar-Apr 2020). It suggests an average percentage decrease of 35.9% out of all five waves. In terms of NO_2 concentrations, the values attained during different COVID-19 waves of Tokyo were significantly lower than corresponding periods of the previous three years, except possibly the 5th wave (Jul 2021 onwards), where the average NO_2 concentration is 11.2 $\mu g\, m^{-3}$, as compared to 11.5 $\mu g\, m^{-3}$, 12.6 $\mu g\, m^{-3}$ and 8.9 $\mu g\, m^{-3}$ in 2018, 2019 and 2020 respectively. For the other four COVID-19 waves, the NO_2 concentrations have decreased by 7.69% (3rd wave: Dec 2020-Feb 2021) to 31.0% (1st wave: Mar-Apr 2020) when compared with the average values attained in the previous three years. As for O_3 concentrations, the values observed during the COVID-19 pandemic were similar to that in 2017 to 2019, thus the impacts of SARS-Co-V-2 on changes of O_3 are negligible for Tokyo.

From the datasets obtained from the four stations in Taiwan, it is interesting to notice that the outbreak of COVID-19 pandemic did not affect the local air quality much. In particular, the average $PM_{2.5}$ concentration of the 1st wave, during February 2020, was only slightly lower than that during the same period of 2019. For the 2nd wave (early January-February 2021), the $PM_{2.5}$ concentration was just below that of 2018. Finally, during the 3rd wave (April 2021- now), the observed concentration was in between the values attained in 2018 and 2019. All these indicate that slight changes were induced by COVID-19. In fact, the numerical values of NO_2 concentrations at these four stations were quite similar for all four years from 2017 to 2021. According to Yu et al. (2021), only a slight reduction of $PM_{2.5}$ could be observed during the 1st pandemic wave (from January to March 2020) in Taiwan, even in industrial areas in northern or southern Taiwan. Such a slight decline occurred mainly because of decreased domestic emissions of $PM_{2.5}$, as well as the reduction of concentrations of some of its precursors [66]. As for O_3, an increase of O_3 concentrations could be detected during the 1st and the 2nd COVID-19 waves in Taiwan. For the 3rd wave (20 April 2021-now), not much temporal variations of O_3 could be seen so far.

As for Seoul, the effects of different COVID-19 waves varied. During its 1st wave (29 Feb-late March 2020) and 3rd wave (4 Nov 2020- now), $PM_{2.5}$ concentrations decreased by an average of 27.8% and 9.1% respectively when compared to the 3 previous years. The city's NO_2 concentrations also reduced by 27.5% and 9.8%. A notable point is that the reduction of the 1st pandemic wave was more attributed to a reduction of normal daily life activities and lockdown. For the 3rd wave, the decrease of pollutant concentrations actually occurred starting from 2019. In other words, the reduction observed was not completely attributed to environmental and behavioral changes due to the pandemic. Due to the reduction of NO_2 concentrations during these two periods, corresponding O_3 concentrations have increased by 7.3% and 12.0% respectively. As for the 2nd pandemic wave (13 August – 18 September 2020), $PM_{2.5}$ concentrations increased unexpectedly by 10.7%, and so did the NO_2 levels. Yet, there was a reduction of O_3 concentration by around 15%.

In summary, a common temporal characteristic was shared among all these five East Asian cities, namely a reduction of $PM_{2.5}$ and NO_2 concentrations during the 1st wave of COVID-19, which took place during February to March 2020. During those months, all these cities were very concerned about the new worldwide pandemic, when nobody in the world could find out its causes and potential transmission path and rationale. National and provincial governments had all imposed strict regulations that restricted mobility and social distancing, reduced normal traffic routes, provided alternative working arrangements, and implemented precautionary measures in all walks of life. All these seriously "interrupted" the normal way of living of residents, but at the same time brought better air quality and social awareness towards the pandemic. Most industrial and anthropogenic activities were either completely stopped, or being hindered during this critical period. Thus, less pollutants were emitted to atmosphere. However, the partial resumption of daily activities at the end of each pandemic wave in respective cities have led to a rebound of $PM_{2.5}$ and NO_2 concentrations. More importantly, as time goes, advanced technologies and preventive measures were designed and sorted out to combat the COVID-19 pandemic, and defeat potential medical challenges within local communities, thus the anthropogenic emission and domestic activities were not completely halted in subsequent pandemic waves. Over time, the reduction of $PM_{2.5}$ and NO_2 concentrations have become less obvious. In some cases, a slight increase of pollutant concentrations could be observed somehow.

2.3. Monitoring Changes of Pollution Concentrations during the Pandemic

In the above section, the pollutant measurements obtained from ground monitoring stations were used for statistical and temporal analyses. However, air quality sensors and relevant equipment could only be installed in limited locations, and the meausrements are too sparse for obtaining a complete understanding of the spatial distribution and changes of pollutants among different places of a city. Therefore, a combination of these raw measurement values and alternative statistical or technical approaches is essential. In this section, we briefly review the existing literature and conclusion based on studies of environmental changes during different stages of the COVID-19 pandemic. These papers usually combine datasets obtained from different means, for example, numerical modelling, satellite remote sensing, measurements obtained from remotely sensed instruments, and ground-based monitoring network as aforementioned. This section also highlights the importance of data integration for smart city development, which will be further discussed later.

2.3.1 Numerical Modelling

In Asian cities, the Weather Research and Forecasting (WRF) and Community Multiscale Air Quality (CMAQ) models are commonly used to simulate the meteorological fields and air quality conditions of individual cities. The modelling system is usually conducted on a 4-nested run preset on a spatial domain, gradually zooming down from a larger spatial coverage to the eventual region of interests, with runs of two intermediate spatial resolutions in between. Different cities have adopted modelling approaches to govern the changes of meteorological attributes and local pollutant concentrations, and to assess the effectiveness of particular city-based policy implemented during COVID-19, via an integrated analysis framework that combines different real-time monitoring datasets.

In Beijing, Lv et al (2020) combined the hourly vehicular emission from a street-level on-road emission inventory, air quality and meteorological monitoring datasets, and the outputs from the enhanced WRF-CMAQ model to detect and investigate changes of traffic emissions and connections with NO_x and volatile organic compounds (VOCs), as well as the occurrence of winter haze before and during COVID-19 (i.e., from 10 January 2020 to 25 February 2020) [67]. To improve the accuracy of meteorological field from WRF simulations, an urban canyon model (UCM) was applied and ingested into WRF before conducting simulations. In this way, the updated land use patterns and canyon effects within urbanized areas can be better reflected, and the modelling results can become more realistic [68]. To focus on the lockdown effects and changes of transportation mode, the Integrated Source Appointment Methods (ISAM) was incorporated in the CMAQ model version 5.0.2, to analyze the source origins (either local or regional pollution sources) of $PM_{2.5}$ and PM_{10} concentrations within Beijing during the study period [69]. The categorization of vehicle types, road types and sectors were all conducted, while a series of daily-life scenarios based on fluctuations of on-road emissions were pre-set in the WRF-CMAQ modelling system so that the corresponding air quality predictions during different stages of COVID-19 can be obtained, namely the pre-lockdown period (10 January 2020 – 20 January 2020), the transition period (20-23 January 2020), and the lockdown period (24 January 2020 – around 20 February 2020). Modelling results show that during the lockdown period, the traffic flow in main roads has reduced by 37-60% when compared to the pre-lockdown period. Overall vehicle emissions reduced by 51-76%. For NO_x, a significant emission reduction of 76% occurred when all potential sources were taken into consideration. If only on-road traffic was considered, the corresponding NO_x and $PM_{2.5}$ emissions decreased by 44-49% and 52-55% respectively. As a result, the huge reduction of local anthropogenic emission sources have led to the removal of $PM_{2.5}$ precursors during the COVID-19 pandemic. In particular, NO_2 concentration has reduced by 58%. Despite the lack of gaseous precursors, increased oxidant concentrations within the atmosphere have enhanced the formation of secondary fine particles. For example, the NO_3 concentrations have increased abruptly at night during the entire lockdown period. Such phenomenon has also been detected in real-time WRF-CMAQ simulations within most areas of Beijing. Furthermore, surface O_3 concentrations have also increased by 62% on average from the pre-lockdown period to the end of the lockdown period. However, the rise of O_3 concentrations consists of urban-rural discrepancy, where relatively less O_3 increase could be detected in rural regions of Beijing because the regime for ozone formation at rural regions is usually NO_x limited, which is different from urban regions (i.e., VOC-limited regime) [70, 71]. Such spatial difference also led to differences in $PM_{2.5}$ concentration changes during the COVID-19 period in Beijing because of different rates of atmospheric oxidation processes. For urban areas of Beijing, half of the days suffered from high levels of $PM_{2.5}$ concentrations during the lockdown (i.e., exceeding 75 $\mu g/m^3$, which correspond to Level II standard of the Chinese national Ambient Air Quality Standards). Overall, the average daily $PM_{2.5}$ concentrations increased from 48.0 $\mu g/m^3$ to 99.0 $\mu g/m^3$ after the lockdown policy were implemented, and the temporal patterns of $PM_{2.5}$ during polluted scenarios obeyed the asymmetric "sawtooth" pattern [67], i.e., with a gradual increment few days before reaching the peak due to the formation of secondary inorganic aerosols, followed by a sharp decrease after the concentration peak is observed [72]. Furthermore, modelling results also show that unfavorable meteorological conditions like reduced wind flow velocity, lower planetary boundary layer height, and higher relative humidity will enhance $PM_{2.5}$ formation within urban areas.

Apart from adopting WRF-CMAQ for meteorological and air quality predictions, modelled meteorological attributes have also been used to illustrate the transport of pollutants within the lower troposphere during COVID-19. In particular, selected meteorological parameters before and during the implementation of social distancing in Seoul were acquired from the ERA5 datasets. The datasets were based on the European Centre for Medium-Range Weather Forecasts (ECMWF) [73], which include zonal and meridional wind components, and geopotential heights at 900 hPa level. They were combined with aerosol-optical depth (AOD) from MERRA-2 (a satellite-based dataset), and used for analyzing the flow of $PM_{2.5}$, NO_2 and CO within the lowest part of the Earth surface [74]. The results in Han et al (2020) [74] are comparable to studies conducted in other megacities, where there was a reduction of pollutants like $PM_{2.5}$, NO_2, CO, and SO_2 during the social distancing; and that was accompanied by the increase in O_3 concentrations (by 47.0%) due to reduced NO titration. Although social distancing is a less stringent strategy when compared to the lockdown of a city, the 30-day average $PM_{2.5}$ concentration in all stations of Seoul has reduced by around 10.4% during 2020 (as compared to an increase of 23.7% from the same time period of 2015-2019), and the number of pollution episode days also decreased during the period of social distancing. Further, from MERRA-2 and modelling outputs, AOD over Seoul before social distancing was 0.368, and was slightly higher than other cities of South Korea. This could be attributed to the aerosol transport from external emission sources [74]. From pre-social distancing to the implementation of social distancing restrictions, AOD over Seoul has reduced by 16.5% mainly caused by the reduction of local emissions, reduced long-range and transboundary transport processes of pollutants, and modifications of synoptic circulation patterns. The latter two reasons have been validated by taking into account transboundary pollution sources from China, Japan and other neighboring countries [75, 76]. Thus, social distancing has led to reduced transport of pollutants and harmful chemical compounds from neighboring countries to South Korea, which partially explains the reduction of $PM_{2.5}$ and other pollutant concentrations over Seoul.

2.3.2 Satellite Remote Sensing

Satellite informatics are usually applied onto a larger spatial domain, or being adopted for country- or city-wise comparisons of land use and meteorological changes, as well as air quality conditions, due to its relatively coarser spatial resolution, as compared to point-source measurements and modelling approaches. Despite its deficiencies, the temporal changes and spatial distribution of pollutants during a prescribed period can be well-captured and analyzed by combining with other numerical techniques, like projection and regridding. Further, long range and short range transports and dynamic evolution of pollution sources can also be monitored, and remote sensing is particularly useful for countries/cities that have insufficient or no in-situ measurements. Generally speaking, sensors onboard satellites can be divided into two major types of orbits, namely “polar orbiting” and “geostationary”. Some well-known satellite instruments for monitoring environmental pollution in East Asian domain include TROPOspheric Monitoring Instrument (TROPOMI), Ozone Monitoring Instrument (OMI), Advanced Himawari Imager (AHI), and Geostationary Environment Monitoring Spectrometer (GEMS).

In particular, Ghahremanloo et al. (2021) have gathered a total of 106 swath images from TROPOMI onboard the Sentinel-5P satellite to detect changes of tropospheric NO_2 and formaldehyde column densities, and total SO_2 and CO column densities during February 2020, when compared to February 2019 [77]. The collected datasets are resampled at a resolution of 7 km × 3.5 km for NO_2, formaldehyde, and SO_2, while 7 km × 7 km for CO. Then, 56 daily AOD images of 5 km × 5 km were also acquired from AHI onboard the geostationary satellite (i.e., Himawari-8) to trace for any changes of AOD in four major areas, namely Beijing-Tianjin-Hebei (BTH) region, Wuhan, Seoul metropolitan area, and Tokyo metropolitan area. The relationship between changes of respective pollution levels with meteorological factors attained from the Global Land Data Assimilation System (GLDAS) and MERRA-2 was also investigated. In terms of AOD, the decrease was attained at cities that are highly impacted by the COVID-19 pandemic, with a magnitude of 30.9% in BTH region in terms of monthly average AOD, as compared to the slight increase ocurred in Seoul (12.46%) and Tokyo (1.38%) from February 2019 to February 2020. Nevertheless, more homogeneous AOD levels could be found in BTH region due to the combination of temperature effects and lockdown policies. For Seoul, the high AOD levels in upwind regions of Seoul were mainly caused by the transport of dust from desert regions like Gobi Desert, as well as the north-westerly wind flow directions. For formaldehyde pollution, the local governmental responses to the pandemic could influence its tropospheric column density and concentrations, where a decrease of 13%, 22% and 8% could be detected at BTH, Seoul and Tokyo respectively. The correlation with meteorological parameters is not clear, mainly because of the counter-balanced effects of temperature and anthropogenic pollution sources within these cities. For SO_2, different temporal trends could be attained, where an increase in SO_2 concentration could be detected in both Seoul and Tokyo, while the SO_2 column density in BTH region almost remained unchanged during the earlier stage of COVID-19. Despite the reduction of SO_2 emissions from local traffic and industrial sources, there are too many coal-fired power plants and industries within the BTH region. Hence, the overall SO_2 level remained almost unchanged during early 2020. As for Seoul and Tokyo, due to the transport of SO_2 from upwind regions, which are usually more polluted, and the enhancement of wind flow velocity at high altitudes, higher SO_2 concentrations could be detected. A reduction of CO concentrations was found at all investigated areas, with 8% in BTH region, 6% in Seoul, 1% in Tokyo, and 4% in Wuhan. The magnitude of decrease in terms of CO concentrations was much lower than other pollutants, especially for NO_2 and $PM_{2.5}$, which could be mainly attributed to the time delay effects. To be specific, it will take around 2 months for a decrease of CO emissions in nature or anthropogenic source to take into effect, i.e., the actual decrease of CO concentrations in our surrounding atmosphere.

Finally, based on satellite images obtained in Ghahremanloo et al (2021) [77], obvious decrease of tropospheric NO_2 column density was attained during early 2020, and the stringent lockdown policies have contributed to a decline of ground NO_2 concentrations by nearly 83% at the BTH region, and about 33% and 19% in Seoul and Tokyo respectively. However, for Seoul, since the outbreak of COVID-19 occurred not until late February 2020, the amount of NO_2 decrease is relatively less when compared with most cities of China. The same reason applies to Tokyo, where voluntary stay-at-home strategies were implemented in many parts of the city. The decrease of NO_2 concentrations can also be attributed to meteorological factors as well, where the rising temperature actually motivates and encourages the upward air motion, which directly facilitates diffusion within the atmosphere [78], as a result leading to lower NO_2 concentrations.

Apart from the capabilities of governing changes of pollution levels within East Asian cities, TROPOMI datasets can also assess the sensitivity of ozone level to NO_x and VOCs, as validated in Duncan et al (2010) [79]. In general, an increase in VOC or NO_x will lead to increase in ozone concentrations. By analyzing the pixels with tropospheric NO_2 column density exceeding 1×10^{15} molecules/cm^2, the formaldehyde to nitrogen dioxide ratio (FNR) has hugely increased by 75% in the BTH region, as compared to 16% and 20% in Seoul and Tokyo respectively. This indicates that changes of NO_2 level constituted the major reason for changes of chemical regimes in China during the COVID-19 pandemic. As a result, ground ozone concentrations in February 2020 have also increased by around 20% in BTH and East China when compared to 2019, due to the reduction of NO_x concentrations and saturation in atmosphere.

2.3.3 Ground-based Monitoring in Hong Kong

Despite the lack of satellite-based retrieval studies that focused only on Hong Kong, its systematic and comprehensive ground monitoring network comprises of three roadside and 13 ambient air quality monitoring stations. These stations are situated in different districts of Hong Kong, with roadside stations placed in commercial districts like Causeway Bay, Central and Mong Kok, and ambient stations positioned at a certain height above ground (usually at rooftops) of different districts, to capture the air quality conditions at pedestrian and building height levels [80]. Huang et al. (2020) has conducted a mini-study to compare pollutant concentrations during January to April 2020 with that in previous several years, and evaluate the impacts of COVID-19 lockdown towards roadside and ambient air quality conditions, in particular, the reduction of pollutant concentrations due to certain lockdown policies, and potential seasonal and monthly variations induced [58]. Within the study, January 2020 and February-April 2020 were defined as the "pre-COVID-19 period" and the "COVID-19 period" respectively so that random fluctuations of air quality can be removed upon comparison and adjustments. Based on the datasets obtained from ground monitoring instruments, $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO concentrations showed reductions in both pre-COVID-19 and COVID-19 periods, when compared to historical data from 2017 to 2019. For roadside monitoring stations, reductions during January 2020 for these pollutants were 19-33%, 14-31%, 13-18%, 17-32% and around -2-7% (in that order), and were 1-44%, -8-37%, -10-28%, -42-52% and -40-21% (in that order) for the COVID-19 period (i.e., from February-April 2020). Interestingly, emissions obtained in April 2020 were higher than the average emission figures during 2017-2019, despite many policies to forbid local emission activities within that period. One of the potential reasons could be the unfavorable meteorological conditions that lower the pace of gaseous dispersion, thus leading to higher NO_2

concentrations found at street level. Further, O_3 concentrations during both periods of 2020 were 24-39% and 1-72% higher than the previous three years.

For ambient air quality stations, the reduction of concentrations of different pollutants were of a larger range. In particular, for the “pre-COVID-19 period”, $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO showed reduction of 25-36%, 23-35%, 16-32%, 30-49%, and -7-17% when compared to historical data. During the COVID-19 pandemic, these reductions have of an even larger range, ranging from negative 21% to positive 44% for some of these five pollutants. In general, $PM_{2.5}$ and PM_{10} concentrations were only slightly lower; NO_2 and CO became much lower, while SO_2 concentration was quite similar as previous years.

The study based on ground monitoring datasets also effectively captured the huge seasonal and monthly variations of average pollutant concentrations during both “pre-COVID-19” and “COVID-19” periods. Even when strict social distancing rules have been implemented in Hong Kong, the total number of passengers and vehicles only dropped by 15.7% and 7.7% respectively. Hence, the effects of pollutant reduction during the COVID-19 pandemic might not be that obvious. Huang et al (2020) concluded that lockdown and social distancing policies during the COVID-19 might not necessarily lower pollutant concentrations, and a series of other parameters have to be incorporated into the spatial analysis, including meteorological quantities, seasonal trends, and inventories of anthropogenic emissions especially in industrial districts of Hong Kong [58].

Due to the complexity of capturing air quality trends during the COVID-19 pandemic and other major events of East Asian cities in an accurate manner, as well as the potential impacts based on meteorological changes, dynamic social mobility patterns, improvements of healthcare measures, the implementation of environmental and healthcare policies, one should gather all available datasets from different sources, and build up a graphical dashboard or user-interface, so that all these attributes and instantaneous changes could be better captured and delivered to the public, in a prompt manner.

3. Assessments of Official Healthcare and Environmental Datasets during the Pandemic

3.1. Importance of Data Openness Initiatives

The concepts of “open data” and “open access to scientific data” were first brought up during the International Geophysical Year (i.e., 1957-1958), when the World Data Center system was set-up [81]. The foundation being laid down has enhanced the effective communication between authority and citizens, encouraged the participation of public in improving existing service and national systems, transmitted instantaneous messages and announcements to targeted groups of the society [82], with the aim of promoting innovation and steering cities forward. When we speak about “open data”, both data availability and data accessibility are equally important because all official and useful datasets are supposedly to be available to the general public, with a possibility of redistribution or reuse for any kinds of purposes without much legal restrictions nor concerns [83]. “Data availability” generally refers to the existence of some datasets on a website or server, which can easily be accessed by general citizens. “Data accessibility” has further implications, for example, whether users or visitors can download and/or retrieve these datasets for further usage or personal scientific studies [84]. Further, visualization scores and effects also determine whether the website or database is eye-catching, which could effectively attract public attention to the information or news released on the site.

Despite concerted efforts of many city governments in encouraging entrepreneurs, industries, and different organizations to release digital data and information to the public, which could ensure a higher degree of transparency [84] and more cross-discipline collaboration [85], there are some potential practical challenges. The lacking of open data initiatives could hinder the progress of promoting “open data”, and the gathering of information from different fields and organizations at one go. In particular, some data sources are commercially valuable, and can directly lead to huge profits and benefits within the field [84]; while other data sources can also impose huge political burdens to the government’s management system, like the cancellation or postponement of certain policies and economic activities [86, 87]. Hence, the company or organization may not be willing to release these sensitive data in public domains or data portals. Also, the combination and integration of environmental, health and pandemic datasets are extremely complicated, and have to undergo many administrative processes, especially those at city or national level. Several problems could arise. First, the lack of consistent principles and rules in terms of data collection could be a potential issue. Second, after respective datasets were collected, modelled or estimated, relevant datasets must have gone through quality assurance procedures, and be formally approved by relevant authority and experts in order to avoid unnecessary fear and anxiety of local citizens; yet, such expertise to analyze all these relevant datasets before release may be available from time to time [88]. Third, some governments may need to take care of potential ethical issues based on datasets in environmental and health perspectives [89]. Some collected datasets from patients are highly sensitive, which should always be kept confidential. All these mitigated the progress of data openness initiatives with regard to the environment and public health aspects.

Nevertheless, many countries have recently joint hands in combining environmental and health datasets, and released useful information to citizens for personal exposure assessment, health risk prediction, and planning individual's travel routes. In particular, Sweden was recently developing potential open data initiatives so that public agencies and scientists can easily gain access to latest environmental attributes, which are usually updated on an hourly basis [90]. Moreover, after identifying the datasets that are of the highest demand from the general public, the European Commission has determined the latest five thematic data domains for future usage and assessment purposes, including (1) geospatial data; (2) earth observation and environment data; (3) traffic data; (4) statistics; and (5) datasets from companies [91]. Till now, the European Data Portal could offer 90,883 sets of "open data" that can be connected with environmental informatics [91]. In terms of changing land use patterns in less developed or developing cities, the United States has allowed public access and downloading of satellite-based datasets acquired from Landsat, as well as the provision of time series obtained from different machine learning and satellite-based algorithms [92] so that the rural-to-urban spatial transitions and ground features can be better understood and analyzed. This is particularly important for cities that have no proper monitoring and measurement frameworks, or developing cities that plan to expand their develpment areas soon and need environmental impact assessments. Moreover, in terms of improving air quality conditions, the European Data Portal has also collected relevant information in the entire Poland so that current fine-scale air quality conditions and smog events can be effectively traced, analyzed and improved in the future [84].

Different cities have developed different "open data portals" for their own citizens and registered users. However, an integrated scoring index has to be developed to assess the current open data practice of the five East Asian cities. The index should ideally account for concepts as aforementioned, including "data availability", "data accessibility" and "visualization". And the assessment will only be conducted based on the official data source and websites of air quality conditions and pandemic. Suitable indicators must be established for each of the three concepts so that a wider point of view and coverage can be acquired when spatial analysis is necessary for making national-wide decisions. In terms of assessment, the Open Data Inventory (ODIN) quantifies whether datasets released by individual countries via their official websites can reach international openness standards [93]. Two major groups of criteria have been set up for ODIN -- one for coverage, and another for openness. According to the information from ODIN [93], coverage scores concern the availability of key environmental indicators, and whether geographic subdivisions exist from time to time; while openness scores mainly focus on the potential for downloading, whether the downloaded documents are easily interpreted, and whether user-selection interface, APIs and data license exist in corresponding official websites [93].

Following the proposed themes of ODIN, and with the aim of promoting open data initiatives with respect to environmental and health perspectives, especially for combating large-scale pandemic and sudden climatic risks, as well as enhancing the interactions between official parties (e.g., national statistical offices) and data readers/users [93], the next section focuses on the development of frameworks that assesses and evaluates the extent of delivering related information and openness of data within the five East Asian cities, namely Beijing, Hong Kong, Seoul, Taipei and Tokyo. Indices within each tier of this framework symbolize the importance of different perspectives, including the provision of datasets to the public, the delivery and clarity of relevant information, the reliability of sources, data transparency and accessibility, as well as the centralization of websites within city or provincial levels.

3.2. Existing Practices in Delivering Pandemic-related Data to the Public

As aforementioned, the release of information related to air quality conditions and epidemic in an instantaneous manner is very important for local citizens, especially in the digital age nowadays where people normally receive the latest news and precautions via an app or their personal smartwatches. The engagement of the public and the provision of a two-way feedback system within these websites and communication channels are considered as bonus because they can encourage a conductive environment for smart city development in the long run, and the participation of the public for data centralization and integration. As a result, the gathering of different attributes can enable in-depth spatial and temporal analysis when the next epidemic wave and other sudden weather/pollution events happen.

Following the approach of the three-tier scoring process proposed by Mak and Lam (2021), a list of criteria of data availability and data accessibility of air quality attributes and COVID-19 related platforms are laid down. Then, the overall scores of each of the five East Asian cities are evaluated based on an additive model, i.e., the linear combination of all scores attained in each criterion according to prescribed weighting imposed [28]. Tables 3 and 4 show the criteria and weighted score of each criterion within the scoring frameworks of air quality and COVID-19 informatics respectively. The assessments have only considered officially recognized websites released by local governments, i.e., they will not include the contents of any unofficial forums nor self-managed websites and platforms. This is to ensure the fairness and objectiveness of our assessments. In general, Tier 1 focuses on the provision of real-time attributes and openness in terms of data acquisition and sharing. Tier 2 focuses on the existence of historical datasets, together with higher levels of requirements imposed on data provision, for example, the display manner, file format and user-friendliness. Tier 3 mainly concerns about the extension of data provision and its connection with sources at a country level. These three tiers together provide a comprehensive assessment of the present way of information delivery and centralization.

Table 3. Criteria and weighted scores (in bracket) of the 3-tier scoring framework of official air quality websites in the five East Asian cities.

Tier 1 (T_{1A})	**Tier 2** (T_{2A})	**Tier 3** (T_{3A})
(1) Real-time Air Quality Index / Pollutant Concentrations [2] (2) Graphical representation of Air Quality attributes (e.g., time series, spatial distribution) [1] (3) Provision of mobile apps / opinion collection boxes / contact information [1] (4) Properly understood languages [2] (5) Existence of Data Portal for storing Air Quality attributes [2] (6) Existence of Web APIs / Web Accessibility Initiatives [2] (7) Precautionary Messages or Public Education [1] **Total: 11**	(1) Historical Air Quality Index / Pollutant Concentrations [Max. 3] (2) Forecast Air Quality Index / Pollutant Concentrations [Max. 2] (3) Existence of Annual Report (up to 3 or more years) [Max. 2] (4) Provision of Averaged Options (e.g., 24-hr, daily, MDA8) [1] (5) User-friendliness of the websites, quantified by the time for gaining relevant information [Max. 2] (6) Record / Crosstab display of Datasets [1] (7) File Format of the display of Historical Information [1] **Total: 12**	(1) Web-based download and sharing interface [Max. 2] (2) Existence of weather or meteorological attributes within the same site / linked with meteorological organizations [Max. 2] (3) The use of low-cost sensors and city-wise monitoring network [Max. 1] (4) Website Centralization (e.g., Central Panel, Links between websites, Integration of data) [2] (5) Potential connection with the country website(s) [1] **Total: 8**

Table 4. Criteria and weighted scores (in bracket) of the three-tier scoring framework of official COVID-19 websites and dashboard in the five East Asian cities.

Tier 1 (T_{1C})	**Tier 2** (T_{2C})	**Tier 3** (T_{3C})
(1) Instantaneous COVID-19 cases & categorization (Confirmed / Suspected etc. & Area) [Max. 3] (2) Graphical dashboard of COVID-19 cases (e.g., time series, spatial distribution) [2] (3) Provision of mobile apps / opinion collection boxes / contact information [1] (4) Properly understood languages [2] (5) Existence of Data Portal for storing COVID-19 information [2] (6) Existence of Web APIs / Web Accessibility Initiatives [2]	(1) Past COVID-19 cases & categorization [Max. 3] (2) Existence of weekly Reports [2] (3) Provision of toolbars / animation effects for adjusting temporal trends / selection of particular information [1] (4) User-friendliness of the websites, quantified by the time for gaining relevant information [Max. 2] (5) File Format of display of Historical Information [1] **Total: 9**	(1) Web-based download and sharing interface [Max. 2] (2) Existence of full descriptions of COVID-19 cases [Max. 2] (3) Linkage and connection with other medical websites [Max. 1] (4) Website Centralization (e.g., Central Panel, Links between websites, Integration of data) [2] (5) Potential connection with the country-wise COVID-19 website(s) [1] (6) Connection with information of vaccine and precautionary measures [1]

(7) Precautionary / Warning messages or Public Health Education [1] **Total: 13**		(7) Arrangements of quarantine after arrival [1] **Total: 10**

Table 5 below shows the officially recognized websites of both environmental / air quality and COVID-19 informatics used for the scoring analyses within our established frameworks.

Table 5. Officially recognized Air Quality / Environmental Informatics and COVID-19 websites, in both city-wise and national manners.

City	Air Quality websites	COVID-19 websites
Beijing	Local: http://www.bjmemc.com.cn/ National: http://www.cnemc.cn/en/	(1) http://wjw.beijing.gov.cn/wjwh/ztzl/xxgzbd/ (Beijing Municipal Health Commission) (2) https://news.qq.com/zt2020/page/feiyan.htm#/area?pool=bj (Tencent COVID-19 dashboard) (3) http://2019ncov.chinacdc.cn/2019-nCoV/ (National dashboard)
Hong Kong	https://www.aqhi.gov.hk/tc.html	(1) https://www.coronavirus.gov.hk/chi/index.html (2) https://chp-dashboard.geodata.gov.hk/covid-19/en.html (3) https://data.gov.hk/en-datasets/search/COVID-19 (COVID-19 data portal)
Seoul (South Korea as a whole)	(1) https://www.airkorea.or.kr/eng (2) https://cleanair.seoul.go.kr/	(1) https://kosis.kr/covid_eng/covid_index.do (2) http://ncov.mohw.go.kr/en/ (3) https://www.data.go.kr/en/index.do (for downloading local datasets of COVID-19)
Taipei	(1) https://airtw.epa.gov.tw/ENG/default.aspx (2) https://airbox.edimaxcloud.com/ (Community-based website)	(1) https://www.cdc.gov.tw/En (2) https://english.gov.taipei/covid19/ (3) https://data.cdc.gov.tw/en (Data Portal of diseases)
Tokyo	(1) https://www.taiki.kankyo.metro.tokyo.lg.jp/taikikankyo/realtime/index.html (2) https://venus.nies.go.jp/	(1) https://stopcovid19.metro.tokyo.lg.jp/en (2) https://www.japantimes.co.jp/liveblogs/news/coronavirus-outbreak-updates/

After checking all websites of Table 5 to see whether the criteria of Tables 3 and 4 are satisfied, we convert available raw information and observations into scores (with full scores as indicated in the two tables). The full scores of Tiers 1, 2 and 3 for the assessments of Air Quality websites are 11, 12 and 8; while the corresponding full scores for assessing websites that provide COVID-19 informatics are 13, 9 and 10 respectively. Following the approach and arguments proposed in Mak and Lam (2021), a coefficient (α) that can reflect the importance of each tier is imposed, and these coefficients add up to 100 [28]. For the assessment of data openness of air quality attributes, the following formula is adopted:

$$\text{Air Quality score (out of 100)} = \frac{T_{1A}}{11} \times 60 + \frac{T_{2A}}{12} \times 25 + \frac{T_{3A}}{8} \times 15$$

where T_{1A}, T_{2A} and T_{3A} represent the scores achieved in respective tiers as shown in Table 3, with $\alpha_{1A} = 60, \alpha_{2A} = 25$ and $\alpha_{3A} = 15$, similar as the proposed coefficients in [28].

As for the assessments of data provision and centralization within city-wise dashboard and websites of the COVID-19 pandemic, the following formula is used:

$$\text{COVID-19 score (out of 100)} = \frac{T_{1C}}{13} \times 50 + \frac{T_{2C}}{9} \times 20 + \frac{T_{3C}}{10} \times 30$$

where T_{1C}, T_{2C} and T_{3C} represent the scores achieved in respective tiers as shown in Table 4, with $\alpha_{1C} = 50, \alpha_{2C} = 20$ and $\alpha_{3C} = 30$.

For both assessments, the highest weighting has been imposed to Tier 1 because real-time information delivery, effective conveying of message to general public, and the smart utilization of these available information are particularly important in terms of data openness. The coefficient of Tier 3 in COVID-19 assessment is higher than that of Tier 2. This is because the connections between city-wise COVID-19 situation with country-wise pandemic, the centralization of all related information in one or two websites, and the delivery of important messages to different groups of people like local citizens, residents, visitors and even healthcare professionals, are more practical and vital, when compared to the provision of historical information, allowance of downloading related datasets for statistical analyses, as listed in Tier 2 of Table 4. The scores of each East Asian city were calculated according to the two aforementioned formula, and the summary of scores in each tier, total scores, and rankings based on the criteria of Tables 3 and 4 is shown in Table 6 below.

Table 6. Summaries of scores assigned to different tiers of the data openness assessment of air quality attributes and COVID-19 information, based on the criteria listed in Tables 3 and 4.

City	Tier 1 (AQ)	Tier 2 (AQ)	Tier 3 (AQ)	Total (AQ)	Tier 1 (COVID)	Tier 2 (COVID)	Tier 3 (COVID)	Total (COVID)
	_11_	_12_	_8_	_100_	_13_	_9_	_10_	_100_
Beijing	5	8.75	5	**54.88**	7.5	5	6.5	**59.46**
Hong Kong	10	9.75	5.1	**84.42**	11	8	8.5	**85.59**
Seoul	11	10.5	7.3	**95.56**	10.5	5.5	6.5	**72.11**
Taipei	10	12	7	**92.67**	8	2.5	7	**57.32**
Tokyo	3	8.25	4.9	**42.74**	12.5	8	8	**89.85**

Figures 9 and 10 show the normalized scores of each tier, as well as the weighted total Air Quality and COVID-19 scores of each city (i.e., all scores shown in bars and dots are out of 100). In terms of air quality data provision and openness, Seoul and Taipei are the high achievers, followed by Hong Kong. These three cities led the other two cities, Beijing and Tokyo, by a huge gap in terms of the total score. Seoul obtains full score in Tier 1, while the same goes for Taipei in Tier 2 assessment. Seoul gains a slightly higher score because it has provided a comprehensive data portal for storing air quality attributes, and consists of API and smart accessibility in its official website. Generally, the data portal of Taipei is not as comprehensive and user-friendly. Nevertheless, Taipei has recently updated its official air quality website to include more easily interpreted signals, information and graphical representations in its dashboard or interface. Thus, the provision of various data formats for public access and downloading, and the nice artistic utilization of colors, have enhanced the user-friendliness and attractiveness of Taipei's websites. Overall, all five East Asian cities have done a great job in terms of providing real-time and historical air quality information to the public, as well as the forecasting of future Air Quality Index (AQI) or pollutant concentrations. Except Beijing, all cities have provided English-version annual reports. Air quality information in either .csv or .pdf files was uploaded but only Taipei has provided different averaged options (e.g., 24-h running average, daily average and daily maximum 8-h average (MDA8)) for various groups of targeted readers, from layman, general citizens to professional experts.

As for Tier 3 assessment, Seoul and Taipei, with 91.25% and 87.5% of scores, have obtained much better performance when compared to the other three cities. Only these two cities allow web-based downloading and sharing of air quality information, and provide associated meteorological and weather attributes. Thus, the connections and correlations between different meteorological quantities and changes of air pollution can be better reviewed on the same site, thus fulfilling one of the major principles of smart city development, i.e., data integration and utilization. Hong Kong, Beijing and Tokyo release these meteorological attributes in a separated platform, and there was no coordination between different governmental departments for data sharing or integration. Such disconnected and segregated operations have hugely hindered the opportunities for general citizens to understand how climatic changes affect pollutant concentrations, and associated devastating health impacts. As for languages, the majority of these cities have provided English edition to all readers, except Beijing and Tokyo. For Beijing, some links of the websites, especially those that display sensitive air quality information in Table 5, only have the Chinese version. As for Tokyo, most of the associated links only consist of Japanese edition, and require the efforts of Google Translator to convert important information and notice into corresponding English version. All these undesirable practices could discourage the collaboration of international efforts to combat serious air pollution and haze events, which actually took place in China or Japan in recent years.

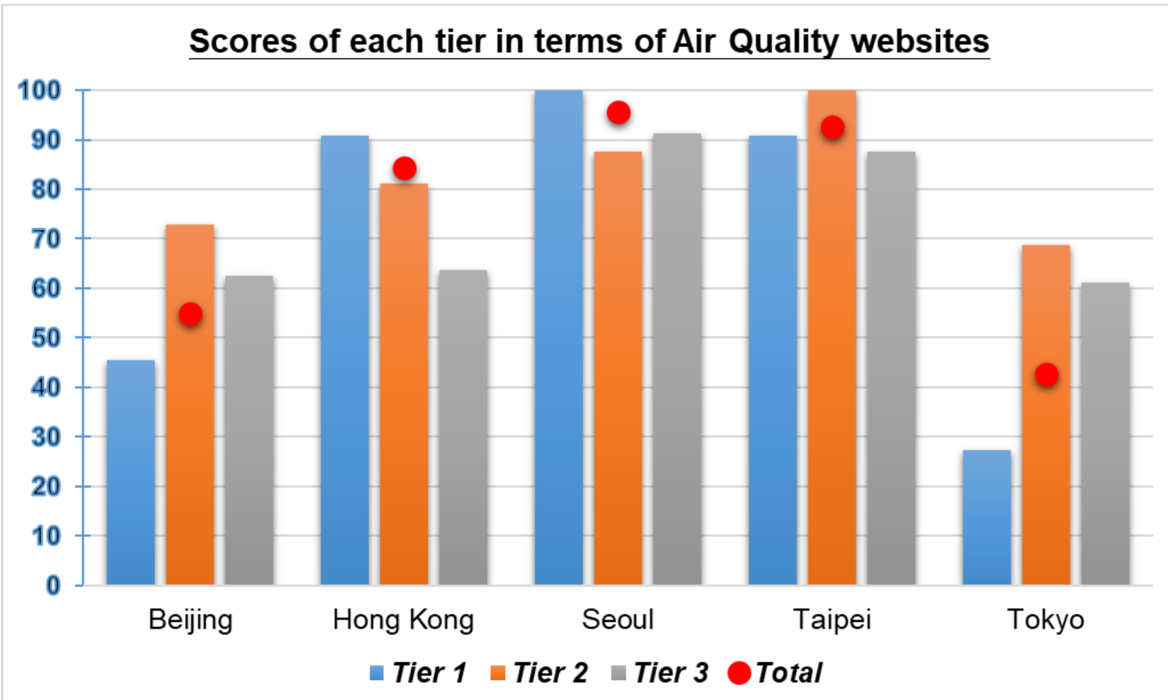


Figure 9. Scores of the five East Asian cities in terms of data openness of air quality websites, including Tiers 1, 2 and 3 scores (indicated by blue, orange and grey bars), and total score (indicated by red dots).

As for the provision and centralization of COVID-19 related datasets and the display of dashboard, Seoul and Taipei have performed steadily well. However, there was a huge contrast for Tokyo as compared with its air quality websites. The COVID-19 websites of Tokyo, particularly for its first link in Table 5, are extremely informative and attractive. The display and integration of different information, for example, the summary table of COVID-19 infected cases, recovered cases, and hospitalization records of patients within different age groups, are clearly displayed and shared with all Japanese citizens. Further, details of cases being tested positive were analyzed in an in-depth manner, and corresponding links for open data and associated records for downloading are provided as well. Both graphical and tabular formats of these pandemic attributes are well-presented to the general readers, which satisfy needs of different age groups and professions. The websites of Tokyo have also tried to incorporate citizen-based insights via the “Leave website feedback" link, so that the community can readily engage in health and pandemic issues, and suggest potential ways to combat health challenges. Further, the comprehensive nature of Tokyo's websites is also clearly reviewed on its left panel, including the linkage with websites on vaccination, self-isolation, prevention of infection, and instantaneous population changes within Tokyo. An app called the "COCOA - COVID-19 Contact App" has been established by the Ministry of Health, Labour and Welfare of Japan for such purposes too [94]. Thus, it has obtained the highest score in both Tiers 1 and 2 based on our assessment framework. As for Tier 3, it ranks the 2nd, right after Hong Kong, mainly because of the lack of direct connections with pandemic websites of other Japanese cities and counties, as well as the absence of information related to the quarantine of visitors when they arrive at Tokyo.

Similar as Tokyo, Hong Kong has also done a good job in taking up the obligation and allowing its citizens to acquire a better understanding of latest pandemic updates, including the number of newly infected cases and their residential or activity regions, graphical display that shows the spatial distribution of infected inhabitants, and details of each case (i.e., whether it is a local or an imported case, the current situation of the person involved, and the details of all infected cases). Also, Hong Kong does a much better job than most of the other East Asian cities, in terms of the centralization and integration of different COVID-19 related information. To illustrate, the compulsory testing/testing services, community vaccination services, specimen collection and distribution venues, available community testing centers, and status of queuing for vaccination in different districts are available online. Citizens can simply reach the central website and browse everything at one go, from reserving for vaccination to understanding the latest updates of the pandemic. The health advice like wearing masks in public spaces, early testing and detection, and latest prohibited activities and social gathering within Hong Kong are also provided in the websites shown in Table 5. Citizens can also learn more about the principles of SARS-Co-V-2 transmission generally. This is in line with the recent focus of the HKSAR government on "STEM education". General learners can acquire some of the factual information, and convert them into scientific innovation. Overall, the websites designed by the Hong Kong SAR Government are suitable for people of all age groups, and all necessary information are readily available. The city has the best performance of Tier 3, and an overall outstanding performance in total score.

Next, although Taipei has been marvelous in terms of air quality data openness, it does not perform well in terms of COVID-19 data provision. As shown in Figure 10, its major weaknesses can be reviewed from Tiers 1 and 2 of our assessment framework. Tier 1 covers the data availability, data accessibility and necessary tools for sharing all latest COVID-19 information, which are essential for a city, particularly for steering city development in combating pandemic and preventing potential upcoming health risks and another wave of COVID-19. However, Taipei's websites simply provide all numerical figures (i.e., the new numbers of COVID-19 cases, recovered cases, whether they are imported or detected from local community) without displaying such useful information in graphical manners. Some of the links only consist of traditional Chinese version, which may be confusing for foreigners or visitors who are staying in Taiwan for business trips or collaborations. As for Tier 2 assessment, due to the lack of graphical display in Tier 1, it does not have of any toolbars for adjustments or observing relevant COVID-19 trends. New and historical cases are not categorized in terms of spatial areas, nor reasons and origins. This can pose challenges for citizens to gain a thorough understanding of the source of origin of the COVID-19 disease. Therefore, Taiwanese may not be able to avoid going to risky places, or plan their daily routes in a safe manner. Regarding the criteria of Tier 3, Taipei actually ranks the 3rd out of these five East Asian cities because it has directly or indirectly linked the website about COVID cases to websites of vaccination, quarantine, health advice, and other medical updates. The only thing that is missing is the lack of web-based downloading and sharing, which are available in Beijing, Hong Kong and Seoul.

Overall, the inclusion of API or accessibility development, integration of health informatics and its connection with external COVID-19 related websites, in both economic, political and social perspectives, have made our assessment framework justified and practical for conducting large-scale spatial assessment, for example, in other European and American countries, as well as in developing nations. With this framework, the strengths and weaknesses of COVID-related data and websites can be easily reviewed. In particular, the global communication and collaboration on data integration should be promoted and encouraged so that all pandemic-related information can be acquired at one site, similar to the Coronavirus Disease-19, Republic of Korea site [95] and the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University [96].

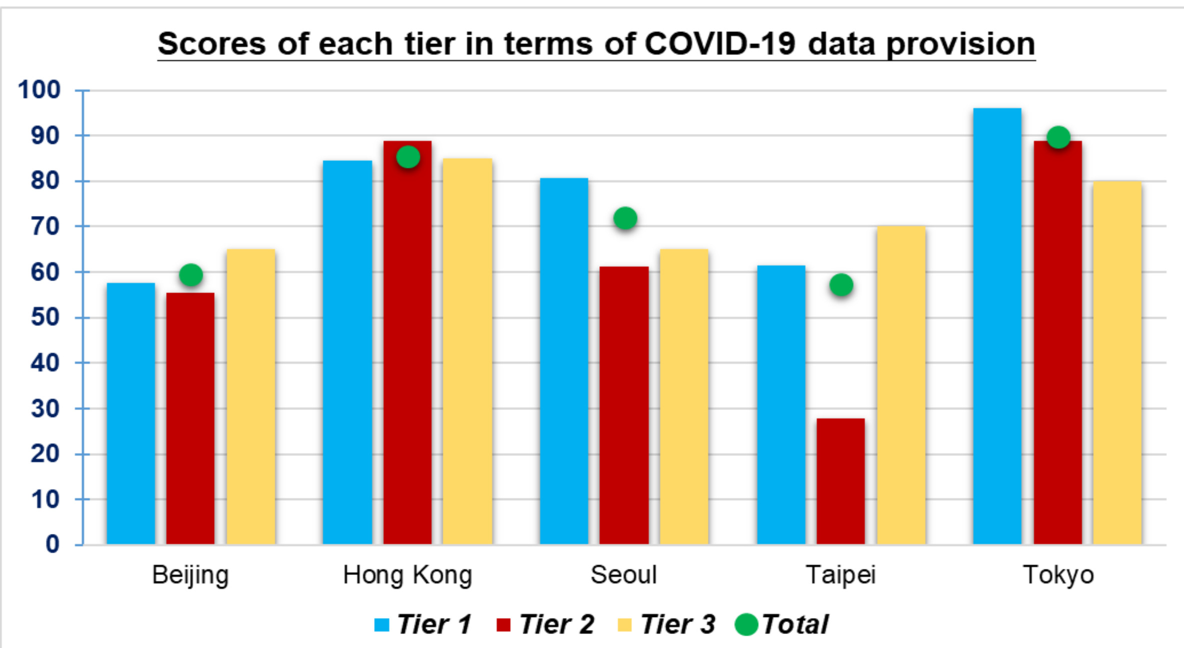


Figure 10. Scores of the five East Asian cities in terms of COVID-19 data provision and dashboard, including Tiers 1, 2 and 3 scores (indicated by light blue, red and pale yellow bars), and total score (indicated by green dots).

3.3. Reflections, Potential Deficiencies, and Needs for Combating the Pandemic and Sudden Environmental Changes

3.3.1 Centralized Planning of Big Data Information System and Public Engagement

Combating sudden environmental changes and pandemic rely much on combined efforts of different stakeholders of a community. First, the government should step forward to implement and facilitate the air quality and health programs in multi-scale levels, for example, among cities, districts and counties within the same country. The program must be first centralized in national government, then gradually zoomed down to city or lower spatial level. All relevant local organizations must communicate and coordinate on several practical issues: (1) exchange of environmental, health and pandemic information; (2) effective data sharing of air quality status and pandemic updates; (3) monitor the meteorological and climatic changes not only locally, but within neighboring spatial areas as well. After the collection and gathering of relevant datasets, a user-friendly big data information system must be set up to incorporate the latest technologies for displaying real-time spatial distributions of pollutant concentrations, air quality indices, weather conditions, as well as the number of infected cases for major diseases. An alert system must also be established within the desired information system, and be connected with mobile devices via an app or other kinds of available e-platforms, so that instantaneous updates can be delivered to the public, especially to groups that are more susceptible to changing environmental conditions, and those with long-term diseases like asthma and pulmonary diseases. Currently, these five East Asian cities have performed well in providing basic air quality and pandemic information to the public via its local or national websites. Yet, the engagement and involvement of general citizens could not be guaranteed because local governments have often ignored the importance of visibility and accessibility in terms of website designs and information delivery.

3.3.2 Public Education

Further, public education is another important issue that we should put heavy emphasis on. As illustrated in our assessment framework, public education messages and webpages are only available for Hong Kong, Seoul and Taipei within respective air quality websites, while all cities except Tokyo have attached education information and medical advice on their COVID-19 websites. It is observed that some important messages of Beijing's websites are only provided in simplified Chinese, which could hinder the progress of technological innovations in the long run. More importantly, the existence of these official advices does not necessarily mean that citizens will refer to this website from time to time. Thus, the government should actively promote and highlight the importance of these websites and channels via social media, talks and seminars delivered to general citizens and students.

3.3.3 Website Centralization

Within Tier 3 assessment, website centralization is considered as one of the criteria in judging whether a city is having good performance in terms of data openness and accessibility of both air quality and COVID-19 websites. As highlighted in Mak and Lam (2021), the provision of a centralized and compatible platform for transmitting all related information is extremely important in terms of emergencies and pandemic [28]. Wang et al. (2016) have shown that the lack of coordination between websites and platforms could result in delays of necessary services, and even jeopardize the survival opportunities of certain groups of people in our society [97]. Thus, we need to consider several perspectives of website and data centralization, namely (1) whether readers and visitors will have to click many links to gain access to environmental, air quality and pandemic information, notably the latest numerical figures, time series, and population flow dynamics; (2) whether the information provided by the websites are interactive and eye-catching, and arranged in an orderly manner; (3) whether the website can be easily linked to other health departments, meteorological bureaus and external non-profit organizations. Citizens usually expect to obtain all latest information of our society at one go. In relation, the HKSAR government has established the GovHK website, which includes detailed information of all sectors, including health & medical services, transport & monitoring, education & training, government websites & officers [98]. This allows visitors to grasp all important messages within a very short period of time, which constitutes the way of success in terms of personal impression, data centralization and user-friendliness. In our framework, the user-friendliness of these official websites has been quantified by the time needed to gather relevant air quality and pandemic information.

3.3.4 Political Barriers and the Integration of Data

Many professionals and science lovers would like to download air quality and pandemic attributes for conducting large-scale environmental assessments, and to minimize their personal health risk and exposure to toxic chemicals or virus within our atmosphere. They will gather all these spatial plots and temporal trends, then share the analysis onto social media platforms so that the latest updates can be delivered to a wider audience, even residents of other neighboring countries. Due to political concerns, some cities may simply display the information in a graphical dashboard on their own websites, but neither allow the public to download the raw datasets nor to conduct further analyses. In particular, the air quality websites of Beijing, and the COVID-19 websites of Beijing, Hong Kong and Taipei only allow limited access to raw pollution and health-related datasets, as reviewed from Tier 2 of our assessment framework. In Hong Kong, the Environmental Protection Department (EPD) does not allow public downloading of historical air quality datasets that are of 24-h beforehand, therefore scientific teams and professionals will have to wait for a long period of time for gaining access to these useful datasets due to Quality Assurance and Control (QA & QC) processes conducted by the local government. In order to be in line with smart city development, it is of tremendous importance to fully explore the possibilities of immediate release and integration of all healthcare datasets and associated information acquired from official means, and set up a data portal to store all historical datasets from now on, for conducting ongoing analyses. The connection between such data portal, apps and graphical dashboard is necessary as well.

Regarding the integration of different socio-economic and medical datasets, we have illustrated and quantified the impacts of different meteorological quantities towards local air quality conditions, and the connections between COVID-19 pandemic and pollutant concentrations. Therefore, to obtain a full picture of our community on a timely basis and in a coherent manner, and to promote citizen science and sustainable development within individual cities, the current segregated operations and practice of reporting and releasing data through different channels must be improved. As an example, for Hong Kong, the Hong Kong Observatory (HKO) and EPD must set up a common data portal for sharing meteorological and air quality datasets, then these attributes should further be integrated with records of patients and diseases, which are managed by Hospital Authority (HA) and Department of Health. On top, human mobility, population changes, traffic routes and spatial maps, as well as potential social events in certain districts could also be integrated into the centralized and computerized system for conducting multi-dimensional analysis, for example, investigating the statistical correlations between each of these parameters. However, this grand vision can only be satisfied and completed if all departments and institutions are willing to share data and contribute to the setting-up and management of the data portal, as well as conducting necessary modelling and visualization tasks for public access. Joint efforts from the central government and different stakeholders of our society are essential for the integration of data and to overcome any potential political barriers ahead.

4. Recommendations and Concluding Remarks

4.1. Recommendations of Data Openness and Integration

Since the outbreak of COVID-19 in early 2020, the number of people infected and died has increased continuously. Different waves of COVID-19 were taking place in individual East Asian cities. Although all local governments have responded very quickly to the sudden and threatening pandemic, by isolating concerned patients, conducting gene sequencing, identifying potential reasons for the spreading of SARS-Co-V-2, investigating the trajectory and mobility patterns of patients, reporting latest pandemic information to public, connecting the pandemic with environmental factors like meteorology and local air quality conditions, and imposing strict prevention and precautionary measures like social distancing, lockdown, and restriction of gathering and social activities, there are still some deficiencies for accurate identification of sources and origins of the SARS-Co-V-2 virus, willingness of sharing pandemic and environmental quantities among districts, cities and even nations, as well as the lack of experience and comprehensive platforms for releasing health-related information and spatiotemporal trends of the pandemic. Thus, the transmission characteristics of SARS-Co-V-2 cannot be effectively monitored, and the knowledge of this disease and ways of protecting healthy neighborhood environment is still extremely limited.

As part of the global community, we should look forward to defeating the pandemic with joint efforts by identifying the causes, processes and devastating consequences of the formation of SARS-Co-V-2, and proposing ways to control the pandemic. More importantly, the use of the latest big data technologies and artificial intelligence approaches of monitoring instantaneous spatial and temporal variations of different health, environmental and humanistic attributes, and the proper sharing and utilization of all these datasets, are of paramount importance for future city development. These scientific innovations and results could possibly allow local governments to gain a better understanding of the epidemic situation, and to develop more appropriate policies and control measures for avoiding potential health risks and social challenges within our living environment [99].

Based on the proposals and recommendations in Zhou et al (2020), the most important component that each smart city should possess is a uniform and consistent multi-scale big data information system for gathering, updating and analyzing epidemic and environmental datasets, at country, provincial, city, neighborhood, and individual scales [100]. On top, the visualization and release of these information, tracking of daily activities of all confirmed cases, prediction of number of cases and severity of the pandemic in foreseeable future, and delivering public education or advising are equally important. There are several highlighted points, as summarized based on the contents and suggestions stated in Zhou et al (2020) [100]:

(1) Building up a virtual perception and graphical dashboard that collects spatial and temporal datasets of epidemic and neighboring environment from multi-source, then convert these instantaneous attributes into real-time systems;

(2) Displaying datasets of different spatial and temporal scales at one go, with different visualization tools, then connecting these attributes to a storage system or cluster for ongoing analyses;

(3) Allowing the conversion of different data formats, usually raster and vector, as well as the interchanging of data formats for various purposes, like statistical training, modelling and prediction; merging with other attributes; and automatic data aggregation and classification;

(4) Provision of daily animation maps for showing spatial and temporal characteristics and severity of the pandemic, and displaying different representations of various types of numerical quantities, for example, bar charts, shading and dot indicators;

(5) Adopting artificial intelligence knowledge and machine learning approaches for exposure analyses. First, the trajectory of all patients' activities could be marked on the graphical dashboard in a systematic and coherent manner. Also, the developed big data system should be capable of analyzing text and voice from patients and their family members, then converting the text information into figures and animations. The function of "automatic corrections" must be designed and incorporated into the system, for health exposure studies and quantifying potential risks within a concerned spatial domain;

(6) Testing more spatiotemporal diffusion models that can effectively govern and predict the inflow and outflow of virus and harmful chemicals within complex environmental conditions. Further, factors like social events, migration, population dynamics, traffic routes and arrangements, or even medical records at private and public hospitals and clinics should also be included in the modelling system so that the eventual trend of the spread of COVID-19 or other diseases can become more realistic. The correlations between the source of origin and population flow can also be obtained. In this way, the epidemic risk and potential prevention levels will be assessed in a timely basis.

The aforementioned datasets can include data released from World Health Organization (WHO) – both international and local, spatial location data, health platform data, trajectories of patients, transportation routes and dynamics (including flights), population distribution and other socio-economic status obtained from Census, land cover data, environmental datasets obtained from remote sensing and modelling approaches, or measurements from ground monitoring network etc.

4.2. Summary and Conclusion

In this study, we have first discussed the challenges, temporal trends and spatial dynamics of the COVID-19 pandemic (from January 2020 – now), and identified potential deficiencies of existing practices for detecting COVID-19 cases around the world. Then, we proceed to investigate different waves of COVID-19 in five East Asian cities, namely Beijing, Hong Kong, Seoul, Taipei, and Tokyo, together with some background information of these waves. Afterwards, the time series of average daily pollution figures (in terms of $PM_{2.5}$, NO_2 and O_3) from 2017 to now were shown, and the inter-comparison of these pollution values at different sites of Taiwan were also discussed. Numerical figures of these average pollutant concentrations during pandemic (i.e., 2020 and/or 2021) were compared with the corresponding figures before the pandemic (i.e., 2017-2019) to observe and look for possible statistical correlations between the severity of COVID-19, imposed policies and air qualities within each East Asian city. At the end of section 2, some recent studies of monitoring changes of pollutant concentrations and their rationale were provided and highlighted. These approaches have laid down the concept of "data openness" in releasing air quality and pandemic information at instant time.

In section 3, we first pointed out the importance of data openness initiatives in conducting environmental assessments, and analyses of unusual pandemic. Several concepts like "data availability", "data accessibility", and "data visibility" were introduced. These concepts underline the three-tier statistical framework and methods for assessing data openness of air quality and COVID-19 information delivery. To be included in the assessment, websites must be officially recognized, and should provide sufficient information and health advice to citizens, via both texts and graphical displays. In terms of statistical assessments, we have illustrated that Seoul, Taipei and Hong Kong have done well in releasing air quality datasets to public, while Tokyo, Hong Kong and Seoul performed exceptionally well in terms of COVID-19 information delivery, together with its connections with external websites and provision of health advice like self-isolation, quarantine after arrival, and latest imposed national or city-wise anti-pandemic policies. Although Taipei performed well in terms of air quality data openness, it ranks the last in COVID-19 information delivery because it does not have a graphical dashboard for sharing pandemic related information, and only provides numerical figures like the latest number of confirmed cases and number of hospitalized patients. Further, there is no categorization of COVID-19 cases in Taiwan, which hinders general citizens and medical experts for conducting further spatial and temporal analysis. Finally, some needs, deficiencies and possible ways of improvements for combating sudden environmental changes or pandemic were outlined.

In the current digital age, data analytic tools and platforms must be established to handle, analyze and display collected datasets, which should be obtained from multi-dimensional sources. Apart from providing spatial information and time series on a graphical dashboard, health exposure studies and risk analysis must also be conducted so that the actual impacts of the meteorology, air pollution, climate changes towards COVID-19 or other diseases can be better reviewed and observed. Further, the concept of "open data initiatives" should be promoted in all walks of life. The key purposes of "open data" in environmental and pandemic perspectives is to deliver instantaneous information to the general public, satisfy the needs of different groups of readers – from layman, general citizens to professional scientists, arouse public awareness to be alert and aware of potential health risk in daily lives, and the sharing of reliable information with others. As a result, the transparency and competitiveness of a city can be raised. This can eventually steer economic development and sustainability of the community in long run.

The strengthening of existing big data analytics and multi-dimensional management system, and the setting-up of a comprehensive data portal, can benefit not only an individual city, but also other neighboring cities and spatial regions because different socio-economic attributes can also be incorporated into the system. Some notable examples are the inflow and outflow population figures, transportation dynamics, flow of air pollutants and toxic chemicals in different directions. Besides, data integration and the connection with websites or platforms of external parties and organizations can also enhance knowledge acquisition, reinforce social coherence, and indirectly contribute to management parties for laying down informed decisions and policies, and help to combat all epidemic challenges ahead.

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