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Spatiotemporal impact of COVID-19 on Taiwan air quality in the absence of a lockdown: Influence of urban public transportation use and meteorological conditions

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\textbf{ABSTRACT}

The unprecedented outbreak of COVID-19 significantly improved the atmospheric environment for lockdown-imposed regions; however, scant evidence exists on its impacts on regions without lockdown. A novel research framework is proposed to evaluate the long-term monthly spatiotemporal impact of COVID-19 on Taiwan air quality through different statistical analyses, including geostatistical analysis, change detection analysis and identification of nonattainment pollutant occurrence between the average mean air pollutant concentrations from 2018–2019 and 2020, considering both meteorological and public transportation impacts. Contrary to lockdown-imposed regions, insignificant or worsened air quality conditions were observed at the beginning of COVID-19, but a delayed improvement occurred after April in Taiwan. The annual mean concentrations of PM\textsubscript{10}, PM\textsubscript{2.5}, SO\textsubscript{2}, NO\textsubscript{2}, CO and O\textsubscript{3} in 2020 were reduced by 24\%, 18\%, 15\%, 9.6\%, 7.4\% and 1.3\% (relative to 2018–2019), and the overall occurrence frequency of nonattainment air pollutants declined by over 30\%. Backward stepwise regression models for each air pollutant were successfully constructed utilizing 12 meteorological parameters ($R^2 > 0.8$ except for SO\textsubscript{2}) to simulate the meteorological normalized business-as-usual concentration. The hybrid single-particle Lagrangian integrated trajectory (HYSPLIT) model simulated the fate of air pollutants (e.g., local emissions or transboundary pollution) for anomalous months. The changes in different public transportation usage volumes (e.g., roadway, railway, air, and waterway) moderately reduced air pollution, particularly CO and NO\textsubscript{2}. Reduced public transportation use had a more significant impact than meteorology on air quality improvement in Taiwan, highlighting the importance of proper public transportation management for air pollution control and paving a new path for sustainable air quality management even in the absence of a lockdown.

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1. Introduction

Air pollution has been recognized as one of the deadliest environmental issues worldwide and has been reported to cause more than 7 million deaths annually (WHO, 2021) by inducing long-term health problems such as lung cancer, heart diseases, asthma, and other chronic respiratory diseases (Landrigan et al., 2018). Tremendous efforts to combat air pollution have been made across the globe, such as formulating numerous frameworks/laws/policies at both the national (Li et al., 2017; Amann et al., 2017) and international levels (Shapiro and Yarime, 2021). Nevertheless, large gaps have been observed in implementation, financing and enforcement capacity (United Nations Environment Programme, 2021), causing air pollution to remain a major health threat worldwide. However, the unprecedented outbreak of fatal 2019 coronavirus disease (COVID-19) has made a remarkable breakthrough in unresolved air pollution management.

Since the end of 2019, COVID-19 has tremendously disrupted the normal rhythm of livelihood and has led to dramatic loss of human life worldwide, with infections and deaths exceeding 531 million and 6.3 million, respectively, as of May 2022 (Worldometer, 2021). COVID-19 is caused by the novel severe acute respiratory syndrome coronavirus 2 that can be transmitted through the air, particularly in crowded areas or poorly ventilated indoor areas (Dinoi et al., 2022) and can survive on a variety of surfaces for hours (van Doremalen et al., 2020). Due to its high infectivity and transmissibility, it was classified as a global pandemic by the World Health Organization (WHO) on March 11, 2020 (WHO, 2020). Therefore, most governments across the globe have imposed restrictive/preventive measures, such as lockdowns, travel restrictions, shelter-at-home policies, social distancing, and mandatory mask wearing in public places, to contain or slow down the spread of COVID-19. These timely and strict measures have effectively slowed virus transmission among people. Concurrently, these measures also reduced emissions from major anthropogenic and economic activities due to the disruption of anthropogenic emissions. Consequently, a remarkable change in air pollutant concentrations was observed throughout the world, particularly in countries that imposed lockdown, creating a silver lining in the dark cloud of COVID-19 (Jephcote et al., 2021; Nakada and Urban, 2020; Känniah et al., 2020). A significant reduction in air pollutant concentration is observed worldwide, wherein the average concentrations of ground-level nitrogen dioxide (NO2) and particulate matter with average aerodynamic diameters less than 10 μm and 2.5 μm (PM10 and PM2.5) declined by approximately 30% and 20%, respectively, compared to 2019 (Yang et al., 2021). Since then, there has been growing attention to utilizing both high-resolution satellite images and/or ground-based monitoring data to quantify the impact of COVID-19 on the local atmospheric environment, particularly to compare the differences before and after lockdown implementation, for instance, in India (Mahato et al., 2020), China (Shen et al., 2021), Singapore (Li and Tartarini, 2020), Malaysia (Abdullah et al., 2020), Iran (Broomandi et al., 2020), Bangladesh (Rahman et al., 2021), Brazil (Nakada and Urban, 2020), and Turkey (Ghasempour et al., 2021).

Most of the studies hypothesized that strict lockdowns were the major contributors to air pollution reduction during the early stages of the pandemic and highlighted that these environmental changes were only temporary due to the small respite before industrial activities resumed (Nigam et al., 2021); however, contradictory findings were reported by Dinoi et al. (2021). Due to the disruption of local economic activities, e.g., transportation and tourism, as well as reduced emissions from local private travel due to the enforcement of smart working in Italy, the authors showed that the concentration of ultrafine particles decreased more rapidly after the lockdown than during the lockdown. Moreover, to date, only a few studies have focused on the air quality changes in countries/regions that did not impose lockdowns, such as Taiwan. Credit must be given to the established public health response mechanism and Taiwanese government’s timely and accurate decision (e.g., border restriction). COVID-19 was contained without imposing lockdown or implementing work-from home policies, and its impact on people’s daily lives was minimized in 2020 (Chen and Fang, 2021). Consequently, in contrast with most of the reported studies, insignificant changes or higher concentrations of major pollutants (carbon monoxide (CO), sulfur dioxide (SO2), ozone (O3), PM2.5 and PM10) were observed in Taipei and New Taipei cities (major cities in northern Taiwan) at the early stages of COVID-19 (Chang et al., 2021). However, according to the report from Taiwan’s Environmental Protection Administration (TEPA), a substantial improvement in air quality was observed in Taiwan for 2020 compared to 2019 (TEPA, 2021), which may indicate a delayed improvement in the COVID-19 impact on the cities that did not impose lockdown. Therefore, further studies are required to evaluate the long-term COVID-19 impact on the environment and identify possible “new normal lifestyles” that can be practiced for future pollution reduction.

Recently, growing attention has been given to investigating the influencing factors of air quality changes during the COVID-19 period, for which the impacts of meteorology and public transportation are most reported. Since meteorological parameters also play a significant role in affecting the dynamics of pollutants (such as dispersion rate, transportation, and transformation) (Singh and Tyagi, 2021), various methods have been introduced, e.g., the application of black-box models to eliminate the associated effects caused by meteorological variability (Grange et al., 2018; Solberg et al., 2021). For instance, Petetin et al. (2020) and Talbot et al. (2021) performed a random forest machine learning algorithm to estimate the business-as-usual (BAU) pollutant concentration based on the emission scenario and meteorological parameters in the absence of COVID-19 in Spain and New Zealand, respectively. Although it is undeniable that black-box models usually have high prediction accuracy, white-box models are still preferred compared to black-box models due to their transparency; additionally, the relative importance of the predictor variables, which are necessary for decision making in air quality management, can be recognized (Fung et al., 2021). Compared to black-box models, white-box models require fewer datasets for model construction and are commonly adopted for practical application due to their simplicity and robustness (Wong et al., 2021; Loyola- González, 2019). However, to the best of the authors’ knowledge, most studies have applied only black-box models to simulate the BAU air pollutant concentration by utilizing meteorological parameters during the lockdown period (Petetin et al., 2020; Querol et al., 2021). In addition, the majority of current studies have considered only the impact of public roadway transportation reduction during the lockdown period (Gao et al., 2021; Tian et al., 2021), but according to the annual transportation report of Taiwan, the use of public urban transportation, including different transportation modes (e.g., railway, air and waterway), in 2020 declined and dropped to almost the lowest level of the past decade (Ministry of Transportation and Communication, 2021). Significant concentrations of air pollutants have been reported in railways (Moreno et al., 2015), air (Psanis et al., 2017) and waterways (Solomon et al., 2021), as different transportation modes have different features and may constitute divergent air pollutants to the environment. Therefore, to provide a comprehensive evaluation of the impact of public urban transportation on air quality during the study period, four transportation modes were included in this study.

In light of these findings and to better understand the impact of COVID-19 on atmospheric quality in the absence of a lockdown, this study proposed a novel research framework to evaluate the spatiotemporal impacts of COVID-19 across five regions in Taiwan through comparative analysis between mean air pollutant concentrations of 2018–2019 averaged and 2020, considering both meteorological and public transportation effects. In this study, to bridge the aforementioned research gaps, the research objectives are set to:

(i) evaluate, compare and illustrate the spatiotemporal variations in air pollutants between 2020 and the base year utilizing a geographical information system;
(ii) identify the major health risk air pollutants;
(iii) identify the changes in different public transportation modes and their impact on air quality;
(iv) evaluate the impact of meteorological parameters and formulate a white-box model to simulate the meteorological normalized business-as-usual concentration; and
(v) identify the underlying reasons during anomalous months (i.e., local emissions or transboundary pollution) through backward trajectory analysis.

Although the impact of lockdown has driven the significant improvement in air quality, as shown in many regions, it is impossible to impose lockdown indefinitely, as it would lead to tremendous losses for the economy and human liberty. Therefore, these findings are expected to reveal the long-term COVID-19 impacts (monthly analysis throughout 2020) on the atmospheric environment associated with public transport and meteorological impacts in the absence of lockdown and provide comprehensive information to relevant authorities for future sustainable planning of air quality management.

2. Materials and methods

2.1. Study area and data collection

Taiwan is geographically located in East Asia (21.5–25.2 °N and 120.0–122.0 °E) with altitudes ranging from -10–3880 m above sea level. The land area of Taiwan is approximately 36,000 km², comprising five major regions: the Northern, Central, Southern, Eastern and Offshore Islands, with a total population of 23.6 million. As Taiwan straddles the Tropic of Cancer, the northern part of Taiwan belongs to the subtropical climate zone, while the very southern part belongs to the tropical climate zone. The mean annual precipitation of Taiwan ranges from 2,000 mm to 4,000 mm, with approximately 70% of the precipitation occurring during the wet-warm season (May to October), primarily driven by monsoon and typhoon events; therefore, lower concentrations of pollutants are usually observed during this period and higher concentrations in the dry cold season (November to April) (Hsu et al., 2020a; Wu et al., 2019).

To ascertain the impact of COVID-19 on air quality in 2020, different base years, e.g., single year (2019) (Naqvi et al., 2021; Mesas-Carrascosa et al., 2020), two years averaged (2018–2019) (Hu et al., 2021b; Tian et al., 2021), and five years averaged (2015–2019) (Nakada and Urban, 2020; Zangari et al., 2020), were proposed. Continual improvements in the overall air quality conditions in Taiwan have been observed owing to effective pollution control strategies implemented by the government (Tsai et al., 2021), and coal use for power generation is gradually being reduced and replaced by liquefied natural gas since the end of 2017 (TEPA, 2021). In light of these findings, for a better and more precise comparison between business-as-usual (BAU) and COVID-19 scenarios, the 2018–2019 average was selected as the base year in this study.

Fig. 1. Topography and geographical location of Taiwan with meteorological and air quality monitoring stations as well as receptor sites for back-trajectory analysis.
To evaluate the spatiotemporal impacts of COVID-19 on air quality across Taiwan, air pollutants and meteorological data were acquired from the TEPA and Central Weather Bureau, respectively (Taiwan Central Weather Bureau, 2020; TEPA, 2021b). The daily data for both air pollutants and meteorological parameters were used to calculate the mean concentrations/values for each month. Due to certain technical errors (i.e., power failure, machine error or under maintenance) (Benis et al., 2015), some data were missing (approximately 5% of the overall data). Stations containing missing data for more than 7 days in a month were removed. Therefore, the numbers of usable air quality and meteorological parameter stations were 69 and 224, respectively, as shown in Fig. 1. The air pollutants included in this study were CO, SO2, NO2, O3, PM10 and PM2.5, whereas the meteorological parameters included were station pressure (Psea), sea-level atmospheric pressure (Psea), atmospheric temperature (Tsea), dew temperature (Tdew), class-A pan evaporation (Evap), wind speed (WS), wind direction (WD), rainfall (RF), relative humidity (RH), sunshine hours (SH), global radiation (GR) and cloud cover (CC).

The monthly passenger volumes (2018–2020) for roadway, railway, and waterway transportation modes were acquired from the Taiwan Ministry of Transportation and Communication to evaluate the impact of volume on air quality (Ministry of Transportation and Communication, 2020). To better understand public mobility behavior in 2020, each transportation mode has been further categorized into intercity/international and local routes, except for waterway transportation. Detailed information on the data used in this study is summarized in Table 1.

### 2.2. Research framework

In this section, the architecture of an integrated research framework for identifying the impacts of public transportation usage and meteorology on air quality during the COVID-19 period in the absence of lockdown is introduced, as shown in Fig. 2. Different statistical analyses were performed and effectively illustrated using a geospatial information system (GIS) to quantify the spatiotemporal variation change in each air pollutant between 2018–2019 and 2020. Correlation and trend analyses were performed to assess the degree of association and temporal changes between public transportation usage and meteorological parameters and air pollutants. A stepwise regression model (SRM) was adopted to simulate the concentration of air pollutants under the meteorological-balanced BAU scenario by utilizing meteorological parameters. To identify the underlying reasons during the anomalous months (i.e., local emissions or transboundary pollution), backward trajectory analysis using the hybrid single-particle Lagrangian integrated trajectory (HYSPLIT) model was applied. A detailed discussion of each step is provided as follows:

#### 2.2.1. Geostatistical analysis

The descriptive statistics (range and mean ± standard deviation) for air pollutants are summarized in Table 2. To analyze the data distribution of the variables included in this study, the Shapiro–Wilk (SW) normality test was applied due to its robustness and suitability for complicated atmospheric interactions (Ventura et al., 2018). One-way analysis of variance (ANOVA) was performed to evaluate the significant differences between the air pollutants in 2018–2019 and 2020. All statistical tests were performed using the Statistical Package and Service Solutions (IBM SPSS version 22). The spatial distribution of the monthly mean concentration and mean percentage difference in air pollutants across Taiwan were determined using the spatial analyst module in the ArcGIS 10.8 platform. To visualize the spatiotemporal variation in air pollutants, the deterministic interpolation technique inverse distance weighting (IDW) method was selected due to its wide application for temporal climate and environmental data analysis (Chen and Liu, 2012; Wong et al., 2020).

#### 2.2.2. Change detection analysis

The monthly mean percentage difference among air pollutants between 2018–2019 averaged and 2020 was computed using Eq. (1) (Hu et al., 2021a).

\[
\text{Percentage Change} (\%) = \frac{\text{Conc}_{2020} - \text{Conc}_{2018-2019}}{\text{Conc}_{2018-2019}} \times 100
\]  

where Conc_{2018–19} and Conc_{2020} represent the mean monthly concentrations of pollutants for 2018–2019 and 2020, respectively.

#### 2.2.3. Nonattainment pollutants analysis

The current Taiwan AQI framework was revised in 2016 (formerly known as the pollutant standard index) by Taiwan’s Environmental Protection Administration to have stricter standards and a more detailed classification of the concentration of each pollutant for air quality evaluation. The Taiwan AQI consists of six air pollutants. Pollutant concentrations are converted into individual dimensionless subindex values (AQI_i) (scaled from 0 to 500) using Eq. (2). The overall AQI is determined as the maximum of AQI among pollutants and is regarded as the major pollutant, expressed mathematically in Eq. (3) (Taiwan Environmental Protection Administration, 2006).

\[
\text{AQI}_i = \frac{\text{SI}_{\text{high}} - \text{SI}_{\text{low}}}{\text{Conc}_{\text{high}} - \text{Conc}_{\text{low}}} (\text{Conc}_{i} - \text{Conc}_{\text{low}}) + \text{SI}_{\text{low}}
\]  

\[
\text{AQI} = \max(\text{AQI}_1, \text{AQI}_2, \ldots, \text{AQI}_6)
\]  

### Table 1 Summary of the parameters used in the study.

| Type         | Parameter/Variable     | Unit          | No. of Monitoring Station | Duration             | Source                                      |
|--------------|------------------------|---------------|---------------------------|-----------------------|---------------------------------------------|
| Air Quality  | Carbon monoxide (CO)   | µg/m³         | 69                        | 2018–2020 (Daily)     | Taiwan Environmental Protection Administration |
|              | Sulfur dioxide (SO₂)   | µg/m³         |                           |                       |                                             |
|              | Nitrogen dioxide (NO₃) | ppm           |                           |                       |                                             |
|              | Ozone (O₃)             | ppb           |                           |                       |                                             |
|              | Particulate matter 2.5 (PM2.5) | ppb |                       |                       |                                             |
|              | Particulate matter 10 (PM10) | ppb |                       |                       |                                             |
|              | Station pressure (Psea) | hPa           | 224                       | 2018–2020 (Daily)     | Taiwan Central Weather Bureau               |
|              | Sea-level pressure (Psea) | hPa          |                           |                       |                                             |
|              | Atmospheric temperature (Tsea) | °C |                           |                       |                                             |
|              | Dew temperature (Tdew)  | °C            |                           |                       |                                             |
|              | Class-A pan evaporation (Evap) | mm |                           |                       |                                             |
|              | Wind speed (WS)        | m/s           |                           |                       |                                             |
|              | Wind direction (WD)    | °C            |                           |                       |                                             |
|              | Rainfall (RF)          | Mm            |                           |                       |                                             |
|              | Relative humidity (RH) | %             |                           |                       |                                             |
|              | Sunshine hours (SH)    | hour          |                           |                       |                                             |
|              | Global radiation (GR)  | MJ/m²         |                           |                       |                                             |
|              | Cloud Cover (CC)       | –             |                           |                       |                                             |
For ANOVA test: # * * p < 0.05.
For Shapiro–Wilk test: * p < 0.05.
For ANOVA test: # p < 0.05.

where AQI represents the subindex value of air pollutant i; Conc<sub>i</sub> represents the measured concentration of air pollutant i; Conc<sub>iq</sub> and Conc<sub>il</sub> denote the upper and lower limit concentrations corresponding to the health category encompassing Conc<sub>i</sub>, respectively; and SI<sub>iq</sub> and SI<sub>il</sub> denote the upper and lower subindex scores corresponding to Conc<sub>iq</sub> and Conc<sub>il</sub>, respectively.

The reference concentrations of pollutants and corresponding sub-index scores are divided into six categories, from Class I (Good): 1–50 to Class VI (Hazardous): 301–500, in association with their impacts on human health (TEPA, 2006). Class I and Class II (AQI <100) are attainment grades, while others are regarded as nonattainment, which may cause adverse health effects (Ma et al., 2019).

### 2.2.4. Meteorological normalization

To eliminate meteorological biases, a backward SRM that successively excluded nonsignificant (p > 0.05) meteorological variables was adopted. The monthly mean concentration of each pollutant and meteorological variable from 2018 to 2019 was used as the training dataset to formulate the best fit equations and to simulate the monthly mean BAU concentration for each pollutant in 2020 for given meteorological conditions and temporal structures (Querol et al., 2021; Jephcoate et al., 2021). Through this process, the monthly percentage change for (i) meteorological-normalized BAU, (ii) COVID-19 (observed – meteorological-normalized BAU) and (iii) overall (total percentage change combining scenarios (i) and (ii)) for each air pollutant could be identified.

### 2.2.5. Backward trajectory analysis

The HYSPLIT model developed with the National Oceanic and Atmospheric Administration Air Resources Laboratory was extensively used to compute backward trajectories of air masses (Draxler and Hess, 1998; Stein et al., 2015). The meteorological fields used in the calculation of 120-h backward trajectory data are driven by the National Centers for Environmental Prediction Global Data Assimilation System (GDAS 1° × 1°). The vertical transport was modeled using the isobaric option of HYSPLIT. The backward trajectories were computed every 6 h at 200 m arrival heights. The clustering method using Euclidean distance is used to reveal the dominant trajectories of air pollution events and thus help to identify the possible causes of pollution (Wang et al., 2010).

### 2.3. Assumptions and limitations

According to the Taiwan Energy Statistic Handbook, the difference in coal and coal products usage (major energy source in Taiwan) for power generation in 2018–2019 and 2020 is insignificant, with an approximately 1% difference. Besides that, the average total energy consumption in 2018–2019 was 86.1 million kiloliter of oil equivalent (KLOE), whereas in 2020, it was 85.4 million KLOE, with less than a 1% difference. Therefore, the emissions from power generation sector in 2020 are assumed to be consistent with those in 2018–2019 and not considered in
this study. In addition, due to the limitation of the dataset available, this study utilized only the public transportation usage volume, the impact of private transportation may not be reflected in this study. Also, as the intention of the study was to evaluate the impact of COVID-19 under the meteorological-normalized scenario, this study utilized only the mean monthly concentrations of air pollutants and meteorological parameters across Taiwan, which may not be capable of providing accurate simulations at high temporal (such as daily or hourly) or spatial (according to station) variations. Moreover, as there are no detailed data available on the local emissions (such as industrial or domestic) and sudden/accidental pollution, which may have further limited the ability to identify the underlying reasons for the improvements in the study.

3. Results and analysis

3.1. Descriptive analysis of air pollutants

The descriptive statistics for the 2018–2019 and 2020 air pollutant concentrations obtained from 69 stations across Taiwan are summarized in Table 2. Among the six pollutants, both PM$_{10}$ and PM$_{2.5}$ showed the highest annual mean concentration reduction in 2020 relative to 2018–2019, by 24% and 18%, respectively, followed by SO$_2$, NO$_2$, CO and O$_3$, with reductions of 15%, 9.6% and 7.4% and 1.3%, respectively. Significant differences between 2018–2019 and 2020 using one-way ANOVA were observed in the parameters with remarkable improvement, which were PM$_{10}$, PM$_{2.5}$ and SO$_2$. Since NO$_2$ was not normally distributed ($p < 0.05$) according to the SW normality test, Spearman correlation was used to examine the bivariate association between air pollutants and meteorological factors. To better understand the impacts of COVID-19 on the atmospheric environment, spatiotemporal analysis of each pollutant was performed.

3.1.1. Spatiotemporal variations in PM concentrations

The mean concentrations of PM$_{2.5}$ and PM$_{10}$ ranged between 5.0–37 µg/m$^3$ and 1.5–80 µg/m$^3$ in 2018–2019 and 2–33 µg/m$^3$ and 6–65 µg/m$^3$ in 2020, respectively. As shown in Figs. S1 and S2, high concentrations of PM$_{2.5}$ (>20 µg/m$^3$) and PM$_{10}$ (>30 µg/m$^3$) are usually detected in the southern region. For both PMS, a contradictory phenomenon was observed, where a deteriorating trend was shown from January to April, even after the declaration of the COVID-19 pandemic. In most of the reported literature, the impact of COVID-19 on particulate matter in other countries/major cities is significant, for instance, India (PM$_{2.5}$: ~-41%, PM$_{10}$: ~-52%) by Jain and Sharma (2020), Malaysia (PM$_{2.5}$: ~-30%, PM$_{10}$: ~-31%) by Kanniah et al. (2020), the Yangtze River Delta of China (PM$_{2.5}$: ~-37%, PM$_{10}$: ~-32%) by Li et al. (2020), and Bangkok, Thailand (PM$_{2.5}$: ~-41%, PM$_{10}$: ~-52%) by Dejchanchaiwong and Tokasakul (2021). However, in the absence of a lockdown, although some anthropogenic activities were restricted, the major industrial and economic activities were not severely disrupted (Summers et al., 2020; Wu et al., 2021). Thus, the improvement was less significant (<20%) for both PMS during the first quarter of 2020 compared to other countries (Fig. 3). A slight increase in PM$_{2.5}$ and PM$_{10}$ concentrations was observed in April, which might be attributed to forest fires in China (Yang et al., 2020) and in Indochina (Chuang et al., 2020) or caused by local emissions; the underlying reasons are to be verified in the

![Fig. 3. Spatiotemporal change detection analysis for (a) PM$_{2.5}$ and (b) PM$_{10}$, Taiwan between 2018–2019 and 2020.](image-url)
following section using HYSPLIT.

The rainy season in conjunction with the COVID-19 restrictions showed significant reductions in both PM$_{2.5}$ and PM$_{10}$, with mean percentage changes of up to $-87\%$ and $-81\%$, respectively. The highest improvement observed during the rainy season was in the central (mean percentage change: PM$_{2.5}$: $\sim-37\%$ and PM$_{10}$: $\sim-33\%$) and southern (mean percentage change: PM$_{2.5}$: $\sim-35\%$ and PM$_{10}$: $\sim-32\%$) regions, which are highly urbanized and heavily industrialized (Chen et al., 2019; Huang and Hsieh, 2019). The associated meteorological impacts coupled with government measures and public awareness (such as reduced mobility and human activity) have resulted in a significant improvement in PM across Taiwan.

An increase in the mean percentage change up to 42\% for PM$_{2.5}$ and 37\% for PM$_{10}$ was observed in the southern region in October 2020. This month marks the start of the Asian winter monsoon, where the cold high-pressure system exits the continent toward Taiwan as the northeast wind system. This wind system enters Taiwan in the north and gradually moves southwards, where a turbulent wake is formed. The latter is conducive to pollution accumulation and is often linked to wind-blown dust, which increases the local PM$_{10}$ level. During 2020, a major dust storm event arose and swept over Taiwan; which was maybe caused by a strong pressure gradient, originated from the deserts of Mongolia and Kazakhstan and carried large masses of PM (Hsu and Cheng, 2019). Under high pressure and low wind speed conditions, the atmospheric conditions are relatively stable, causing pollutants to not thoroughly disperse and leading to the occurrence of pollutant accumulation (Maurer et al., 2019). Nevertheless, due to the blocking effects of the Central Mountain Range, large concentrations of air pollutants accumulate predominantly over the central and southern regions; thus, higher concentrations (up to 70.0 $\mu g/m^3$ and 40.0 $\mu g/m^3$ for PM$_{10}$ and PM$_{2.5}$, respectively) were observed over these two regions.

3.1.2. Spatiotemporal variations in CO and NO$_2$ concentrations

For CO and NO$_2$, the mean concentrations in 2018–2019 ranged between 0.11–1.0 ppm and 0.25–28 ppb, whereas in 2020, they ranged between 0.05–1.0 ppm and 0.3–27 ppb, respectively. As illustrated in Figs. S3 and S4, the mean concentrations of CO and NO$_2$ are usually in compliance with the Taiwan national standard (CO: $\leq 4.4$ ppm and NO$_2$: $\leq 30$ ppb). In agreement with most of the reported literature, an improving trend across Taiwan from January to April 2020 for CO and NO$_2$ was observed, with mean percentage reductions of up to $-11\%$, particularly in the northern region (Fig. 4). The decreases in CO and NO$_2$ were found to be highly associated with reduced mobility and transportation emissions as a result of government measures for combating COVID-19 transmission. As the northern region is the most densely populated region in Taiwan (with a population of more than 10 million or approximately 40% of the whole Taiwan population), improvement due to reduced mobility is particularly remarkable in this region. Therefore, to investigate and validate the impact of traffic volume, a detailed transportation usage rate was collected and discussed in section 3.2.

During the rainy season, a similar phenomenon with PMs occurred, where significant improvements in CO and NO$_2$ concentrations associated with meteorological impacts were observed, with reductions of up to 62\% and 47\%, respectively. However, a substantial increase in CO in September 2020 over northern and central western Taiwan was

![Fig. 4. Spatiotemporal change detection analysis for (a) CO and (b) NO$_2$ across Taiwan between 2018–2019 and 2020.](image-url)
observed. This month is the transition period between the rainy summer and the dry winter season, which explains the mixed changes in different air pollutants. The increase in CO and NO$_2$ concentrations during September 2020 might be due to the diminishing wet deposition ability of precipitation. In early October, the strong winter monsoon cleared out the pollutants in the north, and these pollutants began to accumulate over the southwestern region (concentrations of CO and NO$_2$ up to 0.58 ppm and 28 ppb, respectively). This might be due to the long-range transportation pollution from East Asia as an effect of the summer-winter transition period.

3.1.3. Spatiotemporal variations in the O$_3$ and SO$_2$ concentrations

The mean concentrations of O$_3$ and SO$_2$ in 2018–2019 ranged between 16–59 ppb and 1.2–5.9 ppb, whereas in 2020, they ranged between 13–62 ppb and 0.6–5.2 ppb, respectively. O$_3$ has emerged as one of the major pollutants in Taiwan and has been addressed effectively, and it has progressively increased in the past decade (Qiu et al., 2021). As shown Fig. 5(a), in contrast to the NO$_2$ observation, the mean concentration of O$_3$ showed a significant increase (approximately 20–30%) with a mean concentration ranging between 40–60 ppb (Fig. S5) in 2020 April, and similar observations have been reported worldwide (Li et al., 2020; Siciliano et al., 2020; Cazorla et al., 2021). O$_3$ is a secondary atmospheric pollutant that is formed during the complex photochemical reactions between oxides of nitrogen and volatile organic compounds; therefore, the reduction in NO$_2$ subsequently leads to an increased ozone concentration.

The SO$_2$ are generally formed during the burning of sulfur-containing fossil fuels (particularly coal), residual fuels used in shipping, and during metal smelting or other industrial processes (Merico et al., 2016). Due to continuous efforts of the Taiwanese government to deploy combinations of policies and legislative initiatives to boost the execution of renewable energy sources and gas-fired plants in order to replace coal-fired power generation (Kung and McCarl, 2020), the mean concentration of SO$_2$ is always in compliance with the Taiwanese national standard (≤20 ppb), as illustrated in Fig. S6, and continuous improvement/reduction is observed in Fig. 5(b).

During the rainy season, wet deposition is less significant for both O$_3$ and SO$_2$ than for other air pollutants, with mean percentage changes of −7.4% and −15%, respectively. An increase up to 52% was observed in O$_3$ in September and October, which may have been caused by the similar factors mentioned in sections 3.1.1 and 3.1.2. In contrast, because SO$_2$ is a short-lived gas (Wang et al., 2018), therefore the impact of long-range transport was insignificant as compared to other air pollutants.

3.2. Contribution of the nonattainment pollutants

The contribution of major pollutants to the nonattainment days across Taiwan for 2018–2019 and 2020 is presented in Fig. 6(a). A significant improvement was observed, where the total nonattainment days decreased from 3,736 in 2018–2019 to 2,470 in 2020, with a total reduction of 34%. In both 2018–2019 and 2020, the occurrence of nonattainment days in the central and southern regions was observed to be much higher than that in other regions, accounting for 80% and 78% in 2018–2019 and 2020, respectively. Among the six air pollutants, PM$_{2.5}$ and O$_3$ were observed as the major pollutants, with total

![Fig. 5. Spatiotemporal change detection analysis for (a) O$_3$ and (b) SO$_2$ across Taiwan between 2018–2019 and 2020.](image-url)
nonattainment days of 1,894 and 1,812 (775 and 1,695), contributing 51% and 49% (31% and 69%) in 2018–2019 (2020), respectively, whereas the remaining pollutants had almost negligible contributions (<1%) to the total nonattainment days. Compared to 2018–2019, a significant improvement was observed, where the total nonattainment days decreased by 34% in 2020, and the nonattainment days caused by PM$_{2.5}$ decreased significantly by 59%, while ozone decreased by 6.0%.

Seasonal meteorological impacts on air pollutants have been studied extensively (Yousefian et al., 2020; Liu et al., 2020); however, due to their complex, coupled, and adaptive interactions and dynamic characteristics, the reported findings may vary according to geographical region and intensity of meteorological parameters (Tfwala et al., 2017). Fig. 6(b) illustrates the monthly temporal variation of the nonattainment day across Taiwan. As shown in Fig. 6(b), for both 2018–2019 and 2020, the total nonattainment days for PM$_{2.5}$ and O$_3$ peaked during dry cold season (November to April) and wet warm season (May to Oct), respectively. The PM$_{2.5}$-induced non-attainment days usually peaked during the dry season (similar trends observed in Liang et al. (2016) and Lin et al. (2021)), with a total number of nonattainment days of 2,517 and 1,602 in 2018–2019 and 2020 (accounting for approximately 60% in both periods), respectively. High PM$_{2.5}$ concentrations were usually detected during the dry cold season, which may have been due to the
strong thermal inversion and low mixing layer height, leading PMs to be trapped and accumulate in the troposphere (Sanguineti et al., 2020). During the wet season, PM concentrations were effectively decreased through wet deposition (Wang and Ogawa, 2015). In contrast, non-attainment days caused by O$_3$ were observed to occur mainly during the wet–warm season, as meteorological parameters (e.g., $T_{\text{atm}}$, GR, SH) are more suitable for photochemical reactions (Cheng et al., 2022). However, an unprecedented spike in O$_3$ was observed in April and September 2020, with an almost 2-fold increase compared to 2018–2019. To identify the possible reasons, backward trajectory simulation using the HYSPLIT model was constructed and performed (Sari et al., 2020; Shan et al., 2009).

4. Discussion of findings

4.1. Impact of the traffic volume

The monthly passenger volume and percentage change between 2018–2019 and 2020 for roadway, railway, air, and waterway transportation are presented in Fig. 7. While most of the people were largely unaware of the emerging crisis, the Taiwanese government had implemented strict enforcement of border control measures for immigration entry since January 2020, which resulted in a conspicuous and significant downward trend in all transportation modes in 2020 compared to 2018–2019 (Cheng et al., 2020). The official declaration of the COVID-19 outbreaks as a pandemic, which was made by the WHO on 11 March, promoted restrictive measures (e.g., closure of bars and nightclubs and crowd control at hotspots); these measures were eventually imposed by the Taiwanese government to prevent cross-infection transmission within the community and led to minimal community mobility in April for all transportation modes. The use rates of roadway, railway, air, and waterway transportation were reduced by 32%, 34%, 82%, and 64%, respectively.

As the nationwide COVID-19 condition became relatively more stable, the government eased the restrictions, and a steady upward trend for roadway and railway transportation was observed from May to July; the trend remained relatively stable from August to December. Although international flights were severely disrupted (almost at a standstill after April), the Taiwanese government focused on promoting domestic tourism to boost the local economy and business with support programs and safety measures, which resulted in a strong upward trend in both local flights and water transportation from May to September, reaching a peak during the summer holiday season (August) and gradually decreasing until December.

Spearman correlation was performed to investigate the relationship between transportation volume and air pollutants, as presented in Fig. 8. Although there were no lockdowns or enforced human mobility restrictions imposed by the Taiwan Government during 2020, as shown in Fig. 7, significant changes in traffic volume were observed. Therefore, to incorporate these observed changes to provide a comprehensive evaluation of the nexus of air pollutants with traffic volume, the monthly mean data between 2018 and 2020 were used. Most of the air pollutants were positively correlated with different transportation modes, except for local flights. Although SO$_2$, PM$_{10}$ and PM$_{2.5}$ showed high correlations with different transportation modes, the changes were inconsistent with the transportation usage volume. Conversely, the change trends of the NO$_2$ and CO concentrations (major pollutants emitted from transportation) that demonstrate substantial correlations with roadway and air transportation were congruent with the transportation usage volume, except during the wet season (May to August). Similar findings were reported by Gao et al. (2021) and Tian et al. (2021) in China and Canada during the COVID-19 period, respectively, where NO$_2$ and CO were fairly correlated with the traffic volume, advocating for the importance of proper public transportation planning in addressing NO$_2$ and CO pollution. There was no statistical correlation observed between O$_3$ and traffic volume; however, high concentration up to 62 ppm observed in April may have been caused by reduced mobility (Siciliano et al., 2020). As most of the monitoring stations are located in urban areas, ozone production may be VOC-limited; therefore, the increase in O$_3$ concentrations might have been caused by reduced NO$_2$ concentrations due to reduced mobility (Sicard et al., 2020; Cazorla et al., 2021).

Fig. 7. Monthly variation in public transportation passenger volume for (a) roadway, (b) railway, (c) air and (d) waterway transportation across Taiwan.
4.2. Meteorological-normalized BAU scenario

To eliminate meteorological biases during the quantification of COVID-19 impacts on air quality (improvement/degradation), this study constructed SRM models by utilizing 12 meteorological parameters for each studied air pollutant. The correlations between air pollutants and selected meteorological parameters are presented in Fig. 8 (b). The mean values at all available air pollutants and meteorological stations were used (Teng et al., 2018), as the focus of the study is to find the overall relationship among them across Taiwan despite the different numbers of air quality (n = 69) and meteorological stations (n = 224). Similar approaches were also reported by He et al. (2020), Kwon et al. (2020) and Zhu et al. (2021). Therefore, the representative air pollutant concentration and meteorological parameter value were defined by averaging the monthly mean concentration/value of all the available monitoring stations from 2018 to 2020. Meteorological parameters have a stronger correlation with air pollutants (except for SO$_2$) than traffic volume for different transportation modes in Taiwan; however, contradictory findings were reported by Gao et al. (2021) for China, as the magnitude of the impact may vary across regions. Most of the meteorological parameters were negatively correlated with air pollutants, except for pressures, WS and CC, in agreement with the majority of the literature (Peng et al., 2020; Liu et al., 2020; Talbot et al., 2021).

The statistical performance and equation of the SRMs for each air pollutant are summarized in Table 3. The constructed models achieved satisfactory performance ($R^2 > 0.8$) for the 2018–2019 dataset, except for SO$_2$, which may have been due to the insignificant correlation with meteorological parameters. Fig. 9 presents the monthly and annual percentages of six air pollutants under the three scenarios between 2018–2019 and 2020. In contrast to the meteorological impact, the reduced human activity and mobility due to the impacts of COVID-19 played a major role in improving the air quality. Although the COVID-19 pandemic was declared in March, due to the reduction in long-
range transportation emissions from neighboring countries (Lai and Brimblecombe, 2021), a reduction in air pollutants, particularly particulate matter, was observed in early 2020. In 2020, during the dry season, it could be observed that the percentage change between the meteorological-BAU and COVID-19 scenarios usually followed a similar trend, with a greater magnitude of reduction observed in the COVID-19 scenario. However, during the rainy season, although a significant air pollutant concentration reduction was observed, as reported in section 3.1, as shown in Fig. 9 (a), for most of the air pollutants, the simulated concentration in 2020 was higher than that in the observed dataset. This phenomenon may have been caused by the reduced precipitation (approximately 240 mm) during the rainy season (Fig. S7) (except for May), with an approximately 5% reduction in the frequency of wind speeds of less than 1.5 m/s in 2020 compared to 2018–2019 (TEPA 2021). Therefore, a higher air pollutant concentration was simulated during the rainy season.

Radar diagrams were used to illustrate and compare the mean annual percentage change between 2018–2019 and 2020 among different scenarios, as shown in Fig. 9(b). Under the meteorologically normalized BAU scenario, slight increases in the concentrations of CO, NO₂, O₃, PM₂.₅, PM₁₀, and SO₂ were observed in 2020, where the mean percentage changes relative to 2018–2019 were 2.5%, 4.4%, 0.5%, 1.0%, 5.4% and 2.0%, respectively. This implied that the meteorological conditions in 2020 might have been unfavorable for the dispersion and transportation of air pollutants. Similar findings have also been reported in neighboring areas, such as cities in China (Hu et al., 2021b; Bai et al. 2022).

On the other hand, under the COVID-19 scenario, a significant reduction was observed for PM₁₀, PM₂.₅, SO₂, and NO₂, with mean percentage changes relative to 2018–2019 of −36%, −26%, −27%, and −20%, respectively. The maximum reduction of these four pollutants was observed during the wet season, contributing a 40–60% reduction in concentration. For CO, a satisfactory reduction was observed, with percentage changes of −16%, and a slight increment was observed for O₃, with 1.3%. Despite the unfavorable meteorology of 2020, significant improvements were observed among air pollutants (except for O₃) due
to the reduction of anthropogenic emissions even in the absence of a lockdown. Overall, for 2020, the total change associated with the meteorological-normalized simulated air pollutant concentrations and COVID-19 scenarios, a significant reduction was observed in the mean percentage change relative to 2018–2019, with −13%, −16%, −25%, −30%, and −25% for CO, NO$_2$, PM$_{2.5}$, PM$_{10}$, and SO$_2$, respectively, and a slight increment was observed for O$_3$, with 1.8%.

4.3. Backward trajectory analysis of the anomaly months

In this section, backward trajectory HYSPLIT analysis is used to identify the possible air mass origin affecting the air quality over Taiwan during April and September, as increments of up to 80% in pollutants were observed in 2020 compared to 2018–2019 despite the reduced mobility and implementation of restrictive measures. Applying a similar approach in section 3.1, 2018–2019 was selected to represent the BAU scenario, whereas 2020 was selected as the COVID-19 scenario. For the April scenario, Nantou station in central Taiwan was selected as the receptor site due to the unusually high PM$_{2.5}$ and PM$_{10}$ recorded in the spatiotemporal change percentage between 2018–2019 and 2020 (see Fig. 3). For the September scenario, Wanli station in northern Taiwan was selected as the receptor site due to the substantial increase in CO and NO$_2$ (see Fig. 4). This station is also a background station that is often used to identify the transboundary pollution scenario from East China. Fig. 10 presents the clustered 120-h trajectory pathways driven by the GDAS meteorological dataset at 1.0° × 1.0° in April and September.

As shown in Fig. 10 (a), the air mass reaching Nantou station in April 2020 is mostly from the northeast direction, with the highest proportion accounting for C1 (88%), followed by C3 (8.0%) and C2 (4.0%). These three clusters shared a very similar trajectory pathway, indicating that they might be driven by the same synoptic weather pattern. This weather pattern features a weak anticyclone over the Asian continent and the Pacific subtropical high-pressure system that does not have an apparent influence in Taiwan, which frequently occurs during the seasonal transition period in April (Hsu and Cheng, 2019). Although the trajectories do not originate directly from the continent, the prevailing northeasterly winds associated with the eastward-propagating...
mountain, often leading to serious PM. Northeasterly wind is obstructed by the Central Mountain Range, low lifts in early April for economic recovery, an apparent rebound effect assurances and travel restrictions of neighboring major cities were gradually lifted in early April for economic recovery, an apparent rebound effect was detected (Gao et al., 2021; Hasanin et al., 2021), and trajectories of polluted air masses to central Taiwan were observed originating from neighboring major cities (Wu and Huang, 2021). When the prevailing northeasterly wind is obstructed by the Central Mountain Range, low wind speeds and strong subsidence occur over the leeside of the mountain, often leading to serious PM accumulation in central and southern Taiwan. In contrast, the backward trajectories in April 2018–2019 clearly demonstrated the mixture of oceanic air masses from the western Pacific Ocean, C2 (10%), and South China Sea, C3 (18%). The westward stretching of the Pacific subtropical high-pressure system distinctly changed the prevailing wind in Taiwan to southeasterly and southerly flows, bringing more pristine air to Taiwan and eventually reducing the PM and gas pollutant concentrations.

For the September scenario, the backward trajectories C4 (21%) at Wanli station in 2020 clearly show that the possible air mass trajectories are different compared to 2018–2019. Unprecedented elevated ozone concentrations associated with Asian high-pressure ridge incidents were reported and carried from the continent toward Taiwan in high-level (7-1 km) trajectories, particularly in northern and eastern Taiwan, contributing to long-range transboundary air pollution in September 2020 (Wang et al., 2016; Tseng et al., 2019). Meanwhile, backward trajectories in September 2018–2019 were mainly dominated by oceanic air masses from the East China Sea (C1: 79%) and the western Pacific Ocean (C2: 11% & C3: 7%), which are typically cleaner than continental air masses, resulting in lower observed air pollution concentrations during this period (Golubeva et al., 2013).

4.4. Implications

The drastic disruption in normal routine due to the COVID-19 pandemic has provided a unique opportunity to explore the impact of transportation and meteorology on air quality. According to the findings, it could be observed that the impact of reduced transportation usage and a “new normal lifestyle”, such as social distancing, has a more significant impact than meteorology on air quality improvement, in agreement with the findings reported by Nguyen et al. (2020). As demonstrated in Taiwan, although the emission scenario from industries has insignificant changes, an approximately 52% reduction was observed in public transportation usage and may be the key driver of air quality improvements. It may be ambitious to implement policies restricting traffic mobility to sustain long-term improvements (Sokhi et al., 2021); however, proper transportation system management and alternative greener fuel may be one of the most emerging topics at present that should be considered and adopted by governments worldwide for sustainable air quality management. The reduced precipitation in 2020 might have been due to climate change (Yeh and Huang, 2019), and this phenomenon is expected to continue and may worsen air quality over the long-term (Kinney, 2021). There have been ongoing global and regional efforts to address climate change impacts on air quality (e.g., Kyoto Protocol, Paris Agreement, Gothenburg Protocol). However, climate change-driven air pollution mortality has not yet been addressed (Hong et al., 2019) and further contributes to the degradation of the environment and human health. Therefore, decision makers must consider these important implications when formulating and implementing sustainable air quality policies in response to unavoidable climate change in order to maintain/improve air quality in the absence of lockdowns and prevent adverse impacts on the economy and society.

5. Conclusions

This study demonstrated and contributed to the spatiotemporal impact of COVID-19 on air quality variation across different regions in Taiwan in the absence of a lockdown. Different statistical analyses (including geospatial, change detection and non-attainment pollutant occurrence) between air pollutant concentrations in 2018–2019 and 2020 were performed, considering both meteorological and public transportation impacts. Particularly, the occurrence frequency of air pollutants that may cause adverse health effects (O3 and PM2.5) fell by more than 30% in 2020 compared to 2018–2019. The performance of meteorological-normalized SRMs for the studied air pollutant achieved $R^2 > 0.8$ (except SO2), indicating the applicability of statistical models for simulating BAU concentrations in Taiwan. According to the findings in this study, the impact of reduced public transportation emissions may have a more significant impact than meteorology on the air quality improvement in Taiwan.

As the development/usage of public transportation will be further promoted in the future; therefore, to reduce the emission from public transportation sectors, the use of energy-saving, cleaner fuel, and emission-reducing vehicles should be considered (Tian et al., 2021; Muhammad et al., 2020). Also, to reduce traffic emission, strategic transportation network design associated with sustainable traffic planning/management for reducing the traffic congestion issues (Hsieh and You, 2021; Zhai et al., 2022), which could be one of the key drivers to maintain/improve air quality. Nevertheless, although anthropogenic activity and public transportation use seem to have more significant impacts in improving air quality than meteorological parameters, the impact of climate change should be considered when formulating future policies, as increased climate variability is expected. This variability will consequently project incremental changes to air pollution concentrations that lead to adverse effects on both the environment and human health.

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CRediT authorship contribution statement

Yong Jie Wong: Conceptualization, Methodology, Resources, Formal analysis, Data curation, Software, Writing – original draft. Huan-Yu Shiu: Conceptualization, Methodology, Formal analysis, Writing – original draft, preparation. Jackson Hian Hui Chang: Formal analysis, Software, Writing – original draft, preparation. Maggie Chel Gee Ooi: Formal analysis, Software, Writing – original draft, preparation. Hsueh-Hsun Li: Formal analysis, Writing – review & editing. Ryoosuke Homma: Formal analysis, Writing – review & editing. Yoshihisa Shimizu: Resources, Supervision, Writing – review & editing. Pei-Te Chiueh: Funding acquisition, Supervision, Writing – review & editing. Luksanaree Maneechoat: Methodology, Writing – review & editing. Nik Meriam Nik Sulaiman: Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Wu, C.H., Tsai, I.C., Tsai, P.C., Tung, Y.S., 2019. Large-scale seasonal control of air quality in Taiwan. Atmos. Environ. 214, 116868 https://doi.org/10.1016/j.atmosenv.2019.116868.

Wu, L.-F., Achyldurdyyeva, J., Jou, W.-P., Foung, W.-T., Jaw, B.-S., 2021. Relief, recovery, and revitalization measures for tourism and hospitality industry during covid-19 pandemic: case study from Taiwan. Sage Open 11 (3), 21582440211040805. https://doi.org/10.1177/21582440211040805.

Wu, P.C., Huang, K.F., 2021. Tracing local sources and long-range transport of PM10 in central Taiwan by using chemical characteristics and Pb isotope ratios. Sci. Rep. 11 (1), 7593. https://doi.org/10.1038/s41598-021-87053-9.

Yang, J., Zhou, F., Zhang, K., 2020. Efforts to fight forest fire continue in SW China. https://news.cgtn.com/news/2020-04-02/Efforts-to-fight-forest-fire-continue-in-SW-China-PmbgCSLHI4/index.html. (Accessed 15 April 2021).

Yeh, H.F., Huang, C.C., 2019. Evaluation of basin storage-discharge sensitivity in Taiwan using low-flow recession analysis [https://doi.org/10.1002/hyp.13411] Hydrol. Process. 33 (10), 1434-1447. https://doi.org/10.1002/hyp.13411.

Yousefian, F., Faridi, S., Azimi, F., Aghaei, M., Shamsipour, M., Yaghmaeian, K., et al., 2020. Temporal variations of ambient air pollutants and meteorological influences on their concentrations in Tehran during 2012–2017. Sci. Rep. 10 (1), 292. https://doi.org/10.1038/s41598-019-56578-6.

Zangari, S., Hill, D.T., Charette, A.T., Mirowsky, J.E., 2020. Air quality changes in New York City during the COVID-19 pandemic. Sci. Total Environ. 742, 140496 https://doi.org/10.1016/j.scitotenv.2020.140496.

Zhai, Z., Fu, X., Yi, M., Sheng, M., Guang, F., 2022. Haze management: is urban public transportation priority effective? Environ. Sci. Pollut. Control Ser. https://doi.org/10.1007/s11356-021-17871-y.

Zhu, L., Zhang, Y., Wu, Z., Zhang, C., 2021. Spatio-Temporal Characteristics of SO2 across Weifang from 2008 to 2020, vol. 18, 12206, 22.