The impact of COVID-19 on NO₂ and PM₂.₅ levels and their associations with human mobility patterns in Singapore

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ABSTRACT
The decline in NO₂ and PM₂.₅ pollutant levels were observed during COVID-19 around the world, especially during lockdowns. Previous studies explained such observed decline with the decrease in human mobility, overlooking the meteorological changes that could simultaneously mediate air pollution levels. This study aimed to re-evaluate the impact of COVID-19 on NO₂ and PM₂.₅ pollutant levels in Singapore, by incorporating the effect of meteorological parameters in predicting NO₂ and PM₂.₅ baseline in 2020 using machine learning methods. The results show that the mean NO₂ and PM₂.₅ declined by 12% and 19%, which were less than the observed drops (i.e. 54% and 29%, respectively) without considering the effect of meteorological parameters. As two proxies for change in human mobility, taxi availability and carpark availability were found to increase and decrease by a maximum of 12.6% and 9.8%, respectively, in 2020 from 2019. Two correlation analyses were conducted to investigate how human mobility influenced air pollutant levels. One between daily PM₂.₅ and mobility changes at a regional scale and the other between weekly NO₂ and mobility changes at a spatial resolution of 0.01°. The NO₂ variation was found to be more associated with the change in human mobility and a cluster of stronger correlations was found in the South and East Coast of Singapore. Contrarily, PM₂.₅ and mobility had a weak correlation, which could be due to the limit of a coarse spatial resolution.

1. Introduction
The outbreak of the COVID-19 pandemic has led to unprecedented scales of city-wide and nationwide lockdowns around the world to reduce human contact and transmissions (Lai et al. 2020; Yin et al. 2021). Consequently, the restrictions on human mobility within the country drastically decreased emissions coming from public and private vehicular transportations (Chow et al. 2020; Doumbia et al. 2021). Singapore, a Southeast Asian megacity, is no exception to this disruption (Dickens et al. 2020; Li and Tartarini 2020). On 7 April 2020, the Singapore government announced the commencement of a nationwide lockdown locally known as the ‘Circuit Breaker’ (Ministry of Health 2020a). This measure heavily restricted outdoor movements including the commute to work, school, and other activities. This has reportedly led to a reduction in traffic volume by 60% (Tan 2020) during the Circuit Breaker from April to May 2020, accounting for at least 44% reduction in emissions from transport-related sources (Jiang et al. 2021). The Circuit Breaker was then followed by three reopening phases (Ministry of Health 2020b).
which led to a rebound of vehicular greenhouse gas emissions as mobility increased (Di Domenico et al. 2020; Jiang et al. 2021; Velasco 2021; Zhu, Mao, and Zhang 2020).

Unlike cities suffering from severe air pollution where lockdown has reportedly resulted in an improvement in air quality (Liu et al. 2021; Bao and Zhang 2020; Fu, Purvis-Roberts, and Williams 2020; Kerimray et al. 2020), Singapore generally experiences a low level of air pollution mainly in the form of PM2.5 even in the pre-COVID days (Zhu, Mao, and Zhang 2020). Vehicular emissions constitute one of the constant and major sources of air pollution in Singapore (National Environment Agency (NEA) 2021a). In addition, the occurrence of transboundary haze as a result of agricultural land clearance in the neighbouring countries (i.e. Malaysia and Indonesia) periodically affects Singapore’s air quality particularly from August to October during the Southwest monsoon season (National Environment Agency (NEA) 2021a). In this context, the change in human mobility in the forms of vehicular traffic during and after Singapore’s Circuit Breaker could therefore potentially lead to a spatial-temporal variation in air quality.

Since the onset of COVID-19 and the enforcement of lockdown measures, a plethora of studies investigated the effect of lockdown on air pollution around the world (Addas and Maghrabi 2021). The decline in air pollutant levels was observed during COVID-19 around the world, especially during lockdowns (Archer et al. 2020; Bao and Zhang 2020; Li and Tartarini 2020; Otmani et al. 2020; Zhu, Mao, and Zhang 2020). Nevertheless, these studies overlooked the meteorological changes (e.g. rainfall, wind speed) that could affect air pollution levels simultaneously with the decrease in human mobility. In this regard, the effect of COVID-19 on air pollution could potentially be over- or under-estimated. Consequently, this study aims to re-evaluate the impact of COVID-19 on PM2.5 and NO2 in Singapore by taking meteorological changes into account.

2. Literature review

Studies on air pollution during lockdown generally concluded that there was a substantial reduction in air pollution levels during the COVID-19 lockdown period compared to the pre-lockdown period (Addas and Maghrabi 2021; Archer et al. 2020; Bao and Zhang 2020; Faridi et al. 2021; Kanniah et al. 2020; Li and Tartarini 2020; Otmani et al. 2020; Zhu, Mao, and Zhang 2020). Several air pollutants were being studied, among which NO2 and PM2.5 were found to have the most prominent decline during the lockdown period (Faridi et al. 2021). For instance, Sale city (Morocco) experienced 96% reduction in NO2 during the lockdown period (Otmani et al. 2020), and reduction in PM2.5 was reported ranging from 76.5% in Malaysia, 58% in Spain and 53.1% in Delhi (Faridi et al. 2021). The decline in PM2.5 and NO2 levels during lockdown has been largely attributed to the reduced mobility (Addas and Maghrabi 2021; Calafiere, Macdonald, and Singleton 2022; Faridi et al. 2021; Syed et al. 2021). This is potentially due to that vehicular emissions and road transport are the most notable sources of ambient PM2.5 and NO2 (Al-Naimi, Balakrishnan, and Goktepe 2015; European Environmental Agency 2019). Bao and Zhang (2020) reported strong associations between the decrease in air pollution and travel restrictions in 44 cities in northern China. In the U.S., Archer et al. (2020) also found a strong correlation between the decline in NO2 level and reduced mobility index (MI), but found a slight increase in PM2.5 level and no correlation between PM2.5 and MI during April 2020. This was likely due to the unchanged operation of the major sources of PM2.5 in the U.S., that is, diesel-based commercial trucks and coal-based electricity generation. Overall, this suggests that the degree of the impact of restricted mobility on air pollution is contextual and location specific.

In Singapore, only a few studies (Li and Tartarini 2020; Velasco 2021; Zhu, Mao, and Zhang 2020) investigated the impact of circuit breaker on mobility and air pollution. Zhu, Mao, and Zhang (2020) concluded that workplace mobility had a significant positive relationship with PM2.5 levels between 15 February to 1 June 2020. Li and Tartarini (2020) reported a 29% and 54% decrease in PM2.5 and NO2 levels during the 2020 lockdown period (7 April–11 May) compared to the same period in previous years. Such changes in PM2.5 and NO2 were found to be significantly associated with reduced mobility (i.e. HDB carpark availability, Apple driving mobility index, and Google Public transit index) (Li and Tartarini 2020).

However, most existing studies did not quantify the effect of meteorological changes on air pollutant levels during COVID-19. Besides mobility, it’s well evident that meteorological factors, such as wind speed, wind, wind direction, temperature, precipitation, and humidity affect air pollution levels (Fung and Wu 2014; Hua et al. 2021; Jiang et al. 2021; Seinfeld and Pandis 2016; Syed et al. 2021; Yousefian et al. 2020). To date, most studies only compared the air pollution during lockdown with a baseline value (i.e. the estimated 2020 air pollutant level without COVID-19 measures) calculated from historical pollution data. When meteorology was accounted for, the meteorological data were simply used for qualitative interpretation of the measured air
pollutant level in 2020 (Faridi et al. 2021). Likewise, Li and Tartarini (2020) only used meteorological data to demonstrate that the monthly averaged meteorological parameters (i.e. temperature, relative humidity, daily rainfall and wind direction) in Singapore during April–May 2020 were not significantly different from those of the same time period in the previous years. It thereby justified their conclusion that the meteorology condition didn’t have much influence on the air pollution level of their period of interest. However, this conclusion may not be reliable as it rests on a comparison of the monthly average of the studied period alone.

Otmani et al. (2020) observed increased wind speed, humidity and precipitation during the lockdown in Sale city (Morrocco), which could decrease air pollutant concentration alongside the positive impact of lockdown restriction and reduced transportation. At the same time, unfavourable meteorological conditions can offset the positive impacts of lockdown. For example, Hua et al. (2021) reported that the control measures reduced PM$_{2.5}$ by 12 μg/m$^3$ in Beijing, whereas the meteorology contributed to an increase of 30 μg/m$^3$ in PM$_{2.5}$, resulting in an increased PM$_{2.5}$ level during the lockdown. This paper thus, argues that the effect of COVID-19 on air pollution could potentially be over- or under-estimated when meteorological factors and haze are not considered in their evaluation.

Concerning the meteorological impact on air pollution, we suggest that it is important to quantitatively differentiate the impacts of lockdown and meteorology on air pollutant levels during COVID-19, in order to correct for possible over- or under-estimation. To do so, this study estimated the baseline air pollution level for 2020, the air pollution level without the impacts from COVID-19, and no change in anthropogenic factors, using meteorological parameters (i.e. rainfall intensity, speed, wind direction, temperature and relative humidity). We also included the impact of transboundary haze in the baseline estimation. For instance, we posit that a comparatively haze-free condition in Singapore in 2020 (Taufik 2020) compared to 2019 could suggest a smaller increase in the existing PM$_{2.5}$ and NO$_2$ levels. Moreover, this study made two improvements to have a more comprehensive understanding of the impact of COVID-19 on air pollution. To account for the variability of the lockdown measures and to increase comparability of results, this study analysed the air pollutants concentration trend spanning the entire year of 2020, rather than confining analysis to a pre-defined lockdown period. Singapore had implemented different phases of the measure before opening up in 2020. Expanding the period of interest from months to a year can avoid bias by covering a wide range of situations from complete lockdown, partial lockdown, and gradual opening up, to complete opening up phases. Considering the spatial nature of both air pollution and mobility and the fact that the correlation between air pollution and mobility could vary spatially, this study also conducted spatial autocorrelation analysis to identify clusters of high correlation between air pollution and mobility, or in other words, areas where mobility variation correlated more to air pollution change.

In short, this study has three objectives: 1) To quantify the continuous changes in PM$_{2.5}$ and NO$_2$ throughout the entire year of 2020 in Singapore, with the use of meteorological data to predict the 2020 baseline for comparison of air pollution levels before, during, and after COVID-19 lockdown, 2) to evaluate the association between changes in air pollution and mobility throughout 2020 for both PM$_{2.5}$ and NO$_2$ and 3) to identify clusters of stronger correlation between PM$_{2.5}$ or NO$_2$ and mobility by investigating the spatial autocorrelation. Results from this study can be used to understand the impact of human mobility patterns, in particular the vehicular traffic patterns, on air quality and to inform effective and targeted strategies for reducing air pollution levels in the future beyond the COVID-19 period. Although other anthropogenic factors (e.g. industrial and residential activities) could also be correlated to air pollution levels, this study focuses on the correlation between air pollution and human mobility changes.

3. Material and methods

3.1. Study area and data sources

This study examines the potential impact of mobility changes on air quality at the national, regional, and planning area scales in the mainland of Singapore. The region and planning area boundaries are based on the division by the (Urban Redevelopment Authority (URA) 2021), the urban planning authority of Singapore (Figure 1). Data sources are listed in Table 1. NO$_2$ data was sourced from the Sentinel-5P TROPOMI level 3 product, a global dataset at a high spatial resolution of 0.01º, and a revisit time of around one day. We downloaded the NO$_2$ data from the Google Earth Engine Data Catalogue (Google Developers 2021) for analysis, while we sourced the PM$_{2.5}$ data from the National Environment Agency (NEA) Application Programming Interface (API) (National Environment Agency (NEA) 2021c). The data is of high velocity (temporal resolution) and updated every hour but is relatively coarse with observations provided for five regions in Singapore. We obtained the Housing Development Board (HDB) carpark availability, taxi availability, and total taxi
population information from the DataMall API (Land Transport Authority (LTA) 2021). Carpark data is available at one-minute interval, and taxi availability is available at 30-s intervals. For subsequent analyses, we normalized the taxi availability data according to the total taxi amount change in the monthly data of Singapore from 2019 to 2020.

This study made comparisons between two sets of data. In the first comparison, using a higher temporal resolution of daily data but a lower spatial resolution of regional data, we compared the trend of air pollution change and mobility change. The former is indicated by PM$_{2.5}$ levels and the latter by HDB carpark or taxi availabilities. HDB carpark availability represents the percentage of available parking lots in each HDB building. As approximately 81% of the entire Singaporean population lives in HDB flats (Singapore Statista 2021), HDB carpark availability can be used as a proxy for human mobility in Singapore. Taxi availability represents the number of taxis that is available for hire at a certain time. A higher carpark availability and a lower taxi availability indicate higher human mobility. As PM$_{2.5}$ measurements were only available at coarse resolution (i.e. five regions in Singapore), a higher temporal resolution was used. Considering that mobility could have lagging impacts on air quality, we resampled hourly measurements to daily mean PM$_{2.5}$. In other words, air quality may not change immediately as soon as mobility changes. However, weekly cycles could impact (whether it is weekday or weekend) when a daily measurement was used. The impact of weekly cycles could be hugely different in 2019 and 2020 as influenced by COVID-19. To exclude this difference in our study, we used weekly NO$_2$ in our second comparison. A lower temporal resolution of weekly data but a higher spatial resolution of data at 0.01° was used to compare the changing trends in NO$_2$ levels and taxi availability. The investigation of the correlation between NO$_2$ and mobility focused on the

### Figure 1
Five regions and planning area boundaries of Singapore were used in this study. Data source: URA (2021).

### Table 1
A summary of temporal and spatial resolutions before and after data resampling.

| Data source          | NO$_2$ | PM$_{2.5}$ | Meteorological parameters | Carpark Availability | Taxi Availability |
|----------------------|--------|------------|---------------------------|----------------------|------------------|
|                      | Sentinel-SP TROPOMI level 3 product |                       | National Environment Agency (NEA), Singapore | Land Transport Authority (LTA), Singapore |
| Temporal resolution  | Original | Daily     | Hourly Up to 1 min interval | 1 minute             |
|                      | Resampled | Weekly   | Daily                      | 30 seconds            |
| Spatial resolution   | Original | 0.010°    | Regional Station locations | Exact Locations      |
|                      | Resampled |          | Regional                   | Exact Locations      |

Notes: 1. The daily and regional meteorological parameters were used for 2020 PM$_{2.5}$ baseline prediction, while meteorological parameters of weekly resolution and 0.01° spatial resolution were used for 2020 NO$_2$ baseline prediction; 2. The meteorological parameters and haze level were used for 2020 NO$_2$ and PM$_{2.5}$ baseline predictions. Meteorological parameters include rainfall, wind speed, wind direction, temperature, and relative humidity.
correlation between NO$_2$ level and taxi availability changes because carpark availability was coarse-grained and had scattered distribution, thus may not be suitable for calculating its correlation with NO$_2$ which was sourced at a fine spatial resolution of 0.01°. Moreover, considering that the outgoing cars do not indicate the movement trajectory, carpark availability cannot be used to represent the mobility at carpark locations. Therefore, carpark availability will not be a reliable proxy for correlation analyses in fine resolutions. Compared to carparks which are stationary and constrained to HDB residential locations, taxis travelling around the island can cover a wider range of locations. In addition, we could resample taxi availability to 0.01° so that it has the same resolution as NO$_2$ to calculate their correlation. Therefore, we selected taxi availability as the mobility proxy for the comparison at a higher spatial resolution. In summary, we resampled the original data as described in Table 1.

3.2. NO$_2$ and PM$_{2.5}$ levels from 2019 to 2020

To study the impact of COVID-19 on NO$_2$ and PM$_{2.5}$ levels from 2019 to 2020, this paper estimated the 2020 baseline pollution (i.e. 2020 air pollutants levels without COVID-19 measures), and used this as the basis of comparison, which will be referred to as the baseline value in this paper. Changes in NO$_2$ and PM$_{2.5}$ levels were calculated as the differences between the measured air pollutant level in 2020 and the baseline. We calculated the baseline from the meteorological parameter values to differentiate the impact of meteorological parameters on air pollution levels from that of COVID-19. We first resampled the meteorological parameters (i.e. rainfall intensity, wind speed, wind direction, temperature, and relative humidity) to a daily resolution. Subsequently, we applied the ordinary kriging method (Wackernagel 2003) to interpolate each meteorological parameter value from the locations of weather stations into a continuous surface of spatial resolution of 0.01°. Figure 2 shows the locations of the weather stations. Some stations have all meteorological parameters measured while the remaining stations only have rainfall measurements. Given that the rain gauges used in these two types of weather stations have the same instrument specifications, this study combined the rainfall measurements from both types of weather locations for interpolation. The interpolated meteorological parameters were used to predict the PM$_{2.5}$ baseline. When predicting the NO$_2$ baseline, we resampled the interpolated meteorological data from a daily resolution to a weekly resolution. Moreover, we also included the relative number of haze searches in Google Trends (Google 2021) from 2019 to 2020 as an input variable to account for the influence of transboundary haze in September 2019 on NO$_2$ and PM$_{2.5}$ levels. In addition, we adopted location information, including the longitudes and latitudes, or the categorical regions (i.e. Central, North, South, West, and East) as the inputs to predict NO$_2$ or PM$_{2.5}$ baselines, respectively. The five regions were encoded using one hot encoder. The

![Figure 2](image-url). Location of weather stations in Singapore (National Environment Agency (NEA) 2021d).
location was considered an input variable as they were related to spatially varied factors, such as land covers and land uses that could influence NO$_2$ and PM$_{2.5}$ levels (Xu et al. 2016), or contributions from consistent emissions from sectors other than road transport.

As suggested by Zhan et al. (2018), we applied the Random Forest (RF) machine learning method in this study to predict the air pollutant baseline in 2020. We used meteorological, location, and haze information in 2019 as input variables and the NO$_2$ and PM$_{2.5}$ levels in 2019 as output variables. 80% of 2019 data was used in training, and the remaining 20% was used to validate the trained model. Using the trained model based on 2019 data, we predicted the NO$_2$ and PM$_{2.5}$ baselines in 2020 from the meteorological, location, and haze information in 2020. The changes in NO$_2$ and PM$_{2.5}$ were therefore calculated from the differences between 2020 measurements and 2020 baseline predictions. The change in PM$_{2.5}$ was in a daily resolution in each region. The change in NO$_2$ was in a weekly resolution but with a spatial resolution of 0.01°.

### 3.3. Taxi and carpark availabilities from 2019 to 2020

The changes in taxi and carpark availability were calculated from the differences between measurements in 2020 and 2019. The Stringency Index of Singapore fell from a peak of 82.41 (on 1 May 2020) during the lockdown to 45.37 (on 19 June 2020) after the lockdown and remained unchanged until the end of 2020 (Ritchie et al. 2020). The Stringency Index (ranges from 0 to 100, a higher score indicates a stricter response) is a composite measure based on policy response indicators in different countries. The impact of mobility restriction policies enforced at the beginning of the pandemic, such as workplace closure and restrictions on the social gathering, last throughout 2020. The change in carpark availability for each region was obtained in a daily temporal resolution at a regional scale and the change in taxi availability was obtained in a weekly temporal resolution with a spatial resolution of 0.01°.

### 3.4. Correlations between air pollution and mobility changes

We carried out correlation analysis on two pairs of variables, one between PM$_{2.5}$ level change and mobility change, and the other between NO$_2$ level change and mobility change. We adopted three correlation methods – Pearson, Spearman’s Rank, and Kendall Rank Correlations – to accommodate a large number of data points and the different data properties of these data points (Chok 2010). Pearson correlation evaluates the linear relationship between two continuous variables. Nevertheless, Pearson correlation is very sensitive to outliers, which may lead to a weak correlation for data distributed in high skewness (Akoglu 2018; Chok 2010). Spearman’s Rank Correlation evaluates the monotonic relationship, which is based on the ranked values for each variable rather than the raw data, thus it is not limited to some of the assumptions (e.g. normal distribution of variables). Kendall Rank Correlation is similar to Spearman’s rank correlation but usually has a smaller value (Berg van den 2021). Kendall Rank Correlation is calculated based on concordant and discordant pairs, which is less sensitive to errors, such as null values in the dataset (Tarsitano 2009). Due to the large quantity and spatial variety of data points (421 grid points), a single correlation method (e.g. Pearson) may fail to capture other types of bivariate relationships (e.g. non-normally distributed data). Therefore, we calculated the correlations between the two sets of variables and their significance by three correlation methods: Pearson, Spearman’s Rank, and Kendall Rank Correlations. All the three correlations’ coefficients vary from 1 to −1, indicating positive and negative correlations, respectively. A value close to 0 indicates a very weak correlation.

We conducted the correlation analyses for PM$_{2.5}$ level and mobility changes on both the national scale and regional scale. For NO$_2$ level and mobility changes, the correlation analyses were performed on a national scale, the planning area level (URA, 2021), and at a spatial resolution of 0.01°. The correlation analysis only includes the points with a minimum of 25 observations for both NO2 and mobility during the studied period.

### 3.5. Hot spot analysis on correlations between mobility and air quality changes

We used Getis-Ord Gi* statistic method to determine statistically significant hot and cold spots for the three correlation coefficients (i.e. Pearson’s r, Spearman’s rho, and Kendall’s τ) between NO$_2$ and taxi availability changes. To determine the most appropriate threshold distances, we analysed the incremental spatial autocorrelation by distance for 10 distance bands. The distance band with the peak z-score was selected as the threshold distance.

### 4. Results and discussion

#### 4.1. Impact of COVID−19 on NO2 and PM2.5 levels

The mean NO$_2$ tropospheric column densities in 2019 and 2020 were plotted in Figure 3. Some weeks in 2019
or 2020 had no measurement and were excluded from the comparison in the plot. Overall, NO2 levels in 2020 were lower than those in 2019 in the first half of the year, especially from Week 5 (29 January to 4 February) to Week 20 (14 May to 20 May). Similarly, from the daily comparison of regional PM2.5 concentrations in 2019 and 2020 in Figure 4, we found that there was an overall decrease in PM2.5 levels from 2019 to 2020. This decrease was more significant in September 2020, due to the severe haze in September 2019 and a haze-free condition in September 2020. However, as a result of the coarse spatial resolution of PM2.5 levels, we observed little difference among the five different regions.

Figure 5 compares the predicted and the measured NO2 levels including both training and testing datasets in 2019 using the RF machine learning method. The mean absolute error (MAE), the root means square error (RMSE), as well as $R^2$ from the training and testing datasets, are summarized in Table 2. The trained model shows good performance with small errors and high accuracy. This trained model was therefore used to predict the NO2 baseline in 2020.

Using the RF method, the predicted PM2.5 and the measured PM2.5 levels from the training and testing datasets in 2019 were obtained (Figure 6). The MAE, RMSE and $R^2$ in training and testing datasets are summarized in Table 3. The model did not perform well at high PM2.5 levels (beyond 60 µg/m$^3$), and a difference between predicted and measured values was observed during validation. This could potentially result from the limited number of high PM2.5 records (i.e. only during the haze period) for training and testing. However, there was no severe haze in 2020 and the measured PM2.5 did not exceed 60 µg/m$^3$. Hence, the predicted results maintain their validity.

From the comparison of feature importance of each input variable in the RF model (Figure 7), a relatively similar degree of importance for NO2 modelling while much higher importance of haze (i.e. higher than 0.5) in PM2.5 modelling were found. Locations and wind properties (speed and direction) are comparatively more important (i.e. higher than 0.12) in NO2 modelling. Comparatively, the importance of location is very low in PM2.5 modelling, implying little difference in the PM2.5 comparison across different regions, potentially due to the large study area of the regions preventing finer detection of variation.

From the comparison of the measured NO2 levels before Week 20 (May 14 to May 20), a decrease in NO2 levels from 2019 to 2020 was observed Figure 8. However, there was an increase in NO2 levels from the 2020 baseline to the 2020 measurements during Weeks 11–18 (12 March to 7 May), followed by a significant decrease (i.e. about 38%) in NO2 levels in Week 20. These findings suggest that the impact of COVID-19 on NO2 levels could be possibly overestimated without considering the effect of meteorological parameters in Singapore. To further validate this finding, we also compared our results with the literature. Li and Tartarini (2020) found that the mean NO2 decreased by 34%, while we found that the mean NO2 only decreased

![Figure 3](image_url)

**Figure 3.** A comparison of weekly NO2 measurements in 2019 and 2020. Week 1 represents the week from January 1 to January 7.
by 12% during the lockdown in Singapore (7 April to 11 May 2020). Similarly, without baseline prediction, the effect of COVID-19 on PM$_{2.5}$ levels could also be overestimated. For instance, in Figure 9, by comparing the measured PM$_{2.5}$ levels in 2019 and 2020, there was a significant decrease in PM$_{2.5}$ levels up to 67% during the lockdown period. However, by comparing the predicted baseline and the measurements in 2020, the decrease was only up to 36%. Li and Tartarini (2020) found that the mean PM$_{2.5}$ decreased by 29% while we found that the mean PM$_{2.5}$
only decreased by 19% during the lockdown in Singapore. In NO₂ and PM$_{2.5}$ baseline predictions of this study, the effect of haze and meteorological parameters in each location were taken into consideration, providing a more reliable estimation of the change in air pollutant levels during COVID-19, including both the lockdown and opening-up period. By only taking the lockdown period into the study and simply comparing the measured NO₂ and PM$_{2.5}$ levels in 2020 and 2019, the observed decrease during the lockdown could result in a direct intuition that the lockdown helped in reducing NO₂ and PM$_{2.5}$ levels significantly, which may overestimate the effect of lockdown. However, the overall change in PM$_{2.5}$ is not obvious. This could be due to a change in PM$_{2.5}$ emissions from other sources occurring at the same time when there was a change in PM$_{2.5}$ emissions from road transport. Given household emission is one of the top sources of PM$_{2.5}$ emission (European Environmental Agency 2019), the work-from-home arrangement during COVID-19 can lead to an increased household emission, offsetting the decreased vehicular PM$_{2.5}$ emission on the road.

4.2. Impact of COVID-19 on carpark and taxi availability

Figure 10 shows the weekly comparison of (a) taxi availability and (b) carpark availability across Singapore in 2019 and 2020. The taxi availability was normalized by the

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**Table 2. Summarized errors in NO₂ modelling.**

|        | MAE (mol/m$^2$) | RMSE (mol/m$^2$) | $R^2$ |
|--------|-----------------|------------------|------|
| RF     |                 |                  |      |
| Training | 2.305e-06     | 4.510e-06       | 0.996|
| Testing  | 5.890e-06     | 1.091e-05       | 0.971|

**Table 3. Summarized errors from RF in PM$_{2.5}$ modelling.**

|        | MAE (µg/m$^3$) | RMSE (µg/m$^3$) | $R^2$ |
|--------|----------------|-----------------|------|
| RF     |                |                 |      |
| Training | 1.059         | 1.670           | 0.964|
| Testing  | 2.829         | 4.995           | 0.607|

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**Figure 5.** Predicted NO₂ versus the measured NO₂ levels ($10^{-3}$ mol/m$^2$) from the (a) training and (b) testing datasets using RF.

**Figure 6.** Predicted PM$_{2.5}$ versus the measured PM$_{2.5}$ levels ($10^{-3}$ mol/m$^2$) from the (a) training and (b) testing datasets using RF.
monthly total taxi count. From an overview, the total number of available taxis has little difference between 2019 and 2020 with no clear pattern across the island. However, it is worth noting that the total number of available taxis in April – June 2020 was higher than that for the same period in 2019 by up to 12.6%. On the other hand, the weekly comparison of carpark availability across Singapore dropped significantly at the beginning of April (Week 13) in 2020 by up to 9.8% and remained lower than that in 2019 till the end of 2020. In general, the pattern of the change in carpark availability was more apparent than that of taxi availability. The sudden drop in carpark availability following the start of lockdown in Singapore in early April suggests that more private vehicles were parked at home and implies lower mobility. This is congruent with the findings from Li and Tartarini (2020). Similarly, the increase in the number of available taxis during the lockdown in 2020 as compared to 2019 also implies a decrease in human mobility. After the lockdown, carpark availability increased slowly, but remained lower than the same period last year, indicating the continued impact of COVID-19 on mobility. However, taxi availability decreased back to the same level as in 2019 in a relatively short period.

4.3. Correlation between PM2.5 and mobility

The correlation between PM$_{2.5}$ levels and carpark availability or taxi availability changes was extremely weak and insignificant across Singapore (Tables 4–5). Among the five regions, the correlation result between PM$_{2.5}$ and carpark availability only showed a statistically significant but weak positive correlation in the central region. This is due to the small change observed in PM$_{2.5}$ levels as discussed in Section 4.1. Moreover, little variation was detected across the five regions mainly due to the reason that the data was

![Feature importance in (a) NO$_2$ and (b) PM$_{2.5}$ modelling using RF.](image-url)
Figure 8. Comparison among measured NO$_2$ levels and predicted baselines in 2020. Week 1 represents the week that started on January 1st.

Figure 9. Comparison among measured PM$_{2.5}$ levels in 2019, 2020 and predicted baselines in 2020.
Figure 10. A general comparison of (a) taxi availability and (b) carpark availability in 2019 and 2020. Week 1 represents the week that started on January 1st.

Table 4. Summary of three types of correlation results in between PM$_{2.5}$ level and the average carpark availability changes in the whole island and five regions.

| Region    | Pearson  | Spearman’s Rank | Kendall Rank |
|-----------|----------|-----------------|--------------|
|           | r        | rho             | tau          |
|           | p        | p               | p            |
| Whole Island | 0.029    | 0.026           | 0.017        |
|            | 0.212    | 0.279           | 0.275        |
| Central    | 0.122*   | 0.103*          | 0.071*       |
| East       | 0.077    | 0.093           | 0.062        |
|            | 0.149    | 0.079           | 0.079        |
| North      | −0.052   | −0.057          | −0.039       |
|            | 0.331    | 0.282           | 0.266        |
| South      | 0.043    | 0.032           | 0.023        |
| West       | 0.078    | 0.063           | 0.043        |
|            | 0.139    | 0.237           | 0.228        |

*Statistics are significant at 95% significance level.
Correlation between the correlation of NO$_2$ level and taxi availability changes across Singapore were $-0.320$ ($p = 0.049$), $-0.289$ ($p = 0.081$), $-0.210$ ($p = 0.067$), respectively. In general, the three correlation methods showed similar spatial distributions at a spatial resolution of $0.01^\circ$ and at the resolution of the planning area level (Figures 11). Areas such as the South and East Coast areas, showed significant negative correlations, suggesting that the change in taxi availability in these places had a stronger correlation with the change in NO$_2$ levels when the correlation analysis was performed for each point at a higher spatial resolution. Pearson correlation coefficients for some points were less than $-0.5$, exceeding the island-wide average of $-0.32$, while the correlation coefficients for some points in the northern area were positive. This contrast indicates a variation in correlations across the island. The reason for the positive correlation in the north may be due to its limited taxi availability. There are a few points in the north that have a very limited number of taxis available (i.e. below 20 units per week), as well as the corresponding change, making the change in taxi availability not representative of the mobility change. This spatial variation may also being averaged into five regions, limiting a finer detection of spatial patterns. The spearman’s rank correlation coefficient of the whole island (0.026) was lower than the result (0.14) in Li and Tartarini’s study (2020). This may be due to their overestimation of the PM$_{2.5}$ level as they did not consider the meteorological parameters in estimating the 2020 baseline.

4.4. Correlation between NO$_2$ and mobility

The mean coefficients of Pearson Correlation, Spearman’s Rank Correlation, and Kendall Rank

| Region      | Pearson r | Spearman's ρ | Kendall τ | Kendall p |
|-------------|-----------|---------------|-----------|-----------|
| Whole Island| 0.054     | 0.031         | 0.265     | 0.020     |
| Central     | 0.102     | 0.122         | 0.065     | 0.082     |
| East        | 0.083     | 0.099         | 0.078     | 0.063     |
| North       | 0.064     | 0.023         | 0.276     | 0.027     |
| South       | 0.075     | 0.054         | 0.411     | 0.056     |
| West        | 0.073     | 0.073         | 0.244     | 0.054     |

Table 5. Summary of three types of correlation results in between PM$_{2.5}$ level and the average taxi availability changes in the whole island and five regions.
Figure 12. Hot and cold spots of (a) Pearson, (b) Spearman’s Rank, (c) Kendall Rank correlation coefficients between NO₂ level and taxi changes, for each point representing 0.01° pixel, and URA Planning Areas.
explain the insignificant correlation results observed in the regional analysis between PM$_{2.5}$ and carpark availability changes.

4.5. Spatial autocorrelation of correlation coefficients

We run spatial autocorrelation for each NO$_2$ data point, as well as for each planning area using all observations within the corresponding planning area. The hot and cold spot analysis using the three correlation methods (Pearson, Spearman’s Rank and Kendall Rank) revealed generally similar spatial patterns (Figures 12). Notably, there is a clear north-south division in the statistically significant hot and cold spots, with the cold spots in the South and East Coast area, and hot spots in the north. For the non-parametric Spearman’s and Kendall correlations, the strength of the confidence in the south is slightly weaker but still significant. This suggests that, in the South and East Coast areas, a decrease in mobility represented by an increase in taxi availability was more likely to lead to a reduction in NO$_2$ due to the cluster of stronger correlations compared to other areas.

5. Conclusions

Previous research studies have observed declines in air pollution around the world due to COVID-19 lockdowns. Similarly, this study also found that in 2020, both NO$_2$ and PM$_{2.5}$ declined (by a maximum of 38% and 36%, respectively) from the estimated 2020 baseline in Singapore. However, the mean NO$_2$ and PM$_{2.5}$ declined by 12% and 19%, which were less than the observed drops (i.e. 54% and 29%, respectively) without considering the different meteorological parameters (i.e. rainfall, wind, humidity and temperature). This implies the effect of COVID-19 on reducing NO$_2$ and PM$_{2.5}$ levels in Singapore could be over-estimated if air pollution changes are studied without the consideration of meteorological factors. Taxi availability increased and carpark availability decreased by a maximum of 12.6% and 9.8%, respectively, in 2020 from 2019 during the lockdown. In general, change in NO$_2$ was found to be more associated with the change in human mobility. Only weak correlations were found between PM$_{2.5}$ levels and carpark availability. However, NO$_2$ and taxi availability showed significant correlations. Notable spatial patterns of the correlation between NO$_2$ and taxi availability were found, especially in the South and East Coast. This finding suggests that measures to reduce traffic or vehicular pollution in the South and East Coast could be effective in reducing NO$_2$ levels in these regions. Location-specific air pollution measures (e.g. car volume control in the South and East coast) can be considered.

The paper is, nevertheless, limited in certain aspects. First, a larger data volume of PM$_{2.5}$ that spanned over a longer time period is recommended in future studies for better model performance. Second, we only correlated the change in NO$_2$ and PM$_{2.5}$ to the change in mobility and did not correlate that with other anthropogenic factors (e.g. industrial, manufacturing, and residential activities) due to a lack of data on these aspects in Singapore. As emissions from other anthropogenic activities also affect NO$_2$ and PM$_{2.5}$, future studies should investigate the correlation of the changes in NO$_2$ and PM$_{2.5}$ to the change in other anthropogenic factors in addition to the change in human mobility. Third, the impacts of weekly cycles (i.e. the difference between weekday and weekend) could be investigated using measurement of a finer temporal resolution (i.e daily) instead of weekly measurements of NO$_2$ and taxi availability.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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