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**Trends of Southeast Asian urban $NO_2$, $O_3$, and $SO_2$ concentrations during COVID 19 social distancing and forecast period**

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**Abstract** COVID 19 has caused social distancing and lead to the reductions of various anthropogenic activities. Correspondingly this study has two fold objectives. First, aims to provide quantification measurement of social distancing impacts on air quality. Second, to forecast the air quality if social distancing is continued. The measured air quality parameters consist of $NO_2$, $SO_2$, and $O_3$. According to the results, the order of air quality parameters was $NO_2$<$SO_2$<$O_3$. The $NO_2$, $SO_2$, and $O_3$ levels were observed lower after social distancing than before social distancing was implemented. The reductions of $NO_2$, $SO_2$, and $O_3$ levels were 5%, 3%, and 5% respectively. Likewise, 65% of study periods (30 days) after implementation of social distancing have lower $NO_2$ than before social distancing. The exponential smoothing forecasts show the decreasing trends for $NO_2$ and $SO_{2.}$ While $O_3$ levels are estimated will remain stable after social distancing. This study has shown that the social distancing has an impact on the $NO_2$, $SO_2$, and $O_3$. Correspondingly, if the social distancing is continued, then it is estimated can provide a positive impact on urban quality.
Keywords: COVID 19, forecast, $NO_2$, $O_{3,}$ $SO_2$.

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**Introduction**

One of factors that has an effect on the urban population is the outdoor air pollution. Several important ambient air pollutants including $NO_2$, $O_{3,}$ and $SO_2$. Those air pollutants have consequences on the health of urban population.

In urban populations, $NO_2$, $O_{3,}$ and $SO_2$ have been recorded having high levels and increasing trends. The numbers of urban population exposed to $NO_2$, $O_{3,}$ and $SO_2$ were 70%, 15%, and 25% respectively (Jol and Aalst 2001, Schwela *et al*. 2012).

The origins of $NO_2$, $O_{3,}$ $SO_2$ can be related to either meteorological or anthropogenic activities (Chen *et al*. 2007). Those activities are including coal and oil burning for energy generation, industrial purposes, and vehicle activities as well. Since anthropogenic activities were also major determinant factors of air pollution, it was hypothesized that an activity restriction like social distancing will have an impact on air pollution levels.

Considering recent situation, this study aims to first measure quantitatively the impact of social distancing on urban $NO_2$, $O_3$, and $SO_2$ levels. Second, this study is also aiming to forecast the long term air pollution levels if the social distancing is continued.

**Methodology**

*Air pollutant monitoring*

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The monitored air pollutant parameters including $NO_2$, $SO_2$, and $O_3$ and all measured in $\mu g/m^3$. Those parameters were obtained daily from meteorology agency. The monitoring durations (30 days) were including before social distancing periods (March 2020) and after social distancing periods (April 2020) in Jakarta representing urban cities in Southeast Asian region.

*Wind and rainfall monitoring*

Since $NO_2$, $SO_2$, and $O_3$ levels are influenced by meteorological factors, daily wind speed and rainfall were measured as well. These meteorological data were also collected from meteorology agency.

*Exponential smoothing*

Exponential smoothing has been used widely to forecast the air quality parameters (Mahajan *et al*. 2018). Exponential smoothing has several advantages, first it is easy to implement and second it able to incorporate the dynamic and seasonality trend in the data (Roy *et al*. 2018).

The exponential smoothing principle based on setting smoothed observation ($S_2$) to original observation ($y_1$). The calculations refer to the time periods, 1,2,…,n. For the third period denoted as $S_3 = \alpha y_2 + (1-\alpha)S_2$ and so on. The smoothed series starts with the smoothed version of the second observation. For any time period t, the smoothed value $S_t$ is computed as follows.

$S_t = \alpha y_{t-1} + (1-\alpha)S_{t-1}$, with $0 < \alpha \le 1$ and $t \ge 3$.

In that equation, the constant or parameter $\alpha$ is called the smoothing constant.

**Results**

Results for the air pollutants consisting of $NO_2$, $O_3$, and $SO_2$ during COVID 19 social distancing are presented. Descriptive statistics (Figure 1, 2, 3, 4) shows the correlation of air pollutants with their environmental parameters and only $NO_2$ and $SO_2$ that have notably correlation. Regarding the environmental parameters, the air pollutant levels were not influenced by neither rainfall nor wind speed.

For all observed air pollutant levels, the comparative observations shows that the trends were always lower after social distancing than before. The notably low levels were observed especially for $NO_2$. For 65% of social distancing periods or approximately equal to 18-20 days, the $NO_2$ was lower than before social distancing periods (Figure 5, 6, 7). The reductions of $NO_2$, $SO_2$, and $O_3$ levels were 5%, 3%, and 5% respectively.

Figure 8, 9, and 10 show the autocorrelation function (ACF) of daily air pollutant data. The ACF analysis confirms the stationary of the data. The exponential smoothing forecasts for all air pollutants if social distancing is continued confirm two trends. First, $NO_2$ and $SO_2$ were forecasted have declining trends. The forecasted $NO_2$ will drop to levels <2-3 $\mu g/m^3$ while $SO_2$ will decrease to levels equal to <10

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μg/m$^3$. Secondly, $O_3$ will remain stable at level of 150 μg/m$^3$ (Figure 11, 12, 13).

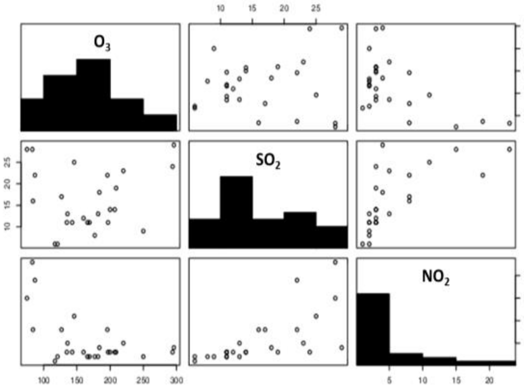


Figure 1. Correlation plots of daily $NO_2$, $SO_2$, and $O_3$.

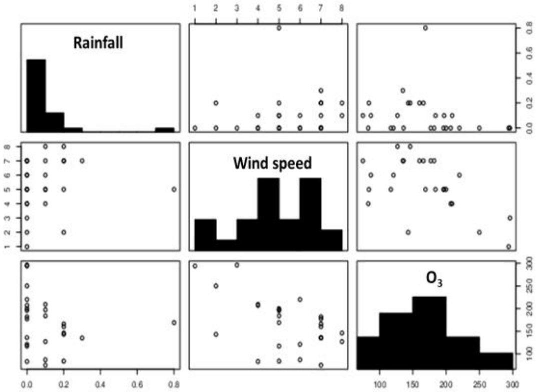


Figure 4. Correlation plots of daily $O_3$ with wind speed (km/h) and rainfall (mm/day).

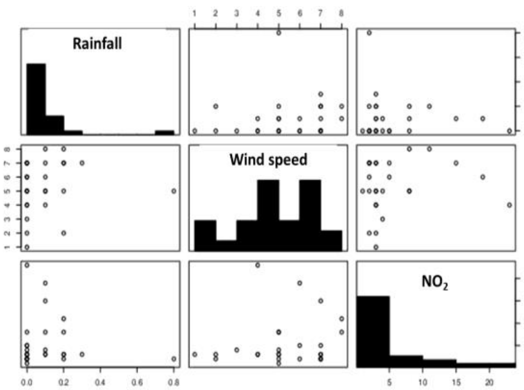


Figure 2. Correlation plots of daily $NO_2$ with wind speed (km/h) and rainfall (mm/day).

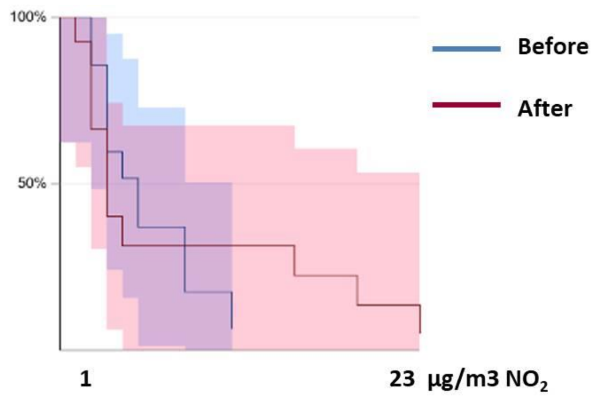


Figure 5 . Trends of $NO_2$ (μg/m$^3$) before and after social distancing.

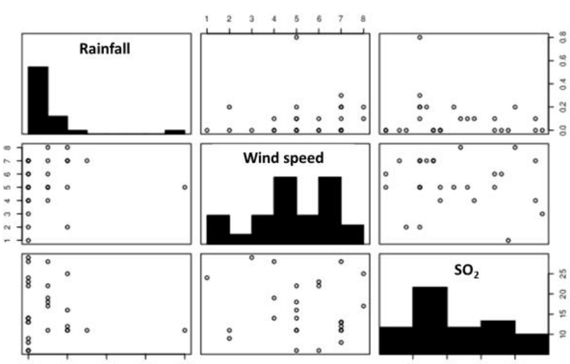


Figure 3. Correlation plots of daily $SO_2$ with wind speed (km/h) and rainfall (mm/day).

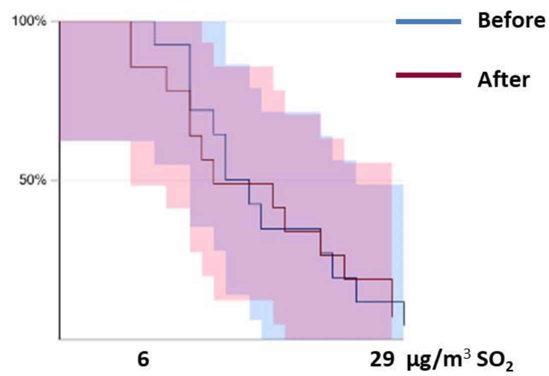


Figure 6. Trends of $SO_2$ (μg/m$^3$) before and after social distancing.

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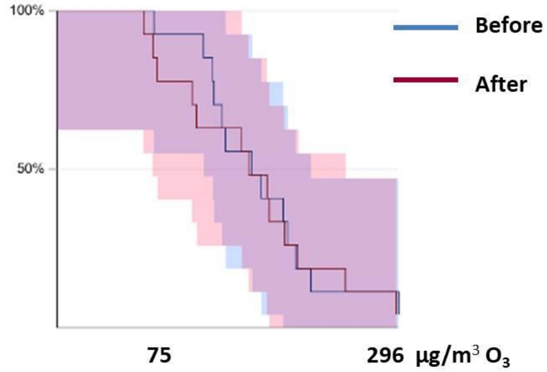


Figure 7. Trends of $O_3$ ($\mu g/m^3$) before and after social distancing.

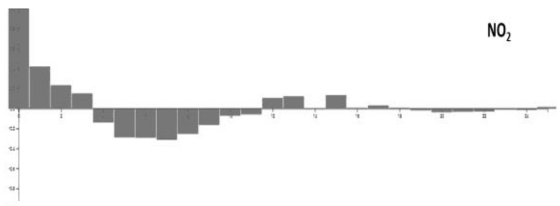


Figure 8. Autocorrelation function (ACF) of daily $NO_2$.


Figure 9. Autocorrelation function (ACF) of daily $SO_2$.

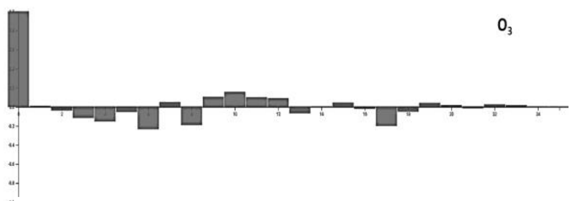


Figure 10. Autocorrelation function (ACF) of daily $O_3$.

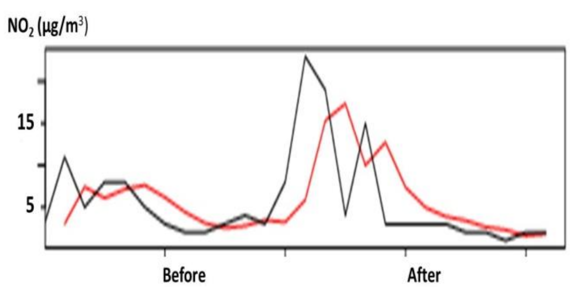


Figure 11. Exponential smoothing forecast of daily $NO_2$ (red line).

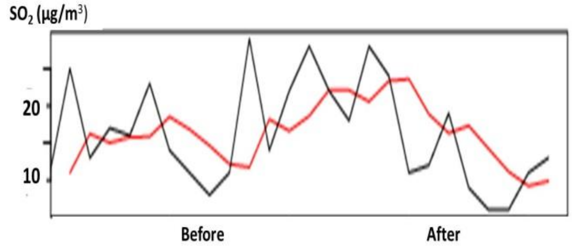


Figure 12. Exponential smoothing forecast of daily $SO_2$ (red line).

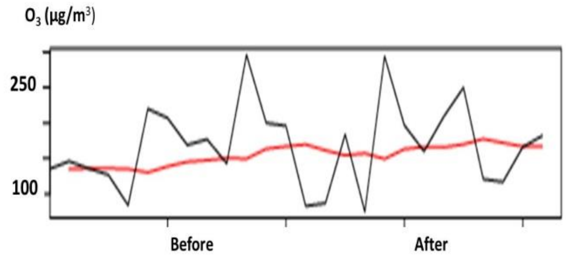


Figure 13. Exponential smoothing forecast of daily $O_3$ (red line).

**Discussion**

The daily $NO_2$ values measured in this study were comparable from results obtained from other urban cities. Zhou *et al*. (2015) recorded the $NO_2$ range (± standard deviation) was 34.9±4.9 $\mu g/m^3$. While Yoo *et al*. (2015) have divided the urban $NO_2$ ranges based on the land use classifications included residence, commerce, and industry. The $NO_2$ ranges for those land uses were 23.2±4.27 $\mu g/m^3$, 28.2±3.91 $\mu g/m^3$, and 23.8±3.55 $\mu g/m^3$ respectively. In this study, the $NO_2$ was dominated by the ranges equal to 1-5 $\mu g/m^3$ followed by 5-10 $\mu g/m^3$ and the maximum was 23 $\mu g/m^3$ (Figure 1). The $NO_2$ values were also lower after social distancing than before social distancing (Figure 1), even though there were some fluctuations observed.

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In this study $SO_2$ was higher than $NO_2$. The frequencies of $SO_2$ values equal to 10-15 μg/m$^3$ were more common compared to $NO_2$. $SO_2$ values exceeded the $NO_2$ were also reported by Zhou *et al*. (2015). They found that the $NO_2$ range (± standard deviation) was 45.0±3.9 μg/m$^3$. While Yoo *et al*. (2015) observed that the $SO_2$ was lower than $NO_2$ with ranges equal to 7.5±0.76 μg/m$^3$.

The measured $O_3$ was the highest parameters compared to $NO_2$ and $SO_2$ in this study and this also reported in other literatures. Ho (2012) reported the $O_3$ ranges were 225-546 μg/m$^3$ as observed in big cities. Likewise, Saini *et al*. (2014) reported that in Agra city, the $O_3$ was equal to 223 μg/m$^3$. In this study, the $O_3$ ranges equal to 150-200 μg/m$^3$ have high frequencies following with 75-149 μg/m$^3$ and 201-296 μg/m$^3$.

This study founds positive correlation between $NO_2$ and $SO_2$. Nonetheless, $O_3$ has inverse correlation with both $NO_2$ and $SO_2$. This trend was also reported by Saini *et al.* (2020). According to their study, the ozone follows a negative relationship with ozone precursors including $NO_2$. This inverse relationship was also observed in study by Freitas *et al*. (2020). In their results, besides negative correlation with $NO_2$ and $SO_{2,}$ the $O_3$ was higher after social distancing than before. Basically, $O_3$ is developed through complex reactions evolving $NO_x$, volatile organic compounds (VOC), and solar radiation. $O_3$ itself was a secondary pollutant with no linear relationship with its precursors and the reduction of primary air pollutants does not necessarily can cause $O_3$ reductions.

Many factors including meteorological and anthropogenic are known having contribution to the dynamics of the air pollutants ($NO_2$, $SO_2$, $O_3$). Meteorological factors are consisting of air temperature, rainfall, and wind speed (Zhou *et al*. 2015). $SO_2$ and $NO_2$ in earth surface were reported having negative correlation with atmospheric temperature. When the temperature is high then the atmosphere is instable. This will cause the thermal convection that makes air pollutants diffuse upwards resulting in lower pollutant concentrations.

Rainfall is also known having negative correlation with the air pollutants. Heavy rainfall will flush air pollutants and cause air pollutants and water droplets collide with each other during the rain. The rainwater functions to capture the pollutant particles and dissolves the pollution gases (Zhou *et al*. 2015). While rainfall tends to reduce pollutants, wind speed is known having dual effects on air pollutants. At low level, wind speed will reduce pollutants through favoring air pollutant diffusion and dilution as well. Nonetheless, at high level wind speed facilitate transports of pollutants from source and increase the pollutant levels.

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The analysis in this study shows that there was no significant correlation of air pollutants with neither rainfall nor wind speed (Figure 2, 3, 4). The study was conducted from March to April which is already near the end of rainfall season. During this time, when the rainfall was decreasing then the air pollutants should be increased as hypothesized. Nonetheless in April all measured air pollutants were decreased and lower than March or before the implementation of social distancing. Likewise, the low air pollutant levels presumably related with the other meteorological factors, in this case it can be the anthropogenic factors.

The high and even fluctuations of air pollutants are known sometimes are related to the anthropogenic factors rather than environmental factors. Zhou *et al*. (2015) identified that the urban air pollutants may be caused by the coal combustion, automobiles, road dust, biomass burning, long range transport dust, and even celebration activities. Even environmental policies, economic development, and industrial structure can also contribute to the air pollutant levels. Zhou *et al*. (2015) found that high recorded $SO_2$ were related due to the fireworks. The fireworks were used as parts of spring holiday festival celebration.

Since the anthropogenic activities have been assumed having direct impacts on air pollutants, then the restrictions of these activities are hypothesized can reduce the air pollutants. During current COVID 19 pandemic, there are restrictions of anthropogenic activities in the form of social distancing. The results in this study inform that air pollutants were lower after social distancing has been implemented and this comparable with other studies. Likewise, 65% of total days included in this study period after implementation of social distancing have lower $NO_2$ than before social distancing. While there were 50-55% of total days have low $SO_2$ and $O_3$ as well. According to Navel *et al*. (2020), there was $NO_2$ decrease by 25% during quarantine in China. A similar decreasing trend was also reported in most cities around the world. In Europe, reduction of economic activity, transportation, and traffic, especially diesel vehicles has causes drop in $NO_2$ (Anjum 2020).

A more comprehensive study on how the social distancing can slash down the air pollutants can be drawn from Freitas *et al*. (2020). Their results also confirmed similar trends observed in here, which is the general trend for $NO_2$ in social distancing period was lower than 2019 with average equal to 10 $\mu g/m^3$. The reductions of $NO_2$, $SO_2$, and $O_3$ levels were 5%, 3%, and 5% respectively as recorded in this study. While Bao and Zhang (2020) reported $NO_2$ and $SO_2$ decreased by 25% and 7%.

Air pollutants have been object of forecasting study. The result obtained from this study is needed and very useful to design and develop the air pollution management framework. Various methodology have been developed and used in air pollutant forecasts, including time-series data regression, autoregressive moving average (ARIMA), and even Adaptive Neuro-Fuzzy Inference System that has been reported more accurate (Zeinalnezhad *et al*. 2020, Zhu *et al*. 2020). By using ARIMA, Sharma *et al*. (2018) have made 365 day forecasts for $NO_2$, $SO_2$, and $O_3$. Based on their study, they have forecasted an increase for $NO_2$, $SO_2$, and $O_3$. This study forecasts the reductions of $NO_2$ and $SO_2$, while $O_3$ remains stable.

**Conclusion**

This study has succeeded to provide more comprehensive data regarding the impacts of social distancing on air pollutants mainly in urban of Southeast Asian. The forecasted air pollutant levels have been developed as well.

**Recommendation**

This study has provided robust evidence regarding the possibility of air pollutant reduction if the social distancing is continued. Likewise continuing the nationwide restriction may benefit the current COVID 19 related slashed down air pollution and this is believed can reverse the future respiratory health. The air pollutant decreasing trends due to slowing down of transport, traffic, and travel in slashing down the air pollutant are expected can encourage the related stakeholders to judicious use of resources and at the end can minimize the global emissions and air pollutants along with their risks on health.

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