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DETERMINING THE LOCAL SPATIAL RELATIONSHIPS BETWEEN COVID-19 AND NO_2 USING SENTINEL 5P AND MGWR

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Abstract: Nitrogen dioxide (NO_2) may become one of the contributing factors to COVID-19 deaths. Nowadays, the effect of airborne epidemics on respiratory-related diseases, like COVID-19, can be demonstrated in the geographical region using GIS and Remote Sensing technologies. Thus, this study aims to determine the relationships between COVID-19 and NO_2 using satellite remote sensing data and the local regression approach. The NO_2 data were derived from Sentinel-5 Precursor satellite images, which were acquired in February and May 2021 respectively. Then, the Multiscale Geographically Weighted Regression (MGWR) approach was applied to determine the local spatial relationships between NO_2 and COVID-19. It was found that the relationships between NO_2 and COVID-19 were extremely low at a global relationship with the Ordinary Least Square (OLS) technique. However, with the use of MGWR, a moderate relationship between the derived NO_2 and COVID-19 data cases was found in February 2021 ($R^2 = 0.49$) and May 2021 ($R^2 = 0.47$). The significant effect of NO_2 on the COVID-19 outbreak was found in Negeri Sembilan, Kuala Lumpur, Johor, and Selangor. Although the lockdown had decreased air pollution, this study reveals that there was still a significant effect of air pollutants like NO_2 on the outbreak of COVID-19 of the selected period in micro-scale areas.

Keywords: COVID-19 spatial variation, MGWR, NO_2, GIS, remote sensing.

Introduction

COVID-19 has spread rapidly throughout the world, which has caused increased vulnerability and death. The first mortality case of COVID-19 was reported in China on 11 January 2020. Shah *et al*. (2020) mentioned the general opening remarks by World Health Organisation (WHO) Director, Dr Tedros Adhanom Ghebreyesus that the infection of COVID-19 influenced more than 200 countries, with 1,524,162 confirmed positive cases and losses of 92,941 since 31 December 2019. According to Comunian *et al*. (2020), COVID-19 is similar to other viruses, where it is an air pollution disease due to airborne transmission. It is a large family of respiratory viruses in the respiratory coronavirus (CoV) family that can bring mild to severe diseases and the common cold to respiratory syndromes. MERS (Middle East Respiratory Syndrome) and SARS (Severe Acute Respiratory Syndrome) are common syndrome. In 2003, SARS caused a minor but equally significant epidemic. Jiang and Luo (2020) revealed that the distribution of airborne disease is strongly connected to the movements of the population, as pathogens of airborne will travel across the journey movements of the population during the spread of the virus, similar to SARS and Influenza. Many factors can influence the transmission of COVID-19 such as airborne particles, pollution, population mobility, age, and temperature. The main symptoms of COVID-19 are fever, headache, muscle discomfort, cough, sore throat, and difficulty in breathing. Some of the symptoms are identical to the symptoms of air pollution illness. The fact was supported by Zoran *et al.* (2020) who stated that air pollution contact reduces lung function and induces respiratory symptoms such as cough, trouble breathing and chest pain or pressure.

Pozzer *et al.* (2020) suggest that air pollution is an important cofactor in increasing the risk of death from COVID-19 with the fact from epidemiological data in the USA and China, whereby 15% of particulate air pollution contributed to COVID-19 mortality worldwide. Most of the related studies on the effects of air pollution on COVID-19 infection, such as those found in Contini (2020), Kanniah *et al.* (2020), Zhengqian *et al*. (2020) and Wu *et al.* (2021) also revealed that air pollution increases vulnerability and have worsened affect the prognosis of patients affected by COVID-19 which may bring the mortality. A study carried out by Comunian *et al*. (2020) statistically found that the rise of 1 ug/m^2 to $PM_{2.5}$ was correlated to a rise of 15% in COVID-19 mortality. According to Suhaimi *et al*. (2020), the relationships between pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO) and COVID-19 cases exhibited modest positive correlations. These findings indicate that longer exposure to poor air quality raises the susceptibility to large serious outcomes of COVID-19. Thus, air pollution could be an influential cofactor of COVID-19 by affecting the transport of viruses in Malaysia is possible. The Department of Environment Malaysia (DOE) analysed the Air Pollution Index (API) during the COVID-19 outbreak. The rate was a rise of 26% of the 'GOOD' level and a decrease of 19% in the 'MODERATE' level in the Air Pollution Index (API). However, further investigation must be conducted to verify the effect of air pollution on the COVID-19 outbreak in Malaysia.

According to Ali and Islam (2020), NO_2 was not shown to contribute to the increased number of COVID-19 deaths and infections. This is due to people believing that during the COVID-19 pandemic, air pollution concentrations had decreased. However, other studies such as those conducted by Daraei *et al.* (2020) and Coccia (2021) found that environmental pollution such as NO_2 may affect the outbreak of COVID-19. Fiasca *et al.* (2020) also found that higher NO_2 levels in the atmosphere can trigger a severe type of SARS-CoV-2 in depleted lungs, which can be fatal. Furthermore, NO_2 is a trigger to the COVID-19 spread and lethality (Copat *et al*., 2020) and long-term exposure to NO_2 increases fatalities due to COVID-19 (Hassan *et al.*, 2020 and Shakil *et al*., 2020). Hoang and Tran (2021) stated that 0.01 ppm growth in NO_2 was shown to be strongly related to a significant rise in confirmed COVID-19 cases. Most of the effects of air pollution on the outbreak of COVID-19 were also triggered by the study area. Although there are many studies on COVID-19, only a few on the spatial dependency between affected variables and the COVID-19 outbreak were carried out. Thus, the appropriate techniques are vital to prove the relationships between air pollutants like NO_2 and the COVID-19 outbreak.

There are many available regression techniques used to determine the effect of any parameters that contribute to the COVID-19 outbreak. However, there are disadvantages of the techniques which had led to unconvincing results. Mollalo *et al.* (2020) over 675,000 confirmed cases of the disease have been reported, posing an unprecedented socioeconomic burden to the country. Due to inadequate research on the geographic modelling of COVID-19, we investigated county-level variations of disease incidence across the continental United States. We compiled a geodatabase of 35 environmental, socioeconomic, topographic, and demographic variables that could explain the spatial variability of disease incidence. Further, we employed spatial lag and spatial error models to investigate spatial dependence and geographically weighted regression (GWR) and Urban and Nakada (2021) mentioned that global regression models like Ordinary Least Square (OLS), Spatial Error Model (SEM), and Spatial Lag Model (SLM) can be used to explore the relationships between variables, but has one prominent disadvantage. These models are unable to consider a spatial non-stationary where the association between independent and dependent variables that may differ at a certain place is unclarified. Global regression did not account for spatial dependency in the COVID-19 research, and it was deemed to provide an incorrect description of the data (Mansour *et al*., 2021).

Brunsdon *et al.* (1998) emphasised the Geographically Weighted Regression (GWR) approach as the local regression technique used to study spatial phenomena and local spatial variations. Instead of generating a global "average" assumption of each relationship, the GWR captures the process of spatial heterogeneity by allowing effects to differ over space. However, in the Classical GWR model, all the processes work at a similar spatial scale (Fotheringham *et al*., 2017). Thus, the model does not allow relationships to be evaluated at different scales since it assumes that the size of all relationships involved is constant over space. In the case of the COVID-19 outbreak, Mollalo *et al.* (2020b) mentioned that the GWR assumption is not valid since it requires a different process with different spatial scales. Alternatively, the Multiscale Geographically Weighted Regression (MGWR) has a significant improvement regression approach over GWR due to the independent spatial scale and the covariate-specific bandwidths which can be optimised (Fotheringham *et al.*, 2017; Oshan *et al*., 2019). According to Cardoso *et al*. (2019), the MGWR model allows the calculation of local parameters instead of global ones, where the modelling of regional variances in data and the essential feature of MGWR are present within the data sampled. Fan *et al*. (2020) also discovered that the MGWR is a regression method that spatial heterogeneity of air quality-related interactions and COVID-19 can be well expressed.

Therefore, this study improvised the possible approach from the local regression technique to determine the spatial variation of COVID-19 due to the effect of NO_2. The objectives are to derive the concentrations of NO_2 from Sentinel 5 Precursor satellite images and to determine the relationship between NO_2 concentrations and monthly cases of COVID-19 outbreak using the MGWR method.

Materials and Methods

Study Area

This study was conducted within Peninsular Malaysia, which consists of 11 states and 2 federal territories with a total of 826 sub-districts. The selection of the study areas was due to the reliability of statistical data processing with a spatial statistic approach like MGWR. As mentioned by Bardin (2020), a minimum of 300 data observations are required to perform MGWR or GWR. The study area lies between 1° to 7° N Latitude and 100° to 104° E longitude as specified by the Department of Information of Malaysia. The normal air pollution reading (IPU) in Malaysia was at a moderate level of 51-100 ppm. However, during the Movement Control Order (MCO), the DOE (2020) reported that there was a rise of 26% in the 'GOOD' level and a decrease of 19% in the 'MODERATE' level in the Malaysia Air Pollution Index (API). There was a 43% to 63% decrease in NO_2 parameters during the 1st MCO.

Research Methodology

In this study, three main phases were carried out (Figure 2). The first phase was data acquisition which consisted of the monthly positive COVID-19 cases, Sentinel-5P satellite images and GIS ancillary data. The COVID-19 cases were acquired from the Ministry of Health (MoH). The Sentinel-5 Precursor satellite images were freely downloaded from the Copernicus Open Access Hub. Due to the availability of and limited Sentinel-5P NO_2 data product, only two sets of data were acquired, which were in February and May 2021 respectively. Detailed descriptions of Sentinel-5P used in this study are listed in Table 1.

In Phase 2, data processing was carried out to build the geo-database of COVID-19 monthly cases and NO_2. The Sentinel-5P satellite images were pre-processed in SNAP desktop software. The images were reprojected from WGS84 to Kertau RSO Malaya Meter. Then, the projected images were used in ArcGIS to derive the concentrations of NO_2 throughout the study

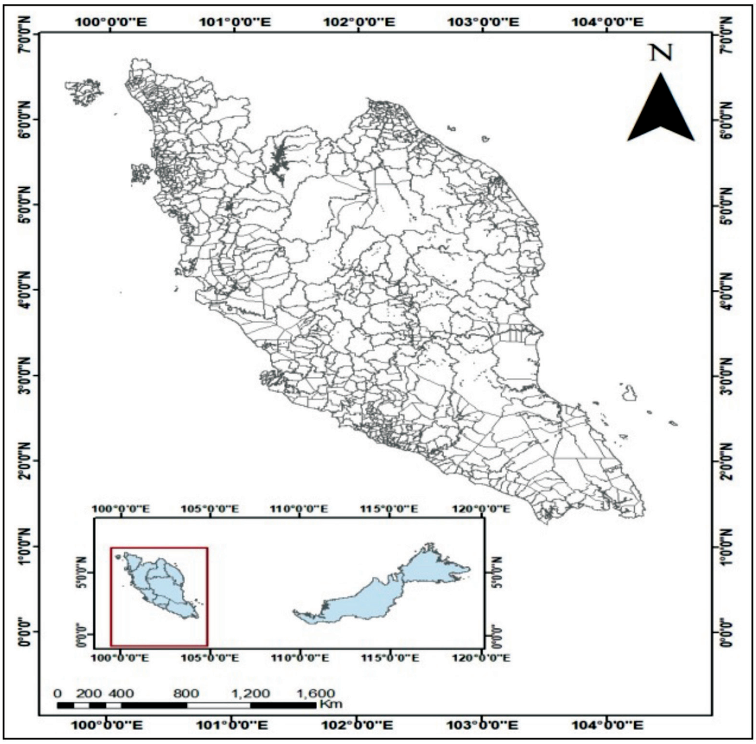

Figure 1: Study area

area (sub-districts of Peninsular Malaysia). Normalisation for raster-based was applied to overcome the radiometric inconsistencies in the NO_2 pixel values as shown in Equation 1. Thus, the geo-database was completed with a mean of NO_2 values which corresponded to the COVID-19 cases and the location of sub-districts in the study area.

$$\text{Normalisation of } NO_2 = \frac{NO_2 - min}{max - min} \tag{1}$$

Table 1: Description of Sentinel-5P images used in the study

Data Used	Description	
Sentinel-5P satellite image	Product/Band	Nitrogen Dioxide (NO_2)
	Product identifier	L2__NO2___ Ex: S5P_NRTI_L2__NO2____20210522T064651_20210522T065151_18683_01_010400_20210522T073452
	Data product	Level 2(L2)
	Sensor	TROPOMI
	Spatial resolution	7x3.5km²
	Temporal	Less than 1 day
	Coordinate system	WGS84
	Processing	Near Real Time (NRT)
	Unit	mol/m²

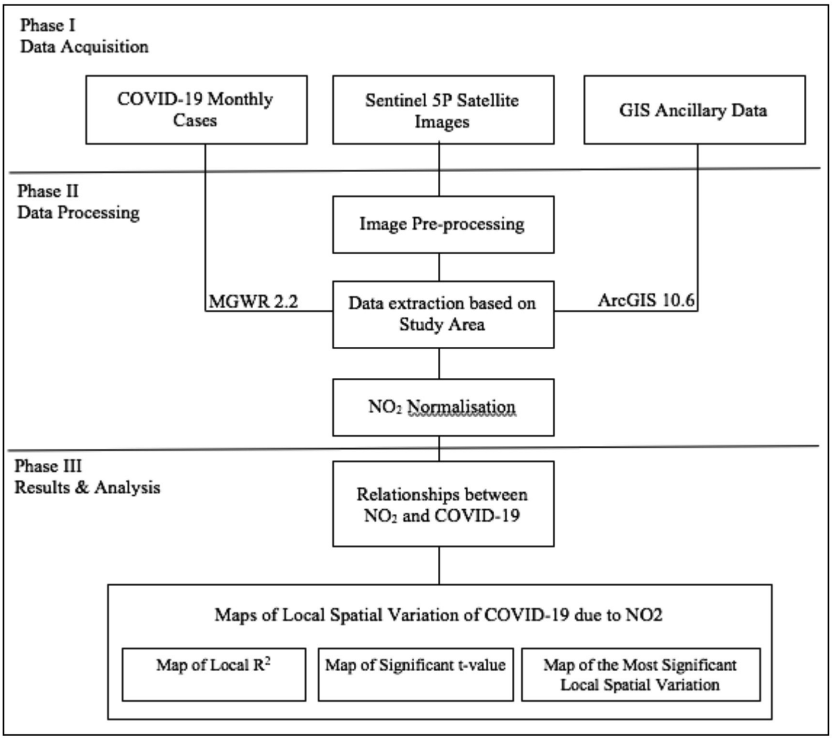

Figure 2: Research flow work

The final phase was the results of local spatial variations in the relationships between NO_2 and COVID-19. The relationships for both datasets were generated using MGWR software. With MGWR, a bandwidth was chosen, and then a goodness-of-fit measurement, i.e. AIC (Akaike's Information Criterion) calibration, was determined within every session since Li *et al.* (2020) had proven that bandwidth uncertainties can be quantitatively measured and Akaike weights can obtain confidence intervals for bandwidths. The ideal bandwidth is the one with the lowest AIC. The output of the MGWR results in this study was then mapped and analysed in the following section.

Results and Analysis

Relationships between NO_2 and COVID-19 Outbreak

MGWR model was used in this study to determine the relationship between NO_2 and the COVID-19 outbreak in Peninsular Malaysia sub-districts. Based on two datasets of the study area, the local and global regression between normalised NO_2 derived from Sentinel-5P images and monthly COVID-19 were carried out. From the overall R^2 from local regression, it was found that the MGWR improved the global regression of OLS. The moderate from MGWR (0.489 and 0.456) was better than global regression, OLS (0.079 and 0.171) in February and May 2021, respectively. The results revealed a possible moderate effect of NO_2 on the COVID-19 outbreak in localised areas.

The models also indicated a lower AIC number of MGWR as compared to OLS for both datasets. The MGWR AIC values obtained were 1,887.574 compared to 2,186.523 and 1,739.189 to 2,026.479 in February 2021 and May 2021, respectively. As stated by Mansour *et al*. (2020), a lower number indicates the superior model and a lower AIC value indicates that the best model fit is present. Thus, the model from MGWR showed the best model fit.

Local Spatial Variation of COVID-19 Due to NO_2

The maps of local regression in the relationship between NO_2 and the COVID-19 outbreak are shown in Figure 3. In this study, the local R^2 were classified as 'Weak' (< 0.2), 'Moderate' (0.2 < R < 0.4), and 'Strong' (> 0.4). The local R^2 in February 2021 ranged between -0.996 to 0.613 while in May ranged from -0.973 to 0.475. There was a strong correlation in the relationship between NO_2 and COVID-19 found within sub-districts of Selangor, Kuala Lumpur, Negeri Sembilan, and Johor in February 2022. A strong correlation in May 2021 was found in Selangor, Kuala Lumpur, and Negeri Sembilan.

Figure 4 shows the significant locations of the relationships between NO_2 and the COVID-19 outbreak in February and May 2021. The maps were generated based on the significant t-values of 95% confidence level. The selected locations to be mapped were identified from t ≤ -1.96 and t ≥ 1.96. In February 2021, a total of 90 sub-districts in Negeri Sembilan, Kuala Lumpur, Johor, and Selangor were found to be the most significant relationship between NO_2 and COVID-19. Tenggaruh, Mersing, and Johor were the significant locations with a strong R^2 value (0.570). In May 2021, the number of significant relationships increased to 144 locations (See Appendix 1). The locations

Table 2: MGWR regression results

Regression Method	R^2		AIC	
	February 2021	May 2021	February 2021	May 2021
Global (OLS)	0.079	0.171	2,186.523	2,026.479
Local (MGWR)	0.489	0.465	1,887.574	1,739.189

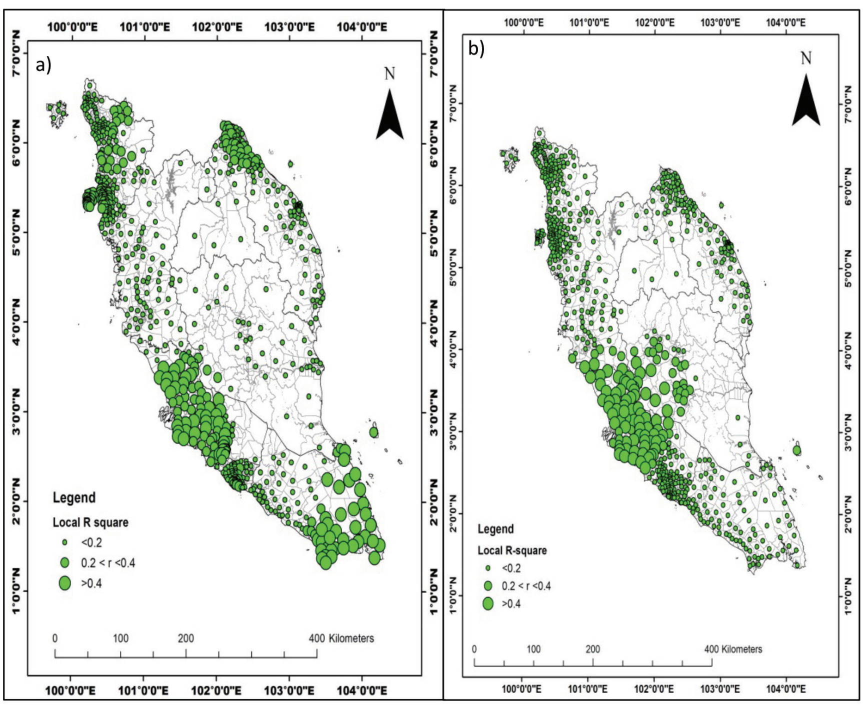

Figure 3: Effect of NO_2 on COVID-19 outbreak [maps of local regression; (a) map for February 2021 and (b) map for May 2021]

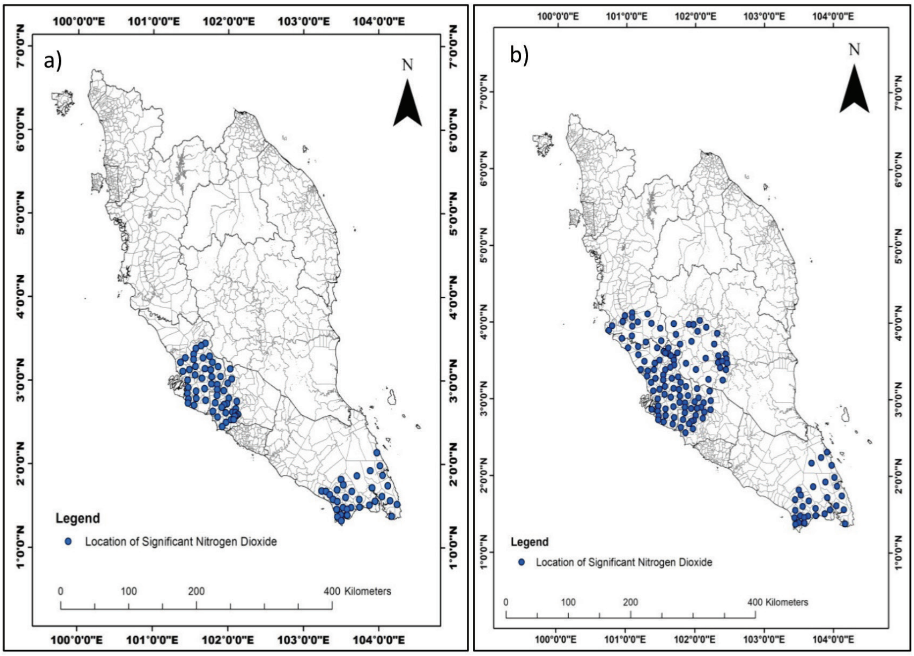

Figure 4: Maps of the significant locations for the effect of NO_2 – COVID-19 outbreak; (a) February 2021 and (b) May 2021

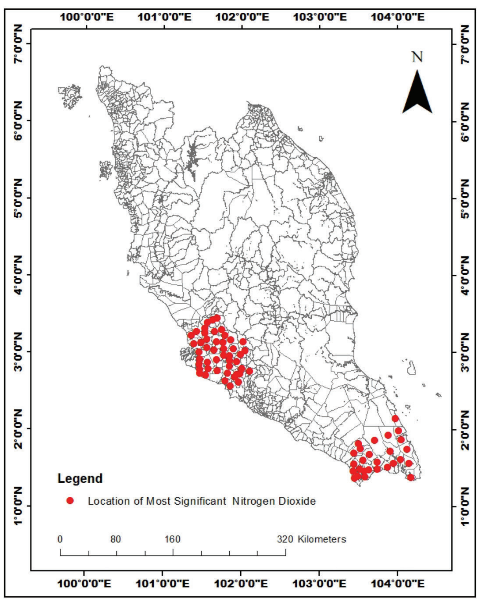

Figure 5: Map of the most significant locations for the effect of NO_2 – COVID-19 outbreak

were in Perak, Negeri Sembilan, Pahang, Kuala Lumpur, Johor, and Selangor. The highest R^2 was in the Jimah sub-district in Port Dickson, Negeri Sembilan (0.475).

The most significant relationships between NO_2 - COVID-19 relationships based on local t-values for both datasets (February and May 2021) are shown in Figure 4.4. The locations were found in Negeri Sembilan, Kuala Lumpur, Johor, and Selangor. The results indicate that there might be other factors affecting the COVID-19 cases within the areas rather than air pollutants like NO_2. Thus, the NO_2 is not the only component of virus transmission. Other related parameters should also be tested while investigating COVID-19 in the sub-districts.

Zoran *et al*. (2020) stated that COVID-19 infections are negatively associated with ground-level NO_2. Airborne aerosols could carry COVID-19 transmission in the open air. Other air pollution parameters like $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO may contribute to this pandemic (Coker *et al.*, 2020; Karan *et al.*, 2020; Magazzino *et al*., 2020; Suhaimi *et al.,* 2020). There are also other factors like temperature (Kassem, 2020) that may affect the COVID-19 cases in the areas.

Conclusion

Overall, the local spatial relationships between COVID-19 and NO_2 can be determined with high temporal Sentinel product of NO_2 and spatial statistics techniques. The use of a local regression approach like MGWR proves that there is a significant effect of NO_2 in the micro-scale area. The findings show that the COVID-19 outbreak in Malaysia during the selected period has a positive significant relationship with NO_2 even though it is a moderate correlation. The NO_2 concentrations in February and May 2021 had moderate positive correlations with COVID-19 cases in Negeri Sembilan, Kuala Lumpur, Johor, and Selangor. Hence, the effect of NO_2 on the outbreak of COVID-19 from Sentinel-5P satellite images and COVID-19 cases using the MGWR method by sub-districts in Peninsular Malaysia has been determined. The findings show that NO_2 can be considered one of the possible factors in the COVID-19 outbreak in Malaysia. Nevertheless, other factors need to be considered such as other pollutant parameters like $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO, population mobility, temperature, humidity, and age when studying COVID-19 for other states. In future studies, more air pollutant parameters as variables of the study should be tested for the COVID-19 outbreak factors such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, and CO. For obtaining a credible and persuasive outcome, it is imperative to obtain NO_2 data from ground samples, such as the data provided by the Ministry of Environment (MoE), to demonstrate the dependability of the air pollutants data. Furthermore, to obtain more dependable NO_2 concentrations, a greater number of satellite images will be required.

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References

Ali, N., & Islam, F. (2020). The effects of air pollution on COVID-19 infection and mortality—A review on recent evidence. *Frontiers in Public Health*, *8*(2). https://doi.org/10.3389/fpubh.2020.580057

Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician)*, *47*(3), 431–443. https://doi.org/10.1111/1467-9884.00145

Cardoso, D., Painho, M., & Roquette, R. (2019). A geographically weighted regression approach to investigate air pollution effect on lung cancer: A case study in Portugal. *Geospatial Health*, *14*(1), 35–45. https://doi.org/10.4081/gh.2019.701

Coccia, M. (2021). How do low wind speeds and high levels of air pollution support the spread of COVID-19? In *Atmospheric pollution research* (Vol. 12, Issue 1, pp. 437–445). https://doi.org/10.1016/j.apr.2020.10.002

Coker, E. S., Cavalli, L., Fabrizi, E., Guastella, G., Lippo, E., Parisi, M. L., Pontarollo, N., Rizzati, M., Varacca, A., & Vergalli, S. (2020). The effects of air pollution on

COVID-19 related mortality in Northern Italy. *Environmental and Resource Economics*, *76*(4), 611–634. https://doi.org/10.1007/s10640-020-00486-1

Comunian, S., Dongo, D., Milani, C., & Palestini, P. (2020). Air pollution and COVID-19: The role of particulate matter in the spread and increase of COVID-19's morbidity and mortality. *International Journal of Environmental Research and Public Health*, *17*(12), 1–22. https://doi.org/10.3390/ijerph17124487

Contini, D., & Constabile, F. (2020). *Does air pollution influence COVID-19 ?Atmosphere, 11*(4), 377. https://doi.org/10.3390/atmos11040377

Copat, C., Cristaldi, A., Fiore, M., Grasso, A., Zuccarello, P., Signorelli, S. S., Conti, G. O., & Ferrante, M. (2020). The role of air pollution (PM and NO2) in COVID-19 spread and lethality: A systematic review. *Environmental Research*, *191*(August), 110129. https://doi.org/10.1016/j.envres.2020.110129

Daraei, H., Toolabian, K., Kazempour, M., & Javanbakht, M. (2020). The role of the environment and its pollution in the prevalence of COVID-19. *Journal of Infection*, *81*(2), e168–e169. https://doi.org/10.1016/j.jinf.2020.06.019

DOE, D. of E. (2020). *Status kualiti udara sebelum dan sepanjang tempoh kawalan pergerakan* (Issue April). http://apims.doe.gov.my/pdf/Analisis_Kualiti_Udara_Sebelum_Dan_Semasa_PKP.pdf

Fan, Z., Zhan, Q., Yang, C., Liu, H., & Zhan, M. (2020). How did distribution patterns of particulate matter air pollution (Pm 2.5 and pm 10) change in China during the COVID-19 outbreak: A spatiotemporal investigation at the Chinese city-level. In *International Journal of Environmental Research and Public Health*, *17*(17), 1–19. https://doi.org/10.3390/ijerph17176274

Fiasca, F., Minelli, M., Maio, D., Minelli, M., Vergallo, I., Necozione, S., & Mattei, A. (2020). Associations between COVID-19 incidence rates and the exposure to pm 2.5 and NO2: A nationwide observational study in Italy. *International Journal of Environmental Research and Public Health*, *17*(24), 1–10. https://doi.org/10.3390/ijerph17249318

Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale Geographically Weighted Regression (MGWR). *Annals of the American Association of Geographers*, *107*(6), 1247–1265. https://doi.org/10.1080/24694452.2017.1352480

Hassan, M., Bhuiyan1, M. A. H., Tanu, S. M., Tareq, M., & Bodrud-Doza, M. (2020). Spatial relationships between COVID-19 infection rates and air pollution, Geo-meteorological and social parameters in Dhaka, Bangladesh. 1–25. https://doi.org/10.21203/rs.3.rs-39091/v1

Hoang, T., & Tran, T. T. A. (2021). Ambient air pollution, meteorology, and COVID-19 infection in Korea. *Journal of Medical Virology*, *93*(2), 878–885. https://doi.org/10.1002/jmv.26325

Jiang, J., & Luo, L. (2020). Influence of population mobility on the novel coronavirus disease (COVID-19) epidemic: Based on panel data from Hubei, China. *Global Health Research and Policy*, *5*(1). https://doi.org/10.1186/s41256-020-00151-6

Kanniah, K. D., Zaman, N. A. F. K., Kaskaoutis, D. G., & Latif, M. T. (2020). Corrigendum to "COVID-19's impact on the atmospheric environment in the Southeast Asia region". *Science of the Total Environment*, *745*, 142200. https://doi.org/10.1016/j.scitotenv.2020.142200

Karan, A., Ali, K., Teelucksingh, S., & Sakhamuri, S. (2020). The impact of air pollution on the incidence and mortality of COVID-19. *Global Health Research and Policy*, *5*(1), 5–7. https://doi.org/10.1186/s41256-020-00167-y

Kassem, A. Z. E. (2020). Does temperature affect COVID-19 transmission? *Frontiers in Public Health*, *8*(December), 1–6. https://doi.org/10.3389/fpubh.2020.554964

Li, Z., Fotheringham, A. S., Oshan, T. M., & Wolf, L. J. (2020). Measuring bandwidth uncertainty in multiscale geographically weighted regression using akaike weights. *Annals of the American Association of Geographers*, *110*(5), 1500–1520. https://doi.org/10.1080/24694452.2019.1704680

Magazzino, C., Mele, M., & Schneider, N. (2020). The relationship between air pollution and COVID-19-related deaths: An application to three French cities. *Applied Energy*, *279*(August), 115835. https://doi.org/10.1016/j.apenergy.2020.115835

Mansour, S., Al Kindi, A., Al-said, A., Al-said, A., & Atkinson, P. (2020). Sociodemographic determinants of COVID-19 incidence rates in Oman : Geospatial modelling using Multiscale Geographically Weighted Regression (MGWR). *Sustainable Cities and Society*, *65*, 102627. https://doi.org/10.1016/j.scs.2020.102627

Mansour, S., Al Kindi, A., Al-Said, A., Al-Said, A., & Atkinson, P. (2021). Sociodemographic determinants of COVID-19 incidence rates in Oman: Geospatial modelling using Multiscale Geographically Weighted Regression (MGWR). *Sustainable Cities and Society*, *65*, 102627. https://doi.org/10.1016/j.scs.2020.102627

Mollalo, A., Vahedi, B., & Rivera, K. M. (2020a). GIS-based spatial modelling of COVID-19 incidence rate in the continental United States. *Science of the Total Environment*, *728*(138884), 1–8. https://doi.org/10.1016/j.scitotenv.2020.138884

Mollalo, A., Vahedi, B., & Rivera, K. M. (2020b). GIS-based spatial modelling of COVID-19 incidence rate in the continental United States. *Science of the Total Environment*, *728*, 138884. https://doi.org/10.1016/j.scitotenv.2020.138884

Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Stewart Fotheringham, A. (2019). MGWR: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. *ISPRS International Journal of Geo-Information*, *8*(6), 269. https://doi.org/10.3390/ijgi8060269

Pozzer, A., Dominici, F., Haines, A., Witt, C., Münzel, T., & Lelieveld, J. (2020). Regional and global contributions of air pollution to the risk of death from COVID-19. *Cardiovascular Research*, *116*(14), 2247–2253. https://doi.org/10.1093/cvr/cvaa288

Shah, A. U. M., Safri, S. N. A., Thevadas, R., Noordin, N. K., Rahman, A. A., Sekawi, Z., Ideris, A., & Sultan, M. T. H. (2020). COVID-19 outbreak in Malaysia: Actions taken by the Malaysian government. *International Journal of Infectious Diseases*, *97*, 108–116. https://doi.org/10.1016/j.ijid.2020.05.093

Shakil, M. H., Munim, Z. H., Tasnia, M., & Sarowar, S. (2020). COVID-19 and the environment: A critical review and research agenda. *Science of the Total Environment*, *745*(July), 141022. https://doi.org/10.1016/j.scitotenv.2020.141022

Suhaimi, N. F., Jalaludin, J., & Latif, M. T. (2020). Demystifying a possible relationship between COVID-19, air quality and meteorological factors: Evidence from Kuala Lumpur, Malaysia. *Aerosol and Air Quality Research*, *20*(7), 1520–1529. https://doi.org/10.4209/aaqr.2020.05.0218

Urban, R. C., & Nakada, L. Y. K. (2021). GIS-based spatial modelling of COVID-19 death incidence in São Paulo, Brazil. *Environment and Urbanization*, 33(1), 229–238. https://doi.org/10.1177/0956247820963962

Wu, Y., Zhan, Q., & Zhao, Q. (2021). Long-term air pollution exposure impact on COVID-19 morbidity in China. *Aerosol and Air Quality Research, 21*(1). https://doi.org/10.4209/aaqr.2020.07.0413

Zhengqian, L., Yuyao, Y., Hong'ou, Z., Hongxu, G., Ji, Y., & Changjian, W. (2020). Spatio-temporal characteristics and transmission path of COVID-19 cluster cases in Zhuhai. *Tropical Geography*, *40*(3), 422–431. https://doi.org/10.13284/j.cnki.rddl.003228

Zoran, M. A., Savastru, R. S., Savastru, D. M., & Tautan, M. N. (2020). Assessing the relationship between surface levels of PM2.5 and PM10 particulate matter impact on COVID-19 in Milan, Italy. *Science of the Total Environment*, *738*, 139825. https://doi.org/10.1016/j.scitotenv.2020.139825