SPATIAL ANALYSIS OF THE AIR POLLUTION EFFECT ON DOMESTIC VIOLENCE AND ROBBERY IN NEW SOUTH WALES

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ABSTRACT: Air pollution is a serious problem that poses human physical and mental health. However, most studies focus on the direct impacts of air pollution to health, and few of them examine the indirect impacts of air pollution on crime. According to the literature, air pollution could cause mental problems and increase crime risks. Also, air pollution reduces human outdoor behaviors and daily activity patterns. Therefore, our hypothesis is that air pollution may reduce outdoor crimes but increase indoors crimes because air pollution reduced people's daily outdoor activities and increase crime risk. Two types of crimes were used for analysis, include: robbery (outdoor crime), and domestic violence (indoor crime). We applied three spatial models, OLS, GWR, and GTWR (Geographically and Temporally Weighted Regression), to define the relationship among air pollution and different crime types. The study datasets include one-year (2016) crime records, socioeconomic variables, and air quality index data (AQI) from the official websites of New South Wales. The result revealed that GTWR model performs best because it includes the dynamic impacts of air pollution change over time and spatial dependence of crimes. In general, the model shows that air pollution has a significant negative relationship with robbery. The impact of the AQI increases from urban to rural area for robbery. In contrast, AQI has a significant positive correlation with domestic violence. The model shows that the impact of AQI increase from rural to urban. The study results can contribute to develop future crime prevention strategy and allocate enforcement resources.

1. INTRODUCTION

In recent years, the problem of air pollution has become more serious. According to the World Health Organization's Global Health Risk report published in 2016; there are 3 million deaths caused by the impact of outdoor air pollution in 2012 globally. About 87% of those fatalities happen in countries with low and middle income, representing 82% of the world's population. There are a lot of air pollution studies focus its effect on human physical health. Human health impacts may vary from respiratory cardiovascular, digestive, and nervous system (Kampa 2008). In addition, air pollution leads to numerous diseases and also known to cause impaired immune systems (Filippini et al. 2015).

However, only a few studies have examined the impacts of air pollution on mental health that could change the behavior of human beings and their daily activities. Dryden et al. (2017) and Shin (2018) have found that air pollution could have an effect on mental health, including stress and inflammation. The findings indicate a link between subjective stress and long-term exposure to ambient air pollutants in daily activity. Shin (2018) on the other hand, explores how air pollution affects the human mind and increases the crime rate. The study result shows that the appearance of severe air pollution illustrates in the interviews will increase the anxiety of the respondents, also leading to a greater inclination to do unethical behavior. Therefore, air pollution can have a direct impact on the human body and mind and then could influence the distribution of its activities and the risk of crime indirectly.

We need to identify the factors induced by crime in order to assess the impact of air pollution on crime. Monk et al. (2010) stated in terms of outdoor crime that perpetrators, victims, place and activity routines contribute to number of street robbery. The immediate need for cash, as an offender, is the primary reason for committing crimes. Thus, unemployment, low income and drug offences are all associated variables to the robbery. The offender act based on the victim's variables (such as their vulnerability, appeal, and lack of awareness) which is an opportunity that used by the offender to rob the victim. Robbery is linked to the amount of pedestrians, according to Wolf and Asche (2009), where the amount of pedestrians is increasing the risk also rise. However, in the event of serious air pollution, expected reduce the outdoor activity of people as well as the probability of robbery.

As an indoor crime, females and kids are the most victims of domestic violence. 49% of the female were abuse with offenders are men influenced by alcohol and drugs according to the Mitchell (2011). Thus, unemployment rate, women's ratio, ages, and drug crimes are all associated variables. Also, they were at greater danger of partner violence than adolescents, such as people who experience child abuse before their ages reach 15. Because of the effects of air pollution on daily activity, this can increase the time of people stay at home but with more stress and also rising the risk of violence crime.

In addition to the above variables, many studies also describe the impact of socio-economic considerations on general criminal number. Buonanno (2003) observed 20 Italian regions between 1980 and 1995 and found a negative correlation between education and crime rates. A later study, Boivin (2018) mentioned that area with more populations, whether in residential or public areas, have more crimes because more people provide more potential targets and offenders. In the crime of domestic violence, besides the above-mentioned demographics and economic conditions, the ratio of male to female, race, and age are also considered to be relevant influence factors (Markham et al., 2016).

In summary, the effect of air pollution on crime number is comparatively few discussed in previous studies, most of them use the traditional statistic model (linear regression models) to create the relationship between air pollution and crime. Previous research did not consider the effects of air pollution on the mental health and behavior of individual offences. This research seeks to investigate the association of different kinds of criminal type between the air quality index. Based on the literature review outcomes, the air qualiry index and other socio-economic factors (such as population, male - female ratio, earnings or unemployment, etc.) are selected to create spatial models to be further analyzed.

2. METHODOLOGY AND STUDY DATA

2.1 Study Area and Data

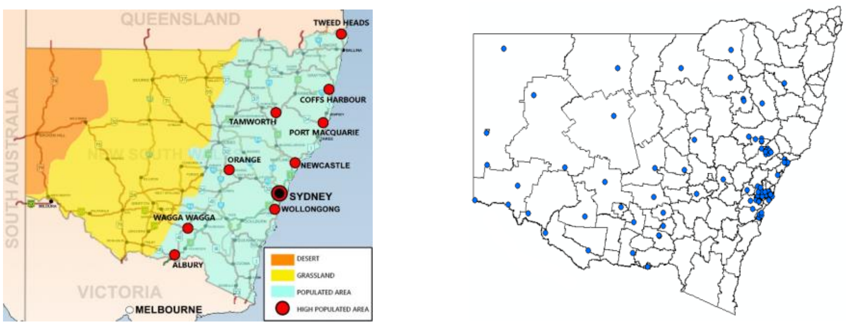
This study take place on New South Wales. There were 129 LGA regions, including 30 towns, 28 counties, 6 municipalities, 8 local councils and 58 shires. This study area was chosen because it is the only area which provides detailed crime on lines, such as domestic violence, robbery. The majority are desert and grasslands in western New South Wales, where rare citizen reside (Figure 1). Therefore, this research will concentrate on the coastal region where the population is denser and the number of crime is greater.

2.1.1 Air Quality Index

The Air Quality Index (AQI) is a general index describing air quality conditions. If the value is larger, more severe the air pollution and the greater the effect on the human. This AQI data was download from the Office of the Environment and Heritage in New South Wales' (OEH) and measured by a total of 87 stations in 2016. The blue point in Figure 1 shows the place of those stations. The website offers monitoring outcomes for six common pollutants: nitrogen dioxide, ozone, sulfure dioxide, carbon monoxide as well as particulates matter (PM2,5 and PM10). As is shown in equation (1), the calculation formula for the determination of the AQI value.

$$Index = \frac{\text{Pollutant Concentration}}{\text{Pollutant Standard Concentration} \times 100} \qquad (1)$$

Pollution standards were based on Australia's National Environmental Protection Measure (Air NEPM) maximum yearly tolerance levels. The domestic standard for 1-hour nitrogen dioxide for is 0.12, but it has been transformed to 12.0 pphm to create a NSW report to suit the standard. The highest daily AQI value, as well as the status and recommendation for the citizen living round the station region, will then be chosen from the pollutants.



(a) (b)

Figure 1 (a) Study area map; (b) station location

Table 1. Pollutant Standard Concentration

Pollutant	Averaging period	Air NEPM Standard	NSW reporting format
Carbon monoxide	8 hours	9.0 ppm	9.0 ppm
Nitrogen dioxide	1 hour	0.12 ppm	12.0 pphm
Ozone	1 hour 4 hours	0.10 ppm 0.08 ppm	10.0 pphm 8.0 pphm
Sulfur dioxide	1 hour	0.20 ppm	20 pphm
PM10	1 day	50 µg/m3	50 µg/m3
PM2.5	1 day	25 µg/m3	25 µg/m3

PM2,5 and PM10 are the highest AQI value based on our findings during the research period. In addition, their missing information are of the smallest among other pollutant. As the numbers of our air-quality monitoring station are limited, we have used spatial inference methods to estimate missing values in some area. There are two common methods that used to predict surrounding Air quality value which is kriging and using MODIS AOD satellite image. However, New South Wales is located in the subtropical region which is not easy to obtain a clear satellite image due to the weather condition. During this study period, many missing observations were discovered that could decrease the prediction accuracy. Ordinary kriging is therefore used to interpolate and assess the AQI value and create a monthly map of air pollution in 2016.

2.1.2 Crime and Socioeconomic Variable

This research describes two kinds of crime that occur in 2016 which is domestic violence, and robbery on New South Wales. The government says that domestic violence in the way of assault, harassment and other comparable behaviors is an offense against or abuse of the individual. Robbery is categorized in New South Wales into 3 classifications that are robbery with a firearm, robbery with a weapon not a firearm, and robbery without a weapon. Data for the crime were observe for the 129 LGA in 2016, which is accessible for download from the New South Wales Bureau of Statistics on Crimes and Research. Table 2 shows that in comparison to domestic violence and robbery. The distribution of crime hotspots is generally illustrated in Figures 2. Larger cities such as Sydney, Newcastle, and other surrounding cities have more criminal cases, while fewer cases occur in rural areas. Most of zero value are located on desert and grassland where it has a less densely populated area.

Furthermore, other variables, such as population, female ratio, median age, income, education degree and the unemployment rate, can directly or indirectly influence offences as well as the Air Quality Index (Liu, 2016). In 2016, we use population, woman ratio, median age, degree in education, weekly incomes and unemployment rate of New South Wales from the Australian Bureau of Statistics website in order to enhance models of accuracy. This variables used as the predictor or independent variable.

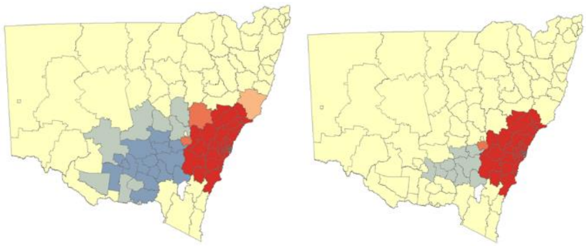
Table 2. Independent Variable Data Descriptive

Variables	Mean	Min	Median	Max
Domestic Violence	18.82429	0	8	241
Robbery	0.880491	0	0	28
Population	57892	1056	22987	346302
Female ratio	50.33488	46.3	49.5	59
Median Age	41.23	6	42	54
Education Degree	17.04	5.1	11.5	53.5
Weekly income (AUD)	1340.19	767	1196	2687
Unemployment rate	6.116	1.7	5.9	16.2
AQI	41.47	18.09	40.38	94.54

2.2 Method

In this research, the data processing and modelling is primarily based on ArcGIS and R software. First, this research combines socio-sconomic and crime variables to form new shapefile data in New South Wales, Australia. Secondly, the AQI value of 25 stations is interpolated with kriging to cover the entire research area and to get the AQI value in each region of Australia. The results were obtained through ordinary kriging method (Section 2.2.1).

Finally, the association of air pollution and crime in New South Wales is evaluated through three methods: ordinary least squares (OLS), geographic weighted regression (GWR), geographically and temporally weighted regression (GTWR). First, without any spatial or temporal considerations, data were analysed using global model which is OLS. Then, to see the effect of the air pollution on crime in every region it continued to performed regressions with the traditional GWR and GTWR, respectively.



(a) (b)

Figure 2 Hotspot of (a) domestic violence; (b) Robbery

2.2.1 Ordinary Kriging: Kriging's concept is to predict values of a regionalized variable at a chosen place (Zk) based on adjacent current values (Zi) (Ivana, 2016). An appropriate weighting coefficient (ωα) is allocated to selected places that represent. Variogram values show the link between the actual (hard) data and the estimation point, or by covariance of second-order status (Malvić and Balić, 2009). Equation (2) shows the formula of kriging. However, a regular kriging hypothesis is a constant unknown average of each local district estimate point.

$$Z(X_0) = \sum_{\alpha=1}^{n} \omega_\alpha Z(X_1) \tag{2}$$

Where:

$Z(X_0)$: X location that will be predict

ω_α : weighting coefficient

$Z(X_1)$: X location that has a current value

2.2.2 Ordinary Least Square: One of the most popular statistical regression testing techniques is the ordinary least square technique (OLS). This technique splits the variables into independent and dependent variables then creates a model of correlation on the base of dataset. By minimizing the squared error, the regression parameters are measured. The variables are set in equation 3, in this research and the OLS regression assessment model for the subsequent GWR is the reference base.

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} + \varepsilon_i \tag{3}$$

Where:

Y_{1i} : number of crime incidents on each city in 2016

X_{ni} : number of independent variable on each city in 2016

ε_i : random error

α, β : regression coefficient

2.2.3 Geographic Weighted Regression: The GWR is an expansion of the linear regression model to provide information from surrounding samples to each region in order to create individual regression model and allow parameters to differ from area to area. Equation (4) sets out the formula for this research

$$Y_{1i} = \beta_0(u_i, v_i) + \sum_{k=1}^{n} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \tag{4}$$

i = 1,2,3 … , n

Where：

Y_{1i} : number of crime incidents in New South Wales, Australia, in each month of 2016

X_{ik} : number of independent variable on each city in 2016

(u_i, v_i) : geographical coordinates of the point i

$\beta_k(u_i, v_i)$: the kth parameter of the i-th point

ε_i : the random error of the i-th sample

2.2.4 Geographically and Temporally Weighted Regression: In contrast, to capture temporal and spatial heterogeneity, the GTWR integrates the space and temporal matrices. The GWR model consider for the non-stationarity of a spatial parameter by constructing a weight matrix based on the distances between point i and every other observation. Using some adjusted current value type or future value calculation, the time variable is normally adjusted by changing the number of event observations to a common date (Wang, 2006).

In parameter estimates, this study represented spatiotemporal non-stationary as an alternative approach by constructing the weight matrix according to the determined distances of (x, y, t) coordinates between observation I and all other observations according to GWR. The GTWR model is expressed in equation (5) (Huang et al, 2010).

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i)X_{ik} + +\varepsilon_i \quad (5)$$

The issue is primarily to estimate $\beta_0(u_i, v_i, t_i)$ for each variable k and for every place in location i. Similarly, $\beta_k(u_i, v_i, t_i)$ can be estimated in equation (6):

$$\hat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i)X]^{-1} X^T W(u_i, v_i, t_i)Y \quad (6)$$

Where:

$W(u_i, v_i, t_i)$: diagonal ($\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{in}$)

$\alpha_{ij}(1 \leq j \leq n)$: space-time distance functions of (u,v,t) corresponding to the weights when calibrating a weighted regression adjacent to observation point i

X : observations on the independent variables

n : number of observations

3. RESULT

3.1 Air Quality Index from Ordinary Kriging Results

In latest years, AQI has been an important national Environmental Protection Measure (NEPM). The ordinary kriging result of the AQI in 2016 is shown in Figure 3. A greater AQI value is the red color where air pollution is more severe. The blue color is a low value of AQI that represent better air quality. This research utilizes the leave one out method as a cross-validation in kriging results. The result shows a small root mean square value of 0.22 and average standard error of 0.285. That value shows a very good performance of ordinary kriging with a tiny distinction between the value of observation and prediction.

The concentration requirements of each air pollutant are distinct. The figures of big towns (e.g. Sydney, Newcastle, etc.) are shown to be greater: AQIs are often more significant in big towns than rural areas. Moreover, Figure 3(a) demonstrates that most Australia AQIs are below 50 $\mu g/m^3$ in summer (January). Figures 3(b)-(c) show a gradual increase in AQI values from autumn to winter. In specific, the value of AQI nearly reached 100 $\mu g/m^3$ in big metropolitan regions, suggesting that the level of air pollution during this time was the most severe.

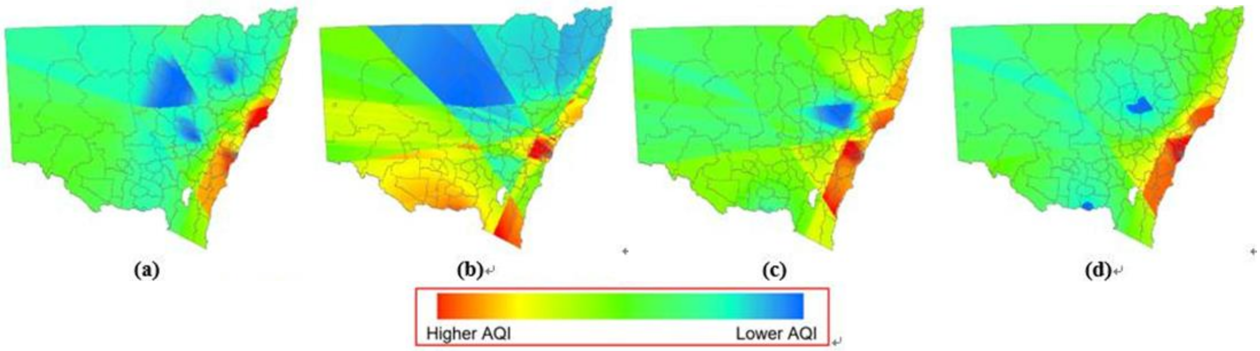


Figure 3 New South Wales Air Pollution Map in 2016 (a) January, (b) April, (c) July, (d) October

3.2 Crime Prediction Model Results

Table 3 shows the coefficient estimators and performances of each of the three models: ordinary least square (OLS), Geographic Weighted Regression (GWR), and Geographically and Temporally Weighted Regression (GTWR) respectively. The model performance could see by the R-square and AIC value. Although the R^2 of OLS is comparable with other models, the residuals in the global models were clustered, not randomly distributed when tested using Morans I (Figure 4). Therefore, the GWR and GTWR as a local model were used to fit these trip data are suggested because of its spatial relationship between the adjusted areas. The parameters of the local model changed from area to area, but the parameters of the OLS model were fixed for the entire study area. The result shows the R^2 value of the GWR and GTWR model increase in domestic violence and robbery prediction.

By comparing the residual standard error, the decreased value further indicates that GTWR gives a better fit of data than the global models shown in table 3. We posit that this is because GTWR can handle both spatial and temporal heterogeneities. Moreover, the GTWR model also has a lower AIC value. A possible reason is that the experimental data only covered a short period, which indicates that the temporal nonstationary effect is less significant than that of spatial nonstationarity. A statistically significant independent variable is essential to the model if it has robust common sense theory support with the dependent variable and it not redundant to any other independent variable in the model. In order to measure the redundancy among variables, VIF value is used. The OLS model shows the VIF value is below on 5, which mean the explanatory variables are independent and not profoundly affect each other.

3.3 Discussion

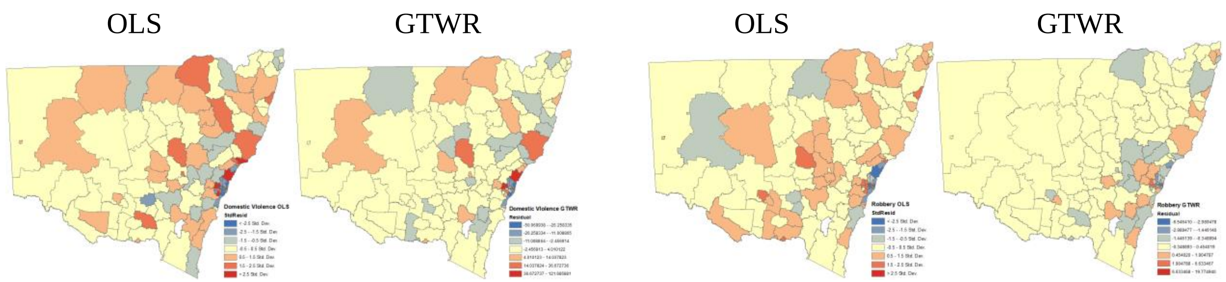
There are no significant different between the result of GWR and GTWR (figure 5). However, because GTWR model show a better performance, this study focus on the effect of air pollution on domestic violence, and robbery where it explained by the GTWR model. The results show air pollution has inconsistent impacts on different crime types. Along with increasing air pollution intensity, it may increase domestic violence (indoor crime) and reduce robbery (outdoor violence) because it changes people’s daily activity. It according to the previous study from Based on Yan, et al. (2018) where increasing air pollution will reduce overall urban activity such as outdoor activities with greater Spatio-temporal flexibility can more easily be re-arranged or canceled to reduce exposure risk

Firstly, in the domestic violence case, air pollution has a positive and significant association with this type of crime (77.5%. positive). The model demonstrates that AQI's effects rise from rural to urban with the -0.09 to 0.26 coefficient of domestic violence. The higher the AQI value

Table 3 Local Model GWR and GTWR

Variable	Domestic Violence							Robbery						
	OLS	GWR			GTWR			OLS	GWR			GTWR		
		Min	Median	Max	Min	Median	Max		Min	Median	Max	Min	Median	Max
Intercept	-2.6514***	-84.68	-11.72	164.77	-24.38	17.96	61.13	19.705***	-2.51	23.80	52.74	-3.76	24.97	59.61
Popuation	0.0003***	1.1e-4	3.4e-4	1.1e-3	1.9e-4	3.4e-4	1.1e-3	0.00002***	8.3e-6	2.1e-5	3.5e-5	8.9e-6	2.1e-5	4.9e-5
Female Ratio	0.5929**	-2.71	0.74	9.52	-3.44	0.68	2.76	-0.3348***	-0.98	-0.37	0.03	-1.12	-0.44	0.05
Median Age	-0.4146***	-5.97	-0.83	-0.01	-1.93	-0.82	-0.02	-0.0468***	-0.12	-0.04	0.01	-0.11	-0.05	0.01
Income	-0.0063***	-0.18	-0.01	0.02	-0.05	-0.01	0.03	-0.0016***	0.00	0.00	0.00	-0.003	-0.001	0.001
Education	-0.4568***	-1.48	-0.45	5.55	-1.57	-0.45	1.93	0.0564***	-0.07	0.05	0.11	-0.11	0.06	0.12
Unemployment	0.6235***	-4.51	0.99	2.19	-2.21	0.97	3.01	0.0102***	-0.11	0.01	0.19	-0.12	0.01	0.17
AQI	0.0201**	-0.06	0.04	0.18	-0.09	0.16	0.26	-0.00120.	-0.13	-0.03	0.09	-0.17	-0.05	0.06
Bandwidth		0.114			0.117				0.115			0.140		
AIC	12082.170	12054.7			12011.6			6121.413	6028.83			6015.16		
R2	0.818	0.8388			0.8421			0.482	0.5514			0.5514		
Spatio-temporal Distance Ratio					0.26876							0.26876		

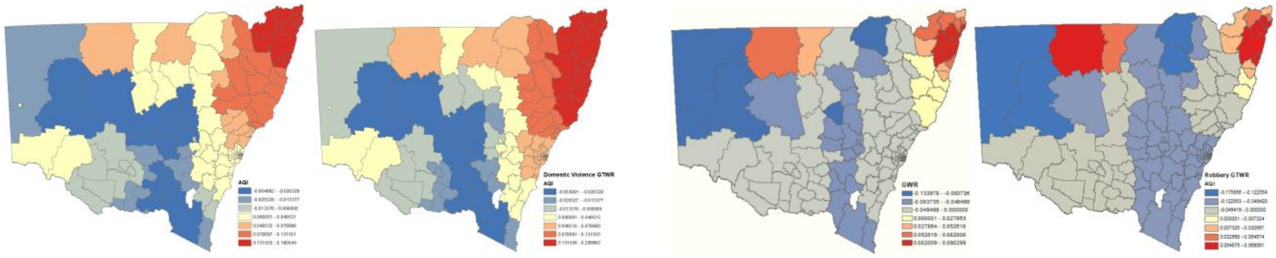
Significant Code: 0.0001'***' ; 0.001'**' ; 0.01'*' ; 0.05 '.' ; 0.1 ' '



(a) (b)

Figure 4 Residual Distribution OLS and GTWR

GWR GTWR GWR GTWR



(a) **(b)**

Figure 5 Spatial distribution of (a) Domestic violence; (b) Robbery as the effect of air pollution

in the area, the higher the domestic violence. People already aware of the effect of air pollution and leaving no choice for them to stay longer at home. It will be very detrimental to people who do not have a job where unemployment in particular is a key determinant of domestic violence (Baker et al, 2010). Latent abusive males who are in fear of losing their jobs or who have lost their jobs may have stress for staying at home longer and tend to do abusive behavior to their partner especially women due to an economic issue. However, when women are at a high risk of unemployment, their economic dependence on their spouses may prevent them from leaving their partners. It also explains another variable of our result that shows the negative relationship between unemployment with domestic violence. This result is like we expected because there are many factors that could lead people to do domestic violence where it mostly happened when they are at home.

Secondly, for robbery the coefficients of AQI are negative and statistically significant, which means this pollutant inversely contribute to the crimes, statistically said. Most local AQI coefficients are negative (81.6% negative), and these increase from urban to rural (coefficients range -0.17 to 0.06). This result also suits with our previous discussion where people will tend to stay at home and postpone or re-schedule their outdoor activity to avoid the health problem that causes by air pollution. By staying at home, it will discourage the offender to commit robbery because they have no target in outside or street. Moreover, it also could prevent property crime because people could protect their belonging when they are at home. However, Population still has a positive and statistically significant relationship with the crime where it means if the area has a higher population number, the possibility of robbery will also increase. It according to Boivin (2018) where areas with large populations, whether residential, visiting, or a combination, are expected to experience more crime because a larger population provides more potential targets and offenders.

4. CONCLUSION

The main purpose of this study is to explore the effects of air pollution on human physical and mental conditions and daily activities, and thus the risks of different types of crimes (domestic violence, and robbery). From several spatial models, GTWR shows the best result based on the R-square and AIC value. The model shows that air pollution is positively correlated with indoor crime (domestic violence). While air pollution has a negative association with outdoor crime (robbery) and its impact is spatially heterogeneous. To determine the association between air pollution and crime, this research uses monthly data. The daily data will be used in the future to see a better illustration of the impact of air pollution on the various types of crime.

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