SPATIO-TEMPORAL ANALYSIS OF AIR POLLUTANT CONCENTRATIONS IN RELATION TO SCHOOL LOCATIONS IN JOHOR

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Thesis submitted to the Universiti Teknologi MARA Malaysia in partial fulfilment for the award of the degree of the Bachelor of Surveying Science and Geomatics (Honours)

JULY 2020

DECLARATION

I declare that the work on this project/dissertation was carried out in accordance with the regulations of Universiti Teknologi MARA (UiTM). This project/dissertation is original and it is the result of my work, unless otherwise indicated or acknowledged as referenced work.

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ABSTRACT

Air pollution can be well defined as the term that contains combustion of thousands of components from a wide range of various sources. Furthermore, air pollution has appeared as one of the main factors that lead to problem health especially in urban areas. Basically majority schools are located near with the busy roads, industrial, commercial and residential area which students have high chances to expose to air pollution. When students are exposed to air pollutant, the number of student having health problem will increase. In this study, interpolation technique is used to identify which school area in Johor has the higher range of air pollutant concentration. There are four parameters involves which are $PM_{2.5}$. CO, O_3 and SO_2 and the study area for this research is Sekolah Menengah Kebangsaan Bandar Penawar, Kota Tinggi, Sekolah Kebangsaan Pasir Gudang (2) Pasir Gudang, Sekolah Menengah Kebangsaan Bandar Putra, Segamat, Sekolah Menengah Kebangsaan Tanjung Pengelih Pengerang, Sekolah Menengah Teknik Johor Bahru Larkin and Sekolah Kebangsaan Seri Separap, Batu Pahat. Furthermore, IDW interpolation method is used to analyze hourly air pollutant concentration data obtained from DOE. Moreover, spatial autocorrelation technique is used to identify the relationship between the air pollutant concentration level and the schools location in Johor. The main purpose of this research is to analyze the air pollutant concentrations in relation to the location of the selected schools in Johor from January 2018 to December 2018. Through this analysis, awareness about the air pollution level within the school area can be informed thus precaution about the air pollution at school can be made especially school that is located near with industrial, commercial, residential and busy road area.

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LIST OF ABBREVIATIONS

API	Air Pollution Index
GIS	Geographic Information System
$PM_{2.5}$	Particulate matter 2.5
CO	Carbon monoxide
SO_2	Sulphur dioxide
O_3	Oxides
DOE	Department of Environment
NO	Nitrogen oxides
AQGs	Air quality guidelines
AQI	Air quality index
AQMN	Air quality monitoring network
USEPA	United State Environment Protection Agency
EPA	Environment Protection Agencies
IDW	Inverse Distance Weighting
NO_2	Nitrogen dioxide
BS	Black smoke
GMI	Global Moran Index
LISA	Spatial association
LMI	Local Moran Index
H-H	Upper right
L-L	Lower right
L-H	Upper left
H-L	Lower right
OSM	Open street map
VOCs	Volatile organic compounds
HTML	Hypertext Markup Language

CHAPTER 1

INTRODUCTION

1.1 Research Background

Almost all schools are located near with the busy roads, industrial, commercial and residential area, not to mention 50% of students spend their time outdoor by walking or cycling to school which exposed them directly to pollution. It can be stated that students are easy to get sick since their bodies are still fragile and their organ is still in the process of developing. Hence, children are more vulnerable to the air pollution effects. Above all, exposing students to pollutant will resulting in a serious health problem such as breathing problem, cancers, allergies, respiratory disease and cardiovascular issues especially when the pollutants reach the permissible limits (Xie et al., 2017). It is irrefutable that children who breathe in polluted air are possible to risk their health and might cause death.

Immediate act are requires in order to protect students from being exposed to air pollution hence strategy or plan to decrease air pollution must be taken, reduce the amount of students being exposed with the pollutant and monitor the pollutant. According to de Gennaro et al (2014), it has been recognized that the airborne particles in the classroom were the major airborne contaminants that affect indoor air quality and the students' health.

According to reviews, there are over 6.5 million deaths allocate to urban outdoor air pollution annually reported by the World Health Organization. As for awareness and precaution about the air pollution and its negative effects, especially towards students' health, monitoring air quality is necessary in order to control the air pollution; this is significant in order to prevent air pollution from getting serious which will affect the health of entire living organism on Earth. It is significant to measure air pollution in order to understand the risk of exposure around the school environment. Next, it has been recognized that the Air Pollution Index (API) is one of the air pollution fundamental indicators that used to record the interface between air pollution and human health (Rahman et al, 2016).

Furthermore, instantaneous air pollution monitoring system has been applied to measure and report the real-time changes in pollution ranks. Monitoring station or systems has been installed across the cities and the measurement obtained from the several stations will reflect the air pollution rate in that particular area around the location. Further estimation of the pollutant concentration at the unmeasured areas using the obtained measurement available will be performed using variety Geographic Information System (GIS) method (Xie et al, 2017).

GIS method is continuously being used for the analysis and management of the natural environment. GIS-based suitability analysis has been performed to establish the air pollution in accordance with the selected schools located in Johor. Generally, the spatial-temporal and interpolation method has been applied in this research. Studying and analyzing the current status of air quality and the spatial-temporal is important because the result help to identify the main air pollution issues thus through this identification, an awareness about air pollution can be raise among the society especially among students.

1.2 Problem Statement

Generally, school located at the centre of urban area is likely expose to pollutants from traffic, industrial and commercial area. Students are exposed to pollutants during dropping off and picking up moment, as students come or leave from school. Hence, the front gates around the school are where the heavy traffic likely occurs especially at the beginning and the finishing of the school day. Above all, particulate matter ($PM_{2.5}$), carbon monoxide (CO), sulphur dioxide (SO_2) and Oxides (O_3) that created directly or otherwise by the traffic has been affecting human health and the environment and in the long-term, it tends to exacerbate the risks to the earth.

Besides, school which is nearer to industrial and toxic waste sites was connected to the factor of health problem. It has been studied that health risk such as chronic respiratory has affect children living close to industrial plants (Nirel et al, 2015).

This study aims to analyze the air pollutant concentrations in relation to school location in urban area. It is necessary to identify the spatio-temporal analysis of air pollutant concentrations in relation to the school in Johor in order to prevent the students from being exposed to air pollution thus having a critical health risk since students spend most of their time in the school area. In addition, students especially children under the age of 15 years are vulnerable to the effects of air pollution during their early development when the brain are still developing (Friedrich, 2018). It is necessary to identify the cause of pollutant in order to reduce the air pollution concentration. Through this analysis, awareness about the air pollution level within the school area can be raised once the air pollutant is identified and the immediate alert can be informed thus precaution about the air pollution at school can be made especially school located nearer with the industrial area, commercial area or residential area. Geographic Information System is used to manipulate and analyze the data collected from school thus the distance between school and industries are measured through this analysis hence the relation between air pollutant concentrations with school can be estimated and present in the form of story map with clearer description and presentations.

1.3 Aim

To analyze the air pollutant concentrations in relation to the location of the selected schools in Johor from January 2018 to December 2018.

1.4 Objective

The objectives of this study are:

i. To digitize the landuse map for selected schools in Johor from Google Earth.
ii. To analyze the relationship between air pollution and school location using spatial-autocorrelation technique.
iii. To create story map for air pollution concentrations in Johor.

1.5 General Methodology

Figure 1.1 shows the general methodology of procedure for this research. Based on the flowchart below, preliminary study was done by reading articles and journal related with environmental study based on Johor air pollution. Secondly, data collection was performed where hourly data of air pollutant concentration in selected station in Johor is obtained from DOE. Next, the data obtained undergo data cleaning in order to remove unwanted data before being process using ArcGIS software to produce output which will be present in story map.

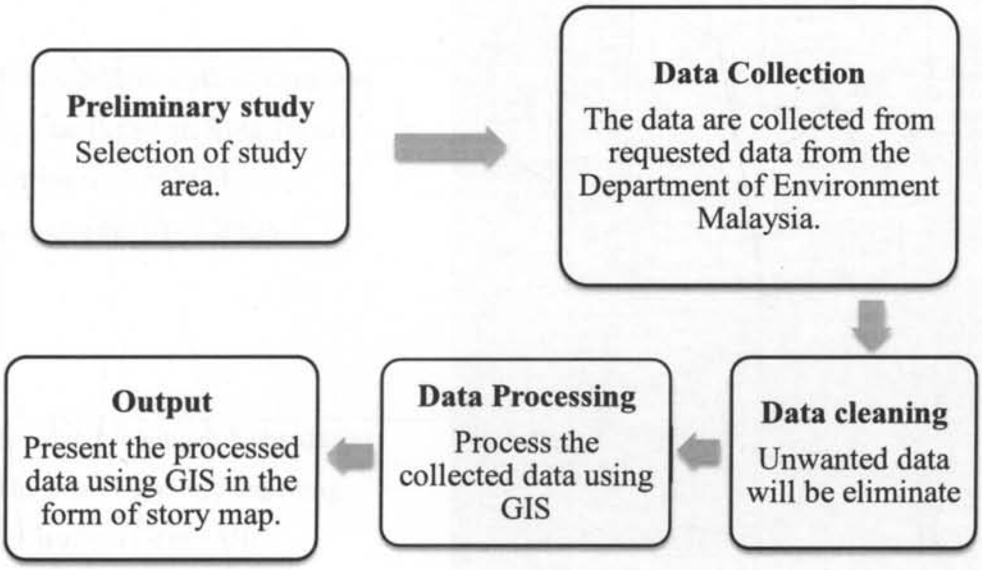

Figure 1.1 Flowchart of methodology

1.6 Scope of study

This study is conducted at Sekolah Menengah Bandar Penawar, Kota Tinggi, Sekolah Menengah Pasir Gudang (2), Sekolah Menengah Teknik Johor Bahru Larkin, Sekolah Menengah Kebangsaan Bandar Putra, Segamat, Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang, and Sekolah Kebangsaan Seri Separap, Batu Pahat. The nearest air pollution monitoring stations are found at the selected schools. Figure 1.2 shows the map with air pollution index of Johor, Malaysia together with the three selected school study area.

Table 1.1 The study area at Johor, Malaysia. (APIMS, 2019)

School	Map
Sekolah Menengah Kebangsaan Bandar Putra, Segamat **Latitude**: 2.500138135 **Longitude**: 102.863692	
Sekolah Menengah Kebangsaan Bandar Penawar, Kota Tinggi **Latitude**: 1.563433 **Longitude**: 104.228828	
Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang **Latitude**: 1.366075507 **Longitude**: 104.1056272	

Sekolah Kebangsaan Pasir Gudang (2), Pasir Gudang **Latitude**: 1.456508 **Longitude**: 103.906469	
Sekolah menengah teknik Johor Bahru, Larkin **Latitude:** 1.90864 **Longitude:** 102.86877	
Sekolah Kebangsaan Seri Separap, Batu Pahat **Latitude:** 1.4933 **Longitude:** 103.7276	

Table 1.1 shows the specific study areas that are selected for this research. These study areas are selected based on their locations which are located near with both residential and industrial area. Based on the school areas, Sekolah Menengah Teknik Johor Bahru, Larkin , Sekolah Menengah Kebangsaan Bandar Putra, Segamat, Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang, Sekolah Kebangsaan Seri Separap, Batu Pahat and Sekolah Menengah Kebangsaan Penawar Kota Tinggi are surrounded with green area, residential and industrial area. Whereas, Sekolah Menengah Pasir Gudang where is located at the city centre consists of industrial and commercial area. Furthermore, most of the school is located near with green area where the green area act as buffer for the industrial area.

1.6.1 Expected Outcome

The expected outcomes for this study are:

i. Spatio-temporal analysis of the air pollutant concentrations in relation to the location of the six selected schools in Johor.
ii. Story map of air pollutant concentrations at the selected schools in Johor.

1.7 Organization of chapters

First of all, the first chapter which is chapter one discusses the research background, problem statement, aim, objective, general methodology, the scope of study and the expected outcome of this research. Next, chapter two discusses the literature review that includes the introduction of air pollution, what are the parameter, factors and the effects of air pollution. Furthermore, chapter two explained more about the air pollution index (API), Geographic information system (GIS) for monitoring air pollution which includes the explanations about the elements of GIS, the tools and techniques used in GIS to analyze the relationship between air pollution and school.

Moreover, chapter three described the methodology for each procedure for this research and the technique used to process the data to analyze the relationship between air pollution and the selected school. Whereas in chapter four, the analysis for this research will be performed to determine the results using GIS technique and display the result in the form of story map.

Last but not least is chapter five where the conclusion for this research will be concluded according to the analysis results and recommendation will be given to prevent serious health problem from affecting students especially school that is located near with busy traffic area, industrial area, residential and commercial area. This research will try to uncover the spatial-temporal patterns of air pollution in school through mapping techniques.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature from previous researches that are related to this research. Previous researches have been conducted on identifying and monitoring the air quality using Geographic Information System (GIS), the definition of air pollution from various sources, the parameter of air pollution, various effects and factors are identified and discussed here. The air pollution index will be explained according to the level of pollution after the parameters of pollutant are measured. Hence, various techniques of GIS were used to analyze the relationship between air pollution and school.

2.2 Air Pollution

Air pollution can be well-defined as the term that contains a combination of thousands of components from a wide range of various sources. Air pollution has appeared as one of the main factors that lead to problem health especially in urban areas. Theoretically, air pollution for both industrial processes and vehicles are maintained high correlation with energy consumption. For example, the main source of many main pollutants which include sulphur dioxide (SO_2) and carbon monoxide (CO) are due to the combustion of fossil fuel (Zhou et al, 2018). Hence, the major pollutants that have caused a serious effect on human physical condition include airborne particulate matter (PM) and other gaseous pollutants which include nitrogen monoxide (NO), ozone (O_3), SO_2 and CO (Salonen et al, 2018). There are two types of air pollution, which are indoor and outdoor air pollution. Indoor pollution defined as the presence of pollutants such as particulate matter, inflammable organic compounds, mineral, biological, physical and chemical factors in the indoor air of non-industrial buildings. Basically, children are very vulnerable to environmental exposures since the most of them are still growing up (Rivas et al, 2018).

2.2.1 Parameters of Air Pollution

Air pollution parameters are waste substances produce from industrial, traffic vehicles and other sources whether directly or indirectly formed. Generally the common parameter of air pollution are particulate matter (PM), ozone (O_3), sulphur dioxide (SO_2), nitrogen oxides (NO_2), carbon monoxide (CO), and lead.

According to Lee et al, (2018), PM can be categorized by the diameter of the particle such as rough particles PM_{10} with a diameter of 10μm or less, thin particles or $PM_{2.5}$ with a diameter of 2.5μm or less and next which is the ultrafine particles with a diameter of lesser than 0.1 μm. The diameter and the structure of particles primarily depend on its source. PM_{10} usually formed from the resuspension of soil where using the soil in suspension repeatedly, dust road travel through wind and moving vehicles, industrial and construction works. Whereas, $PM_{2.5}$ resulting from the combustion of fossil fuel such as power plants, motorized road traffic and cooking activities where heating using wood, oil and coal in residential area. Usually carbon, transitional metals, complex organic molecules, nitrates and sulphate are the particles formed through those activities. Moreover, gaseous pollutants such as SO_2, O_3, NO, and CO. SO_2 usually formed from fossil fuel power plants. NO released from the motorized road traffic, heating activities from the residential such as cooking, generator and other industrial sources.

In addition, according to Kur et al, (2016) can be stated that usually PM is produces through industrial processes and traffic-related sources such as gasoline, diesel, oil fuel combustion, farming, Road combustion and coal. Besides, PM is subdivided into three size classifications which are particle with diameters 2.5 to 10μm (PM_{10}) and particle with diameters that is less than 2.5 μm ($PM_{2.5}$).

Table 2.1 Malaysia Ambient Air Quality Guidelines (DOE, 2019)

Pollutant	Averaging Time	Malaysian Guidelines (Concentration) ppm	($\mu g/m^3$)
Ozone	1 Hour	0.10	200
	8 Hour	0.06	120
Carbon Monoxide**	1 Hour	30.0	35
	8 Hour	9.0	10
Nitrogen Dioxide	1 Hour	0.17	320
	24 hour	0.04	10
Sulphur Dioxide	1 hour	0.13	350
	24 Hour	0.04	105
Particulate Matter (PM_{10})	24 Hour		150
	12 Month		50
Total Suspended Particulate (TSP)	24 Hour		260
	12 Month		90
Lead	3 Month		1.5

Table 2.1 illustrates the Air Quality Guidelines (AQGs) which displayed global guidance based on the air pollutants limits that affect health problems. Generally, AQGs designed in order to prevent everyone especially who are at risk to experiencing health effects when inhaling particular air pollutant.

2.2.2 Factors of Air Pollution

It has been stated that the main factor that increases the level of pollution is due to the rapid growth of motor vehicle traffic and immediate growth of industrialization, especially in the urban area. It has been proved that the main sources of air pollutants that affect the environment which include the emissions from the automobile, current generators and factories activities, road and building construction activities such as mining. Moreover, the main source of fine and ultrafine particles is mainly due to motor vehicle which brings a negative effect especially on urban air quality and human health (Amato et al., 2014). The most concerning major of air pollutants include carbon monoxide, carbon dioxide, nitrogen oxide, sulfur oxide, noise, particulate matter and volatile organic compounds such as benzene, polycyclic hydrocarbons and formaldehyde (Obanya et al, 2018). Moreover, stated that air pollution is intensely influenced by people events and socioeconomic aspects which have been established to maintain a high correlation with air pollution.

Furthermore, it has been approved that the concentration of PM_{10} increase during haze season compare to non-haze season. Generally, the haze has occurred every year and it is a common occurrence that has been affecting Malaysia. Haze has caused a reduction in visibility and affects in human health through the slash and burn from the agricultural activities, deforestation and oil palm plantation on peat areas, particularly in Sumatra and Kalimantan, Indonesia. It has been identified that Indonesia was the main factor that contributes to the highest potency to combustion which resulting in Trans boundary haze in Malaysia (Latif et al, 2016).

Besides haze, the school and class environment are particularly polluted with pollutant due to packed classrooms, limited break times, low ventilation during rest times, insufficient fresh air, lack of mechanical ventilator, impromptu construction of ventilation system and many more. Moreover, the main reasons for the radon existence in indoor spaces are due to underground waters and the building materials which consist of radon. Radon exists due to indoor spaces of underground waters and building material which contain radon hence it enters the indoor through gaps around the drainpipes, cracks between wall tiles and from the sewer pumps. (Argunhan et al, 2018).

Pollutant	Major indoor sources
Fine particle	Fuel/tobacco combustion, cleaning operations, cooking
Carbon monoxide	Fuel/tobacco combustion
Polycyclic aromatic hydrocarbons	Fuel/tobacco combustion, cooking
Nitrogen oxides	Fuel combustion
Sulfur oxides	Coal combustion
Arsenic and fluorine	Coal combustion
Volatile and semi-volatile organic compounds	Fuel/tobacco combustion, consumer products, furnishings, construction materials, cooking
Aldehydes	Furnishings, construction materials, cooking
Pesticides	Consumer products, dust from outside
Asbestos	Remodelling/demolition of construction materials
Lead	Remodelling/demolition of painted surfaces
Biological pollutants	Damp materials/furnishings, components of climate control systems, occupants, outdoor air, pets
Radon	Soil under buildings, construction materials

Figure 2.1 Major health damaging pollutants

Figure 2.1 shows the indoor pollutants generated from the indoor sources, indoor air contains the similar pollutants as in outdoor air but the concentration are unlike and most of the time lower (Jiang et al, 2016). Whereas, the outdoor pollutants usually from industrial production, forest fire, garbage burning and emission released from the transport. Several studies mention that other main sources of particulate matter can be divided into four major sources which include vehicle exhaust, shell particles on dirt ground, industry emissions and secondary sulfate (Jafari et al, 2017).

2.2.3 Effects of Air Pollution

The health effects of air pollution have become a concern worldwide. The numbers of people expose to ambient air pollution has increase morbidity and mortality which is then resulting in the contributors to global disease burden (Cohen et al., 2017). It has been recognized a long time ago but less awareness was taken. According to Kurt et al, (2016), the most susceptible to the effects of air pollution are usually children and adolescents compare to adults. Exposure to air pollution at an early stage especially children will cause a serious effect thus generate the environmental allergies (Sunyer et al, 2015). It has been defined that indoor air pollutants such as particulate matter, inorganic compound, biological, physical and chemical factors and other waste substances have a negative impact to human and environment thus will bring harm to human health. According to this report, the majority of the student reveals to indoor air in the school building during their academic life. All the pollutants from different sources affect the human health, comfort and student presentation and workers in a negative way because it brings harm and negative impact especially on memory and concentration of student (Argunhan et al, 2018).

Besides, all of these pollutants can bring both short and long-term that resulting in critical and chronic toxicity effects. Most of these materials bring negative and bad impact on human health especially their organs that include bone marrow, spleen and lymph nodes. Furthermore, human circulatory systems are sensitive to toxins in exhaust fumes and exposure to these pollutants will cause asphyxiation and anemia. The consequences when exposed to all these pollutants will increase the risk of upper respiratory tract disease that include asthma, inflammation, fibrosis and chronic obstructive pulmonary disease, bring harm to the heart due to hypertension and degeneration of the cells that include blood vessels, irreparable damage to the central nervous system thus will cause cancer. Carbon monoxide emanates primarily from the vehicular and generator exhausts and deprives the bloodstream of oxygen necessary for many vital functions within the haemoglobin. Besides, the main air pollutants such as carbon dioxide which leads to global warming thus affect the greenhouse hence increase the temperature (Obanya et al, 2018).

Moreover, short-term exposure to ozone is significantly associated with increased hospitalizations in children (Sheffield et al, 2015). In this case, poor air quality due to high levels of ozone has been shown to not only contribute to the exacerbation of asthma but to also be a cause in the development of asthma.

A recent 2015 analysis record shows that circumstances exposure to SO_2 and $PM_{2.5}$ from vehicle emissions significantly increases the risk of lung cancer (Chen et al, 2015). As for the respiratory infections two recent epidemiological studies published in 2012 and 2014 demonstrate associations between short-term air pollution such as traffic-related PM, ozone and organic carbon-based $PM_{2.5}$, enhanced respiratory infection symptoms and increased emergency department visits by children (Darrow et al, 2014). Based on Lam (2016), when human expose to air pollutant in utero, the rising of neurodevelopmental delay and autism is associated.

2.3 Air Pollution Index (API)

Generally, API which is also known as Air Quality Index (AQI) has been applied and allocate by several organizations to handover the air quality position to the public, open community, manager and other direct administrator. Commonly, the API is the model which is used to gauge the level of ambient air pollution (Zhou et al, 2018). API reading values are significant in deciding the stage of air quality. Therefore, an immediate action can be taken once the stage of API increase. The first step in addressing the air pollution issue is by monitoring the air pollution by using Air Quality Monitoring Network (AQMN) (Shareef et al, 2016). After monitoring the air quality then only the air pollution index can be classify according to range.

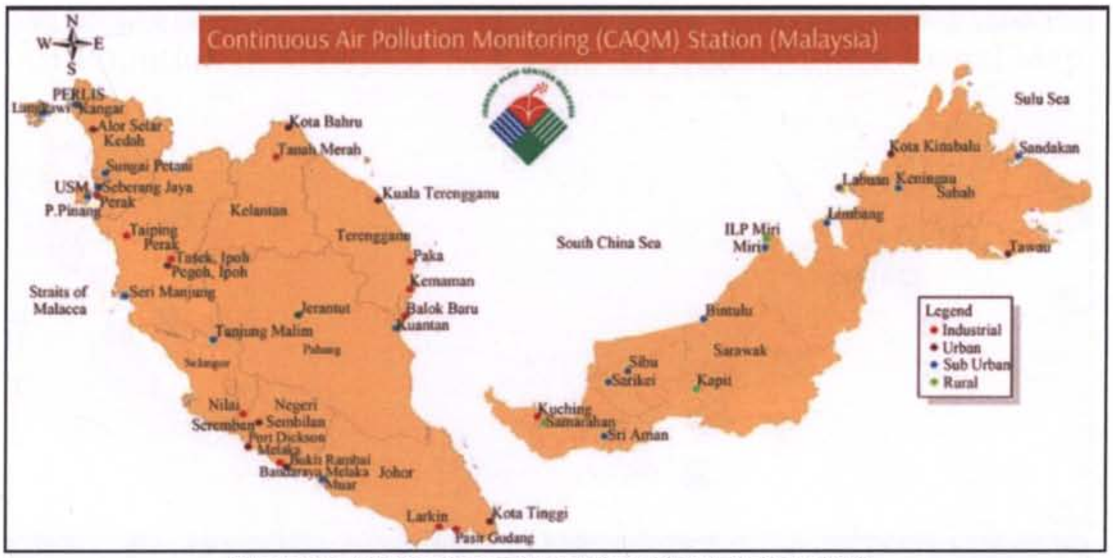

Figure 2.2 Air Monitoring Station in Malaysia (DOE, 2014)

Figure 2.2 illustrates the location of air monitoring station in Malaysia. Four symbols are used to differentiate the area of monitoring system. The Department of Environment (DOE) is where the site code for each monitoring station will be obtained. Stated that the air quality level and status continuosly monitored by DOE for 24 hours every day which is control from the automatic air quality control remote station. Through DOE references, due to the major existance of air pollutant the selected pollutants were measured, which is correlated with the criteria polutants from other countries and the WHO (Mohamad et al, 2015).

The development of API in Malayisa was introduced by the United State Environment Protection Agency (USEPA) and the sub-indexes calculation of five major pollutants was determined. The largest value between all the sub-indexes is selected as the API for the time of interest. Moreover, it is stated that different level of sub-indexes signify different effects on human health (Rahman et al, 2016).

Figure 2.3 Real-time Air Quality index (DOE, 2019)

Figure 2.3 show the Real-time Air Quality Index visual map of air pollution in Malaysia. Analsysis. Basically, in Malaysia there are about 50 continuous monitoring stations.

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warnings of emergency conditions. The entire population is more likely to be affected.

Figure 2.4 Air Quality Index (DOE, 2019)

Figure 2.4 show the specific color which has been assigned by Environment Protection Agencies (EPA) for every AQI to simplify the air pollution rate whether the air pollution reaching the unhealthy stage in one communities (AQI Basics). The API is desegregated measurements demonstrate the levels of three fundamental atmospheric pollutants such as $PM_{2.5}$, CO and SO_2. Other research such as Spearman rank correlation analysis is performed to evaluate the relationships between monitoring stations (Li et al, 2014). Furthermore, seasonal-trend decomposition to analyze the temporal variation and air pollution trend are one of the research are performed (Bigi et al, 2010).

2.4 Geographic Information System (GIS) for Monitoring Air Pollution

A geographic information system (GIS) can be defined as computer system that captures, stored, analyzed and displayed the geospatial data which include the location whether in the form of spatial or attribute data. Furthermore, GIS involves the hardware, software, data, people and organization components (Chang, 2017). Furthermore, GIS able to monitor the various temporal scales thus help in reducing the cost and time of field surveys which play an important role in conservation of environment. According to Ya'Acob et al, (2017), GIS is very powerful software that uses the location to visualize and integrate the information. This can be done through visualizing which detect the spatial pattern otherwise would remain concealed in tables and texts. In addition, users can identified the relationships within a GIS which then will form a complex world that easier to be understand.

Traditionally, a dedicated instrument at fixed monitoring stations is used to measured air pollution and the instruments are located sparsely in urban area. Monitoring stations have been installed by the policymakers across the country for legislator purposes (Kanaroglou et al., 2005). It can be conclude that the current systems tend to measure the air pollution at a very low spatial resolution, for example, there are only 22 stations covering a 50 x 50 km^2 in Beijing, 14 stations covering 1572km^2 in London. Furthermore, Flanders, Belgium with 61 stations which covered 221km^2 per station. Pollution sensors that able to access the personal exposure to air pollution are also placed by the researchers (Semanjski et al , 2016). Variety methods are proposed by the researcher to estimate the unmeasured areas such as interpolation method which include Inverse Distance Weighting (IDW).

2.4.1 Mapping the Distribution of Air Pollution using Interpolation Technique

Generally, interpolation methods used the similar mathematical foundation. All the unmeasured location is estimated as a weighted average of the measurements at surrounding monitoring stations. Different choice in sampling weights and the surrounding stations and there is four interpolation methods commonly used in air pollution estimation and assessment such as spatial averaging, nearest neighbor, inverse distance weighting, kriging and spline.

Spatially averaging usually calculate the average of pollutant measurements from the nearest monitoring stations where it predict the equivalent influence of the measurement at different monitoring stations with different distance to unmeasured location. Next, nearest neighbor can be define when assigning the pollutant measurements of the nearest monitoring stations to the unmeasured area, regardless with the actual distance among that area. It is stated the measurement from other neighbor area are ignored when applying this technique (Xie et al, 2017).

In spatial interpolation, IDW define as a deterministic method. At the monitoring stations, the weighted average of the measurements will be calculated from the unknown location (x, y), u(x, y). Basically, nearer measurements is more influenced than further measurement according to this method estimation for the value u(x, y). In other terms, the closer the locations, the greater the weights and the weights decrease as distance. Moreover, Hoek et al, (2002) has applied this weighted interpolation method to assumes the regional concentration of Black Smoke (BS) and Nitrogen Dioxide (NO_2) by using the measurement gained from the stations of the National Air Quality Monitoring Network in Netherlands.

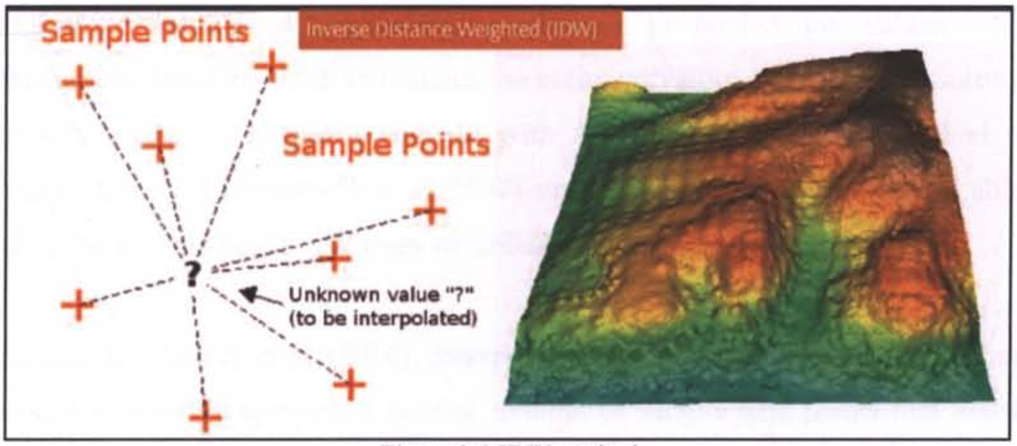

Figure 2.5 IDW method

According to the figure 2.5, during the interpolation process, the sample points are weighted where one point are influence hence relative to another decline with distance from the unknown point that will be created.

Besides IDW, kriging which is a weighted combination of measurement at surrounding monitoring stations. Differ with IDW method, instead of predict inverse distance function as IDW, kriging assigns weights at every concentration by exploiting the spatial correlation among the observed measurements. The benefit of using kriging interpolations is it produces both the estimates and standard errors at the unmeasured locations. Hence, the error will compute the degree of uncertainty in the estimates. Commonly, there are two forms of kriging used in geostatistics which are ordinary and universal. Ordinary kriging estimates an unknown constant mean in local neighborhood whereas universal kriging estimates general polynomial trend model. Generally, ordinary kriging are widely used method compare to universal kriging and usually universal kriging used when there is an existence of certain trend and describable trend (Janssen et al, 2008).

In addition, other interpolation methods have been applied and compared on the similar data set. According to Wong et al, (2004)f who has applied four method in order to determine the concentration levels of O_3 and PM_{10} over the whole USA resulting that the entire methods create related approximations in the areas with low density monitors and different method generated massively different concentration levels in the areas with high density monitors such in California.

Next, spline applied an interpolation technique to predict the values with a mathematical function which minimizes the entire curvature surface then resulting in a smooth surface that match suitable with the input points. This method was recommended by (Leitenstorfer et al, 2007) since this method was discovered able to identify the various health risk from air pollution.

According to Shareef et al (2016), interpolation method was used to predicts cells values in a raster by applying a limited number of sample data points that assist in reducing the unknown points or values of any geographic station. Moreover this method has been applied for the Riyadh city of Saudi Arab observation to observe the air pollution trend (Alharbi et al, 2015).

2.4.2 Assessment the air pollution using spatial autocorrelation

Generally in GIS an analytical tool, the main tools used is spatial autocorrelation. According to O'Sullivan (2010), it enable to authorize the spatial data to prevent similarities with a random distribution and one or more principal processes that bring to this pattern. Generally, spatial autocorrelation can identify the pattern and hotspots, the common method used is Moran's I which able to detect explicit outliers (W. Li et al., 2014). Besides, spatial autocorrelation has been utilized in many disciplines such as disease occurrence (Mohammadi Nia et al, 2015), urban planning and management, social networks studies and soil pollution.

Global and local Moran's I in spatial autocorrelation method are used to measured AQI of one city level by estimating the comprehensive effects and spatial variations of China's urbanization process on air quality (Fang et al, 2015). According to the study performed, 289 cities data in China are being investigate and a significant spatial dependence in AQI value are found. The AQI data gathered based on 2015 from 161 major cities in China are being spatial distribution through evaluation and seasonal spatial variation of AQI with Moran's I indices. Moreover, the common affected urban indicators of AQI were estimated quantitatively (Pu et al, 2017).

According to Réquia et al (2015), applying global Moran's I and Getis tests estimated that vehicle emissions for main traffic routes and evaluated spatial pattern.

This technique is used in order to create map which contain a surface including the spatial relationships with the sample points. Then, geostatistical options are apply in order to eliminate trend thus modeling spatial autocorrelation sample values to produce a more accurate prediction surface (Al-Hasnawi et al, 2016).

2.4.3 Air Pollution data analysis using GIS

Basically, analyzing air pollution data using GIS is superimposed to all spatial data and attributes to the study area. Figure 2.6 show the various combination of input parameter which then create various models. Then, all the models are intergrated accordingly with GIS thus assist in air pollution spatial mapping. The data is then imported into GIS software for further process to spatial datasets. Hence, resulting in overlay of display with sub systems intersection as a geographical map (Kumar et al 2015).

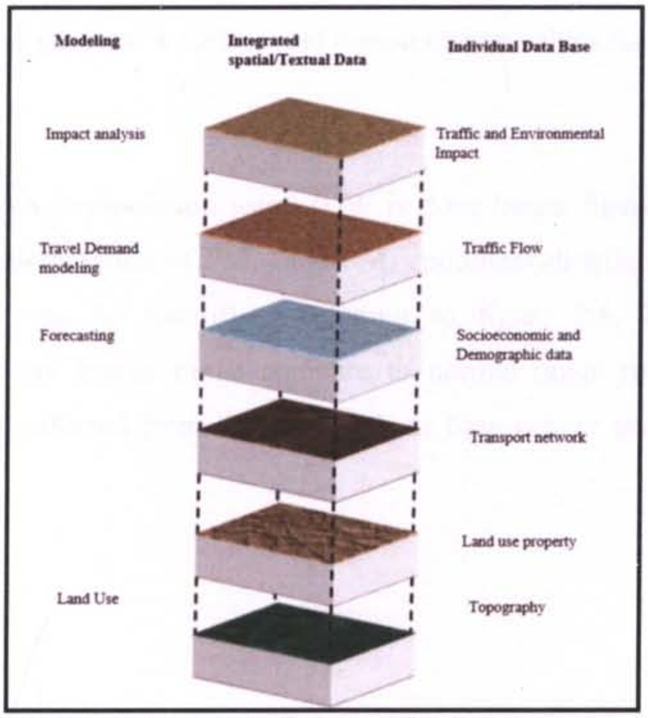

Figure 2.6 Superposition layout of data layers with GIS

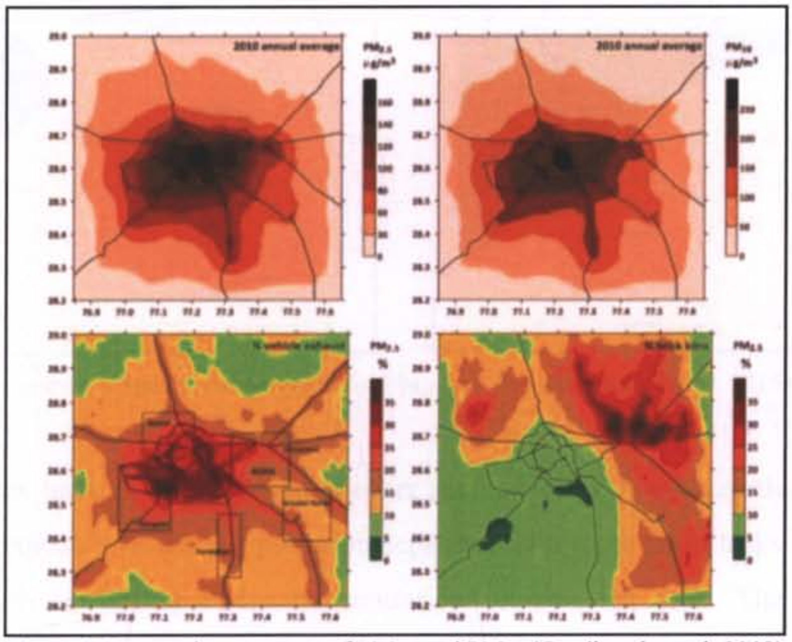

Figure 2.7 Annual percentage of $PM_{2.5}$ and PM_{10} (Guttikunda et al, 2012)

Figure 2.7 display the mapping of $PM_{2.5}$ and PM_{10} in Delhi, India based on the pollutant sources which are from automobile exhaust and brick kilns emission for 2010. Next, analyzing the data using GIS is applied since the of air pollution monitoring stations is limited; a grid is applied to every surface of study area. Using the IDW method to interpolate the concentration level of CO and $PM_{2.5}$ obtained form 38 points and generate a surface and concentration values for each pixel of the grid continuously.

Furthermore, spatial interpolation using IDW is done hence figure 2.8 on the next page shows the interpolation of PM_{10} and $PM_{2.5}$ pollutant distribution over the city hence the factor can be identify. According to figure 2.8, PM_{10} and $PM_{2.5}$ concentration display higher range compare to normal range resulting in higher number of people affected from diseases such as lung cancer and cardio vascular mortality.

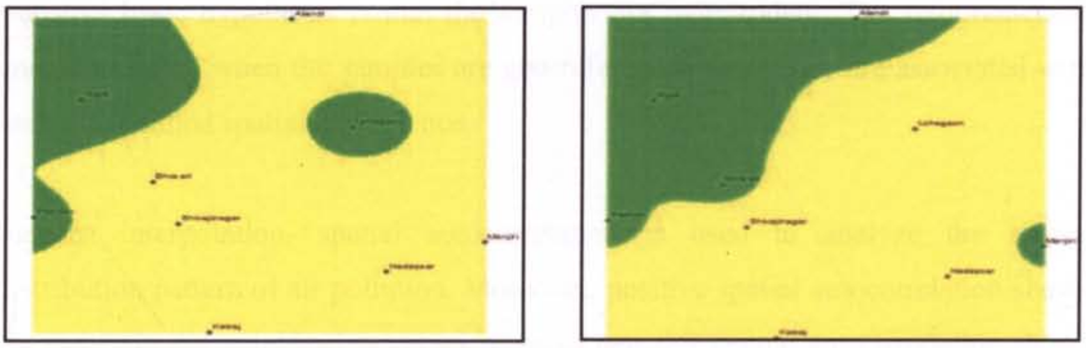

Figure 2.8 Spatial Interpolation for PM_{10} and $PM_{2.5}$ (Kanakiya et al, 2015)

Other sources have mentioned that another method used to analyze the number of population expose to $PM_{2.5}$ air pollution separated into three main tasks that include mapping high resolution $PM_{2.5}$ concentration on selected area. The process of spatializing the number of population at the sub-district level then evaluates the population of $PM_{2.5}$ exposure. Evaluating the $PM_{2.5}$ concentration with ground based monitoring result directly is difficult since the $PM_{2.5}$ monitoring stations are spread sparsely. Various methods are used to manage the $PM_{2.5}$ concentration specializations such as interpolation methods, dynamic models and regression models. An interpolation method which consists of kriging interpolation method are used widely hence it is used to monitor data for the whole area of Beijing together with the spatial resolution of 1km x 1km (Liu et al, 2017).

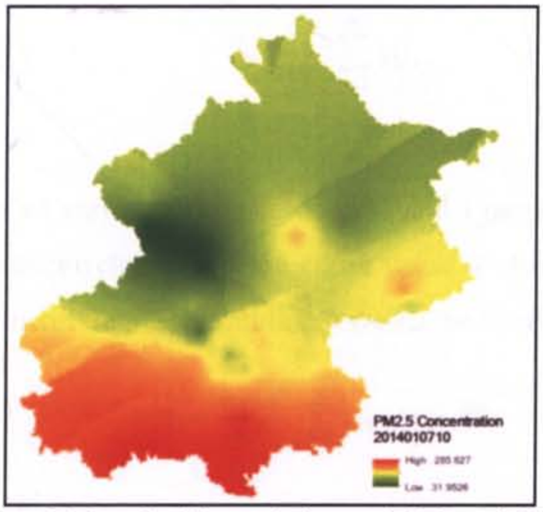

Figure 2.9 Sample of interpolation result.(Liu et al, 2017)

Figure 2.9 shows the $PM_{2.5}$ concentration sample of interpolation result in Beijing, $PM_{2.5}$ which is the particulate matter with diameter less than 2.5µm. The classical statistics basic hypothesis is that the samples are independent. The requirement is unable to fulfill when the samples are geo-referenced since they are associated with each other called spatial dependence.

Besides interpolation, spatial autocorrelation is used to analyze the spatial distribution pattern of air pollution. Moreover, positive spatial autocorrelation shows the same similar neighboring values whereas negative spatial autocorrelation shows the different values. Moran's I statistic and other measurement such as Geary's C are commonly used to measure the spatial autocorrelation. Global Moran's I statistics is used to test the present of spatial autocorrelation by using Moran's I statistic (Xu et al, 2016).

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad 2.1$$

Z_i defined as the deviation of an attribute for feature i from mean (x_i- $\bar{X}$), $W_{i,j}$) is the spatial weight between features i and j, whereas n is the equal of sum number of features, S_0 defined as the aggregate of all the spatial weight.

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} \qquad 2.2$$

Generally, Moran's I varies value is between -1 and 1 that represent the negative and positive spatial autocorrelation and the entire value is closer to zero that shows the weaker spatial autocorrelation. Formula 2.3 shows the local Moran's I statistic.

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j}(x_i - \overline{X}) \qquad 2.3$$

x_i shows the attribute feature j, $\bar{X}$ defined as the corresponding attribute mena, W i,j defined as the spatial weight between feature i and j.

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} w_{i,j}}{n-1} \overline{X}^2 \qquad 2.4$$

Local spatial autocorrelation analysis in GeoDA can specified the cluster of $PM_{2.5}$ pollution. Figure 2.10 show the spatial pattern includes hotspots and cold spots of $PM_{2.5}$ pollution where it can be located in local spatial cluster map.

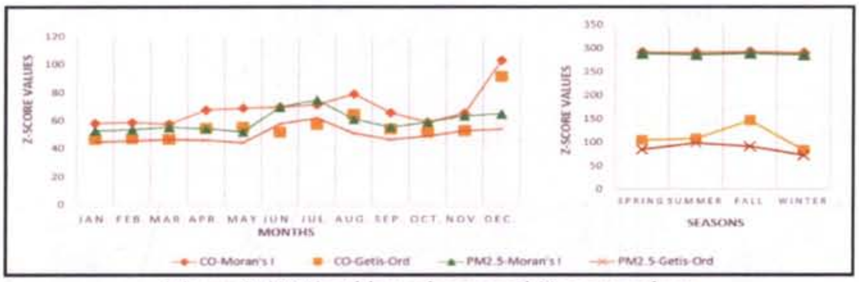

Figure 2.10 Monthly and seasonal Z-score values

Figure 2.10 shows the Z-score value for CO and $PM_{2.5}$ monthly and seasonal. Both pollutants utilize Moran's I and Getis methods and resulting same monthly trends. Hence, the Z-score values of Moran's I is always higher than Getis method.

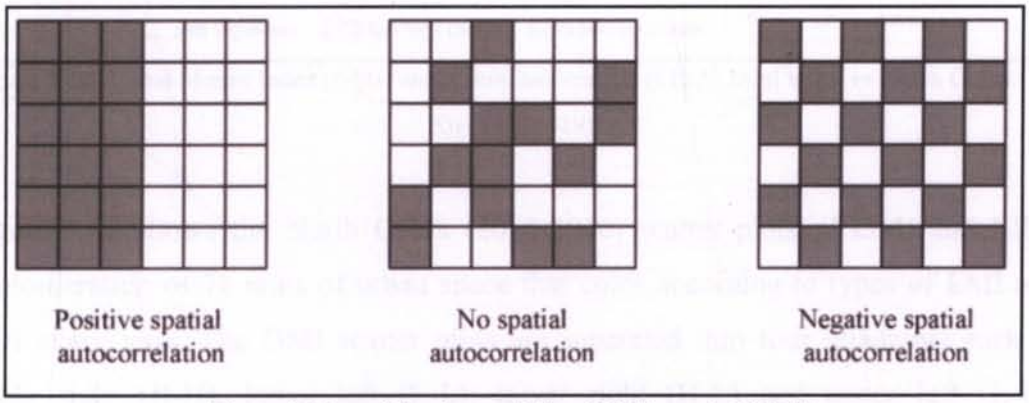

Figure 2.11 spatial autocorrelation (Matthew et al, 2011)

According to figure 2.11, spatial autocorrelation that shows in both positive such as cases nearby are similar and neutral which is neighbor cases having no particular relationship hence no spatial autocorrelation exist. Negative spatial autocorrelation such that cases nearby are dissimilar. Moreover, existence of spatial autocorrelation defined as the cases are not independent hence the degree of freedom are overestimated.

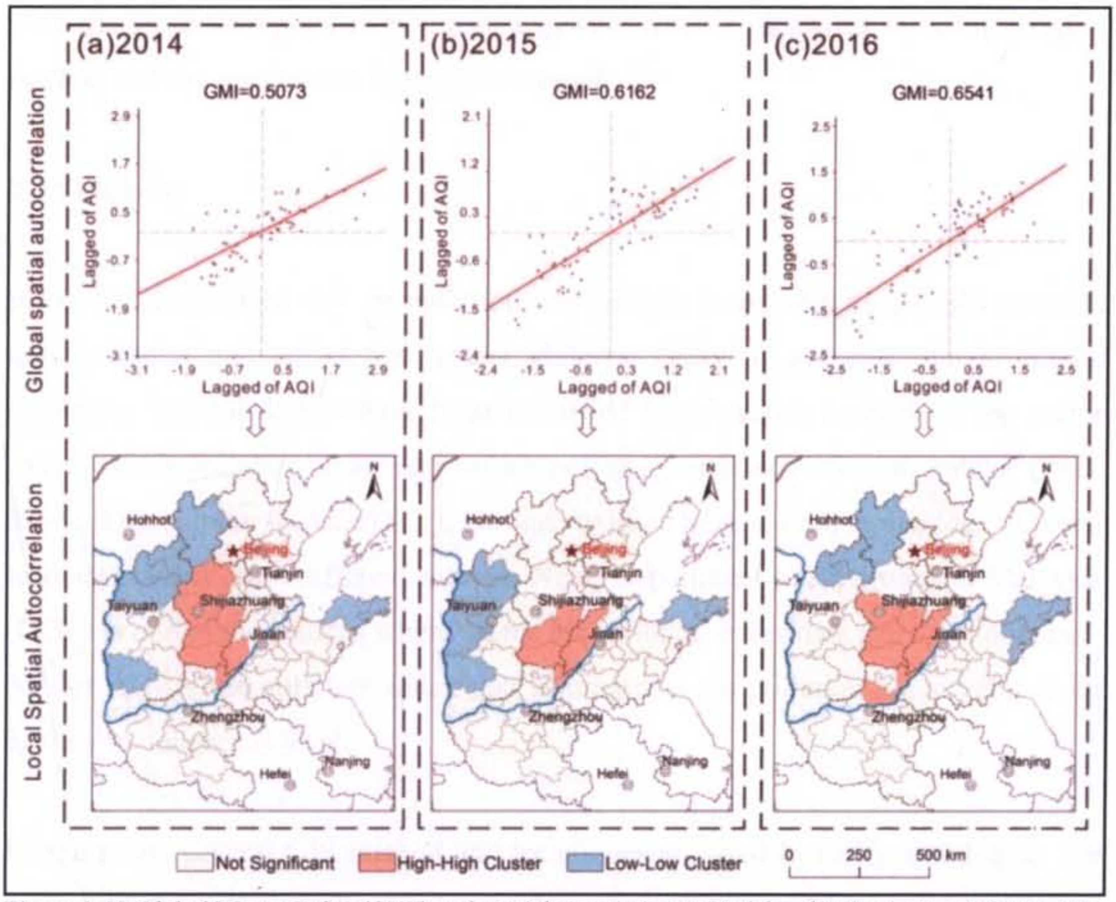

Figure 2.12 Global Moran Index (GMI) and spatial association (LISA) local index in North China (W. Xu et al., 2019).

Figure 2.12 shows the North China (2014-2016) scatter plots of GMI and LISA agglomeration of 71 units of urban space that color according to types of LMI and AQI every year. The GMI scatter plots are separated into four quadrants such as upper right (H-H), lower left (L-L), lower right (H-L) and upper left (L-H). According to the figure above, mostly HH cities of AQI are located in southern Hebei, which is also known as air pollution hot spots in North China.

Moreover, in this research analysis of spatial pattern by using Global Moran's I was conducted in order to identify the spatial clustering or dispersion of the air pollutant concentration in Peninsular Malaysia (Siti Hajar Ya'Acob, 2018). In addition, according to Wang et al (2015), the ambient air pollution is correlated with the AECOPD hospitalization spatially based on the method used which is spatial autocorrelation where the spatial distribution of air pollutant concentration together with the spatial-temporal of pollutant exposure level is identified by using Kriging method and the result show spatially clustered.

2.5 Summary

It can be summarized that air pollution can leads to many effect especially towards human health and stated that young children likely to get sick due to fragile condition. Several factors have been identified from various sources on the major causes of air pollution. Parameter of air pollution such as particulate matter (PM), ozone (O_3), sulphur dioxide (SO_2), nitrogen oxides (NO), carbon monoxide (CO) and lead are classify from different sources. Next, Department of Environment Malaysia (DOE) is one of the sources where all the air pollution index data store and obtained. API or AQI is the pollution index that summarized the pollution range value from healthy to dangerous level.

Furthermore, several GIS method and techniques are used to verify and display the pattern of the pollution. Pearson's correlation coefficient and interpolation method which include spatial averaging, nearest neighbor, inverse distance weighting and kriging are used to and the result of the interpolation method are being compared to identify which method is the most convenient to measure the air pollution on certain area. Different method show different result and different ways to perform the result.

CHAPTER 3

INTRODUCTION

3.1 Introduction

This chapter discusses about the procedure and the method used to analyze the air pollution reading using Geography Information System, GIS. Flowchart is given to explain briefly the process to produce the final output. Johor which is the southern state of Malaysia Peninsular was chosen for the study area and this study focuses on six locations which are Sekolah Menengah Kebangsaan Bandar Putra, Segamat, Sekolah Menengah Kebangsaan Bandar Penawar, Kota Tinggi, Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang, Sekolah Kebangsaan Pasir Gudang (2), Sekolah Menengah Teknik Johor Bahru, Larkin and Sekolah Kebangsaan Seri Separap, Batu Pahat where all of this school are located both residential and industrial areas.

3.2 Overall Methodology

Based on the figure 3.1 shows the methodology flowchart where first phase is the data collection where the dataset of air pollution dataset is obtained from the Department of Environment (DOE) Malaysia and the landuse of Johor area is obtained from BBBike OSM and Google Earth. In this research, the air pollution parameters obtained are particulate matter ($PM_{2.5}$), carbon monoxide (CO), Oxides (O_3) and Sulphur dioxide ($S0_2$). The next phase in section 3.4 is the data cleaning which has been performed for the air pollution dataset in order to remove outlier and unwanted data. The next phase in section 3.5 is data processing involving two methods which are Inverse Distance Weight (IDW) and Spatial Autocorrelation. The result analysis for these two methods will be present in map.

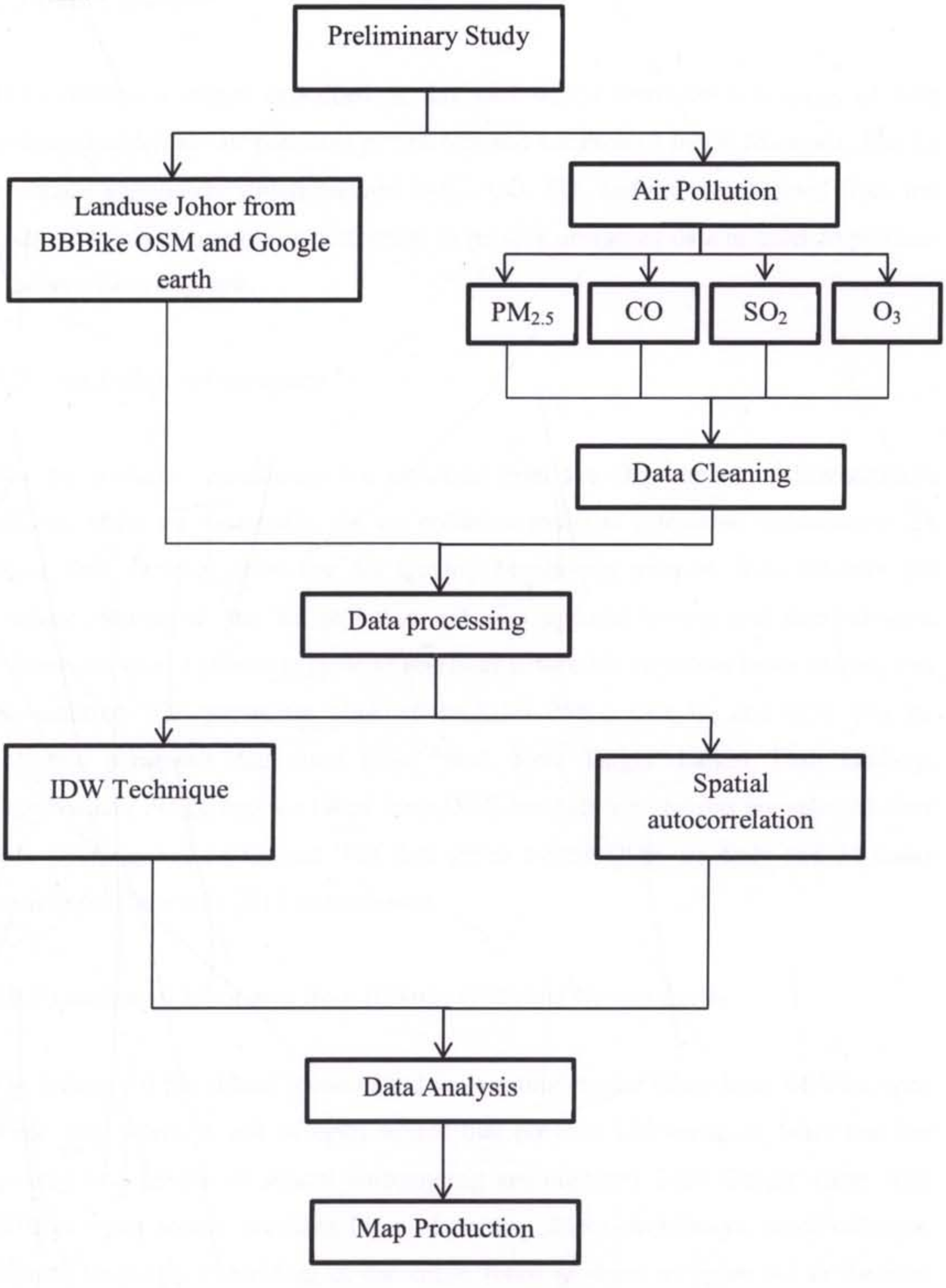

Figure 3.1 Methodology Flowchart

3.3 Data Collection

Data collection stages explained in this part where there are two types of data collected which are air pollution parameters and Landuse of Johor, Malaysia. The air pollution parameters which include $PM_{2.5}$, CO, SO_2 and O_3 are obtained from the DOE and data cleaning was performed to remove unwanted data in order to produce a better vision of graph.

3.3.1 Air Pollution Parameters

The air pollution parameters are obtained from the Department of Environment (DOE), Malaysia. Generally, the air pollution index is calculated according to 24 hours data retrieved from the Air Quality Monitoring network from all over the country. Moreover, the air pollution index is updated hourly and data retrieval process required a complete cycle of one hour before Air Pollution Index reading can be acquired. The parameter obtained includes $PM_{2.5}$, CO, O_3 and SO_2. The air pollution parameter data from Batu Pahat, Kota Tinggi, Larkin, Pasir Gudang, Segamat and Pengerang are taken from DOE but only six stations are selected after data cleaning was performed. The data given by the DOE are daily and 24 hours reading for the whole 2018 as requested.

3.3.2 Landuse of Johor area from BBBike OSM and Google Earth

The landuse of the school location and its surrounding are taken from BBBike open street map which is one of open source that provide a basemap of Johor and the specific and details of school surrounding are digitized from Google earth. The BBBike open source provides layer of points, places, waterways, road, railways, natural, landuse and building of the entire Johor as show in figure 3.2 in the next page.

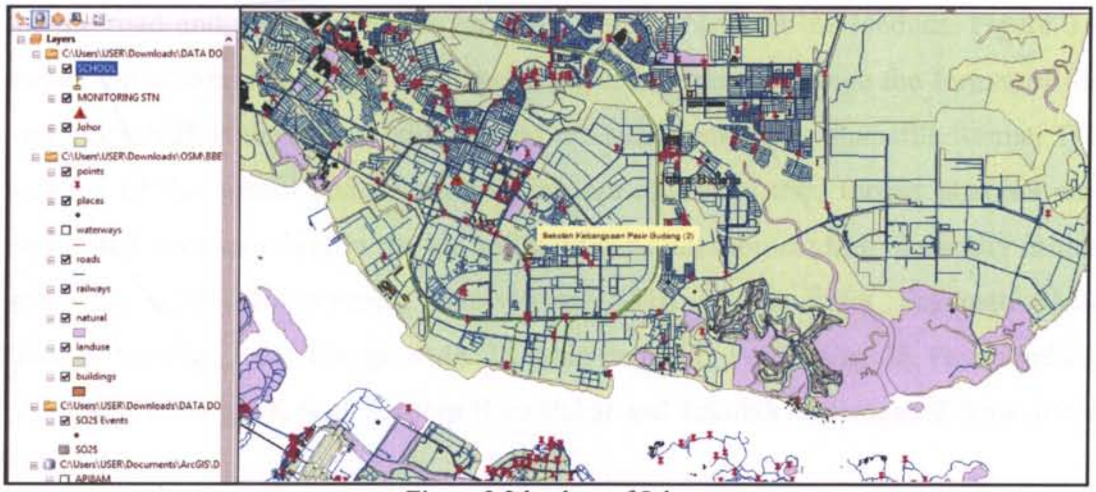

Figure 3.2 landuse of Johor

Figure 3.3 Digitize process on Google Earth

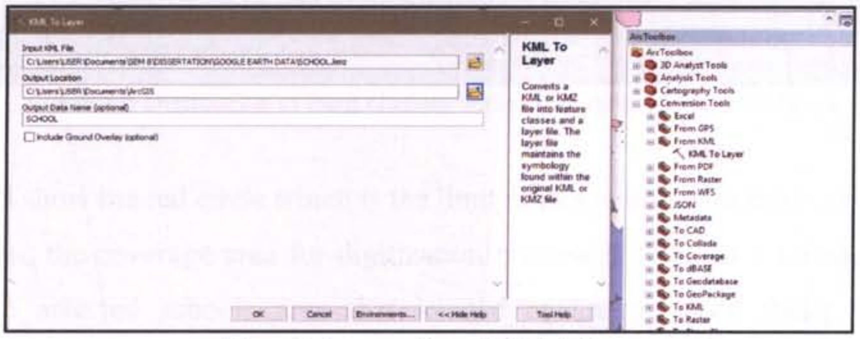

Figure 3.4 conversion of KML to layer

Figure 3.2 shows the landuse of Johor downloaded from the BBBike Open street map. But some of the school environments are not show in detail in Open street map. Therefore, Figure 3.3 shows the school building and its surrounding are digitize from Google Earth by using different tools such as place mark to represent the tree, path for the road and polygon for the building which is add on the landuse. Figure 3.4 shows the conversion of kml to shapefile layer in order to change the format of the save file which is the school building and it's surrounding into shapefile format. The location of the school and its surrounding are identified then further analysis was performed corresponding to the air pollutant concentration reading. Basically in this study the school environment involves are SMK Bandar Putra, Segamat, SMK Bandar Penawar, Kota Tinggi, SMK Tanjung Pengelih, Pengerang, SK Pasir Gudang (2), Pasir Gudang, SK Seri Separap Batu Pahat and Sekolah Menengah Teknik Johor Bahru, Larkin.

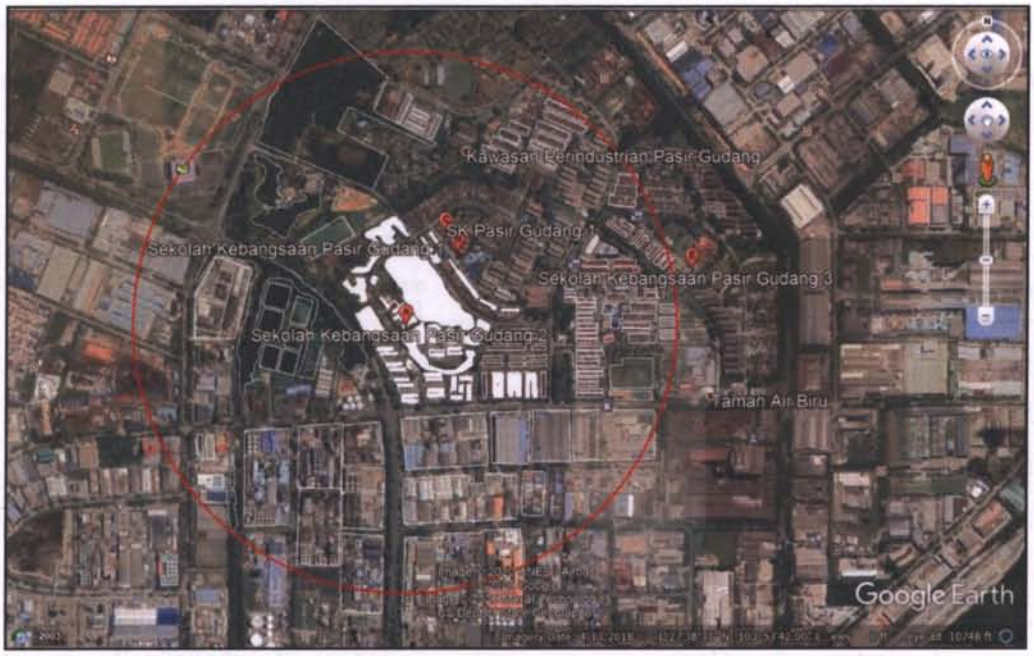

Figure 3.5 Digitization of Pasir Gudang within 1km radius from school area

Figure 3.5 show the red circle which is the limit radius within 1km from school area. In addition, the coverage area for digitization process is fixed to 1 kilometer to all other five selected schools area that located at Larkin, Batu Pahat, Segamat, Pengerang and Kota Tinggi. After performing digitization, there are six layers involves which includes green area, residential area, industrial area, commercial area, school area and road.

3.4 Data Cleaning

Data cleaning is important to remove as many stations as possible and cover the missing information through interpolated values. Data cleaning help to produce a better vision of graph thus remove all the outlier and unwanted data. In this study, data cleaning was done using Excel. Before data cleaning was performed, there are eight monitoring stations and after data cleaning was done, there are only six monitoring station chosen because the parameter reading at Tangkak station and Kluang stations are not available. After the available parameters and stations are identified, the unwanted time duration is filtered and only focus on the required time duration which is from 7am until 5pm according to school operation time. This time duration was selected according to operating hour of the school which is on the morning trial and evening trial.

Table 3.1 Data for $PM_{2.5}$ Parameter before data cleaning

Station ID	Location	Date Time	PM2.5 (µg/m3)	SO2 (ppm)	CO (ppm)	O3 (ppm)
CA36J	Kota Tinggi, JOHOR	1/01/2018 0:00	3.932	0.0015	0.0202	0.506
CA36J	Kota Tinggi, JOHOR	1/01/2018 1:00	9.686	0.0014	0.0214	0.513
CA36J	Kota Tinggi, JOHOR	1/01/2018 2:00	4.109	0.0014	0.0216	0.514
CA36J	Kota Tinggi, JOHOR	1/01/2018 3:00	2.406	0.0013	0.0208	0.501
CA36J	Kota Tinggi, JOHOR	1/01/2018 4:00	3.63	0.0014	0.0202	0.494
CA36J	Kota Tinggi, JOHOR	1/01/2018 5:00	4.988	0.0013	0.0203	0.497
CA36J	Kota Tinggi, JOHOR	1/01/2018 6:00	1.345	0.0014	0.0182	0.503

Table 3.2 Data for $PM_{2.5}$ Parameter after data cleaning

Latitude_X	Longitude_Y	STATION_ID	LOCATION	MONTH	7 AM	8 AM	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	JANUARY	7.08	7.04	8.25	8.27	7.66	6.87	7.91	5.34	6.46	5.82	6.24
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	FEBRUARY	7.19	12.1	13.2	13.3	13.3	14.1	13.0	10.9	11.4	11.8	11.7
1.56446	104.225235	CA36J	Kota Tinggi, JOHOR	MARCH	7.30	11.7	13.5	12.2	10.6	10.3	10.4	8.43	8.66	9.15	9.54
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	APRIL	11.7	13.7	17.3	14.4	11.3	11.0	10.4	10.5	10.9	10.2	11.1
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	MAY	12.3	14.0	17.4	11.7	9.69	8.09	7.91	7.27	7.32	8.13	8.08
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	JUNE	9.20	9.78	13.0	13.5	11.6	11.0	10.9	10.3	10.7	11.2	10.7
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	JULY	12.5	14.1	15.7	14.6	14.3	15.9	14.5	14.8	15.8	17.5	14.1
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	AUGUST	15.3	16.4	19.1	16.3	18.0	19.8	15.7	17.2	15.2	15.8	15.8

1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	SEPTEMBE R	17.0	15.2	20.3	19.5	15.9	17.3	13.	12.9	12.8	12.8	14.4
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	OCTOBER	15.7	16.3	16.5	15.4	12.3	13.4	14.5	14.7	15.8	13.5	12.7
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	NOVEMBE R	12.7	9.73	12.9	10.9	9.89	11.1	10.5	9.10	9.14	9.07	8.41
1.56404	104.225235	CA36J	Kota Tinggi, JOHOR	DECEMBER	8.89	9.50	10.7	9.51	9.33	8.91	7.13	7.97	8.09	7.09	6.95

Table 3.1 shows that the air pollution parameters before data cleaning where the time duration are not filtered and arranged whereas Table 3.2 shows the air pollution parameters after data cleaning process where the unwanted parameters are removed and time durations are filtered and arranged accordingly. The data was arranged accordingly with the complete Latitude_X, Longitude_Y, Station_ID, Location, month, and the selected time duration which are from 7am until 5pm.

3.5 Data Processing using Geography Information System (GIS)

The data is processed using interpolation geostatistical methods which are one of the GIS components. The main software used in this research is ArcGIS10.6. Interpolation method assumes the value for cells in a raster by using a limited number of sample point data points that assist in predicting the unknown values for any geographic station (Shareef et al, 2016). Furthermore, interpolation geostatistical methods allow the construction of map that displays the variability continuously of an analyzed feature. Various application of interpolation methods will result in different valuations of parameter values at interpolations points and thus to the creation of different maps that presenting changes in the values of the analyzed parameter. In this task, Inverse Distance Weighted (IDW) was chosen to estimate the concentration of air pollution at the unknown station. In addition, the technique IDW of GIS has been used in this study to perform interpolation with the help of concentration data on air quality at school locations in Johor. Through this method used, the relationship between the air pollutant concentration and the school location can be analyze and justify. Hence, the most polluted school area can be identified. Finally the final output can be seen once the interpolation technique is performed and display in map.

3.5.1 Inverse Distance Weighted (IDW)

In this research, IDW method was used in order to identify the most polluted area according to the air pollution monitoring station reading in Johor. This method has the ability to predict the every input point contains a local influence which diminishes with distance. Moreover, the air pollution parameters obtained from DOE can be revealed by performing this method. Besides this method allowed identification of specified number of points or all points within a specified radius which is then can be used to identify the output value of each location. This method predicts the variable being mapped decreases in influence according to the distance from sample location. Once identification of most polluted area, IDW then transform point values into a gridded choropleth map. Observations of air pollution phenomena at the selected school location are analyzed using IDW technique. Data from excel is first convert into shapefile to enable further process, it is important to make sure that the air pollution parameter converted into shapefile and make sure the attribute table contain the data similar with the excel data.

Figure 3.6 API data

Figure 3.6 shows the API data are being added into the ArcMap in the form of excel format. In order to change the data format, right click on the Data API Average and click on the display XY data.

The different between csv and xlsx file format is when adding xlsx data into ArcGIS, the attribute table of this excel data will not be shown until it is converted into shapefile compare to csv file format where the excel data is shown even when it is not converted into shapefile as shown in figure 3.7.

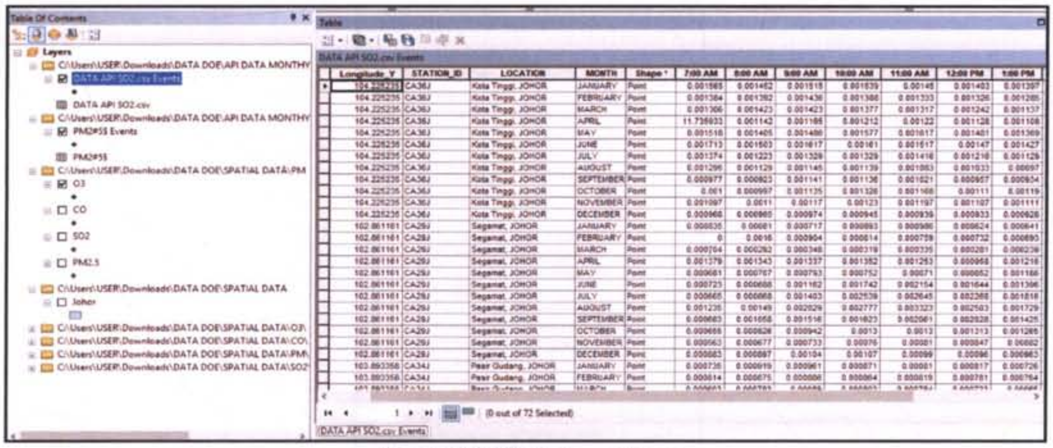

Figure 3.7 file format of csv

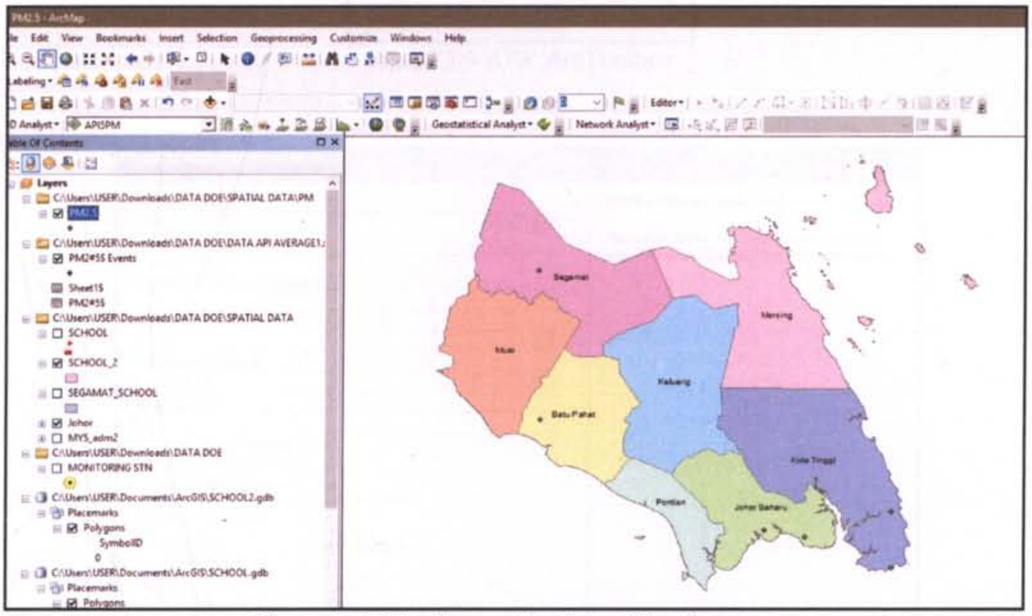

Figure 3.8 $PM_{2.5}$ layer added into table of content

Figure 3.8 is the final output of the API data as shown on the map where the data is in shapefile format. It is important to convert the file format into shapefile to enable further processing. Once the file is converted into shapefile, the other unwanted layer is removed to prevent duplication or avoid confusion.

Figure 3.9 IDW ArcToolbox

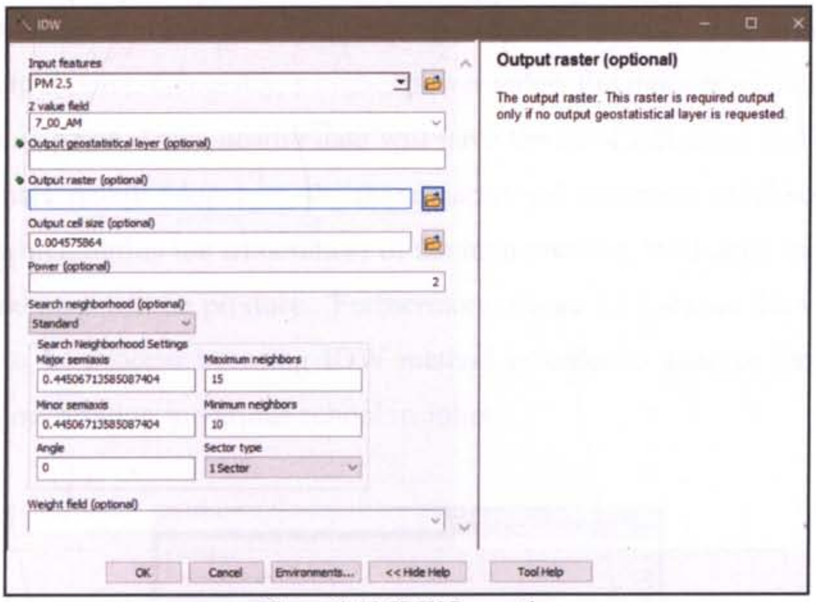

Figure 3.10 IDW Properties

Figure 3.9 shows the processing of interpolation method obtain form Geostatistical analyst tools and Figure 3.10 show the IDW properties where the first hour (7AM) of the SO_2 air pollution data is inserted for processing.

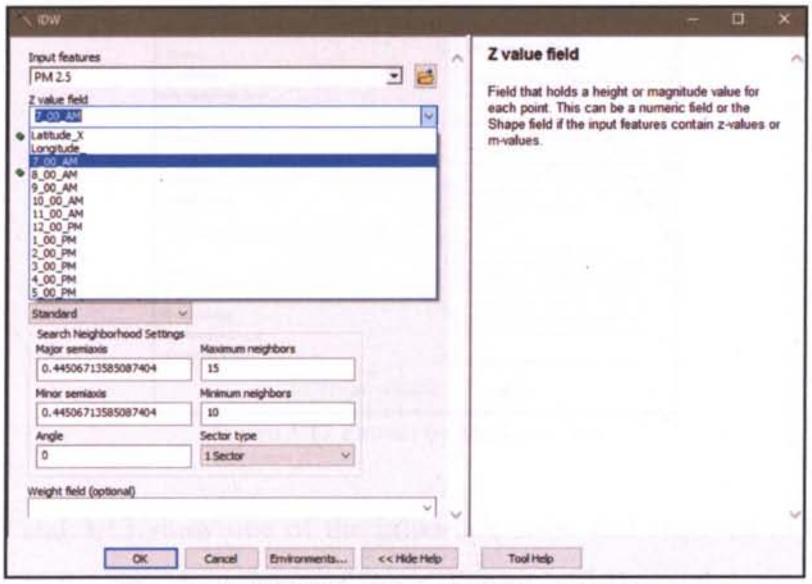

Figure 3.11 IDW Properties with different data hours.

The default value of power used is 2 which is a default value used based on distance from the output point. Generally, a higher power value, the more emphasis can be put on the nearest point. Thus, nearby data will have the most influence and the surface will have more detail. Moreover, the maximumm and minimum neighboor is fix to 15 and 10 which define the smoothness of the map produce, the higher the value, the smoother the map will be produce.. Furthermore, figure 3.11 shows the various data hour need to be process by using IDW method in order to analyze the hourly air pollutant concentration in various school in Johor.

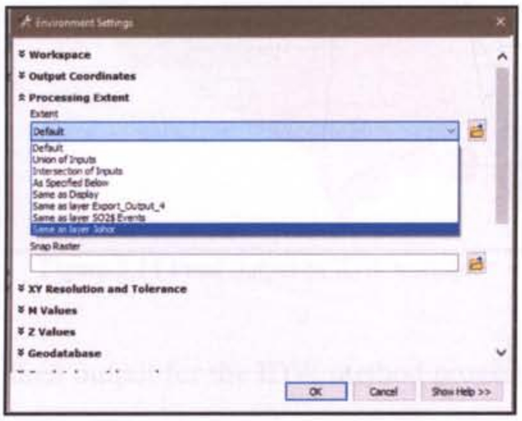

Figure 3.12 Environmental Settings

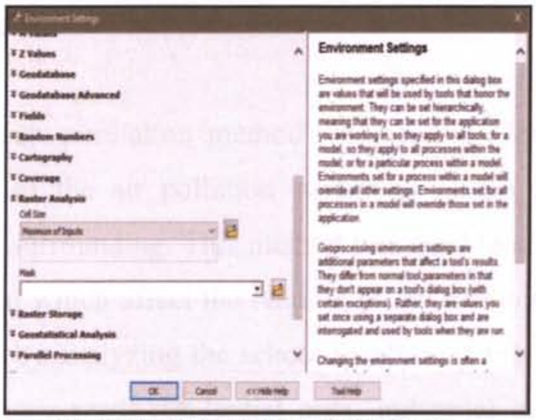

Figure 3.13 Extract by Mask process

Figure 3.12 and 3.13 show one of the important steps that required to be made in order to obtain the boundary shape of Johor. Figure 3.13 shows the extract by Mask tool which was used to indicate the input raster, the raster or entity is then used to define the areas of extraction and the name and location. This tool assist in extracting the cells of a raster which correspond to the areas defined by a maskIf this step is not performed the IDW result will not show up according to Johor boundary despite rectangle shape will appeared.

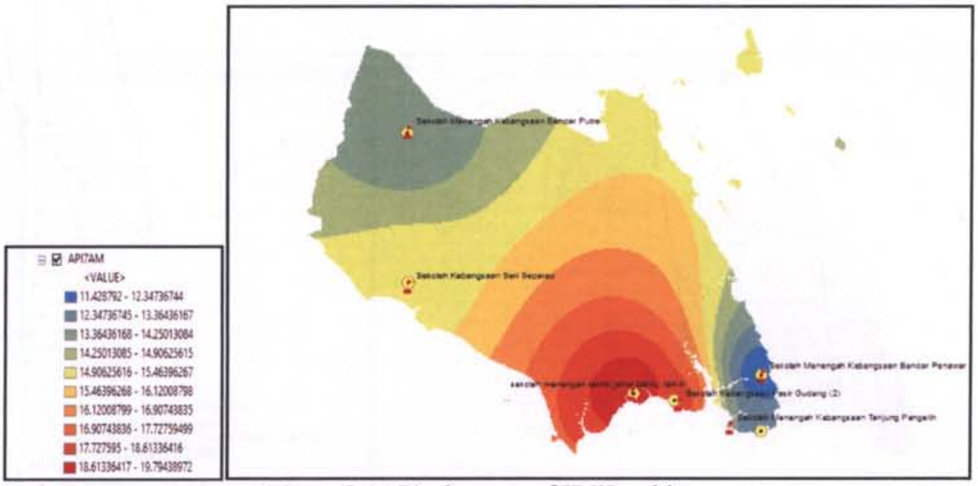

Figure 3.14 Final output of IDW techique

Figure 3.14 shows the final output for the IDW method process where differnet color of concentration has different meaning such as red concentration determine that the school area is at hazardous status which mean the level of pollution is very high whereas for the blue color define as good status which mean that school areas is less pollution.

3.5.2 Spatial Autocorrelation

In this study, spatial autocorrelation method was used to identify the relationship between the readings of the air pollution parameter obtain from the monitoring station with the school surrounding. This method was used to clarify whether both of this situation are related which affect the reading of the monitoring system in Johor. The analysis was done by analyzing the school location and its surrounding either it is located near with busy road, residential area, industrial area or vice versa. In addition, the identification was done by analyzing the selected time duration which are from 7am until 5pm, each of the air pollution parameters where different hour produce different value of parameter readings. The relationship between time and the surrounding can be seen according to the reading of the air pollutant concentration result based on interpolation method result. Therefore, spatial autocorrelation is used and this identification can be performed by using Global Moran's I technique in ArcMap whether the result is disposal, random or clustered. The spatial distribution of pollutant is observed limit to 1km radius based on the digitize features in Google earth.

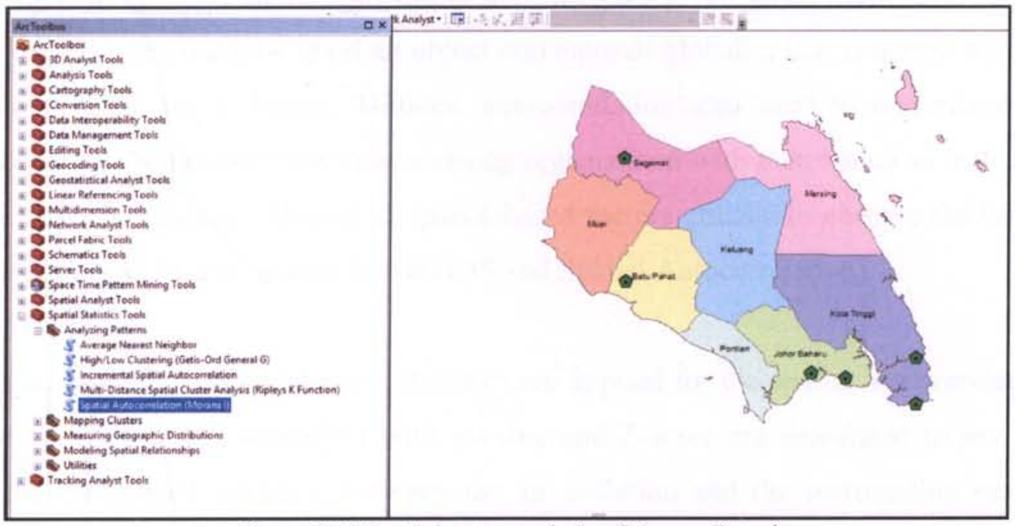

Figure 3.15 Spatial autocorrelation (Morans I) tool

Figure 3.15 shows the spatial autocorrelation process where it observed how well an objects correlate with other nearby objects across a spatial area.

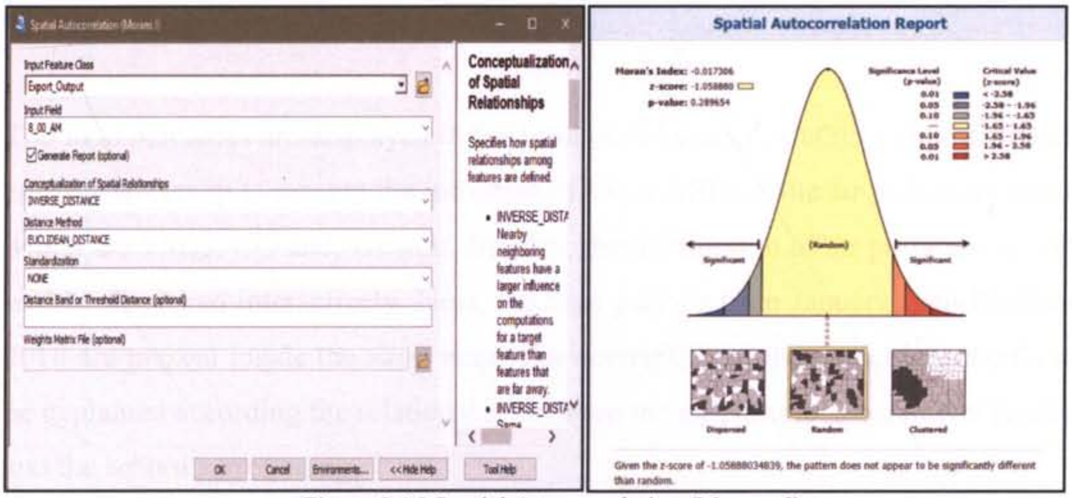

Figure 3.16 Spatial Autocorrelation (Morans I)

Figure 3.16 shows the input feature class inserted is the daily reading for $PM_{2.5}$ parameter and the time duration chosen is 8am for the entire 2018 from January until December. Inverse_distance was selected which allowed nearby neighboring features have a larger influence on the computations for a target feature than features that are far away. Generally, common way to measure autocorrelation is using Moran's I, which now has become incorporated in commonly used packages such as ArcGIS. Correlation measurement are allowed in Moran's I to measure how good something corresponding based on multiple dimensions across a given space. Generally, results are used to measure how good an object corresponds globally, that is across a given defined space for a dataset. Besides, autocorrelation also used to understand an association. Autocorrelation show a strong organization with factor such as language and variety of species. Moreover, spatial-based factors utilized to observe the health care impact and survival rates based (GIS and Spatial Autocorrelation).

In this research, Global Moran's statistics are applied for the spatial autocorrelation analysis in ArcGIS. Moran's I with p-value and Z-score are calculated to test the spatially clustered tendency between the air pollution and the surrounding school area.

3.6 Story map

The final outcomes are displayed in the form of story map. ArcGIS online are used to create a storymap to present the information about API and the air pollutants involve which are $PM_{2.5}$, CO and, O_3 SO_2. Besides, the distribution of air pollution in Johor will be displayed interactively. Next, the time periods from January until December 2018 are present inside the story map. The description of the particular schools will be explained according the relationship between the air pollutions parameter readings and the school surrounding.

3.7 Summary

In summary, this chapter explains the methodology and the procedure in order to collect the data, data clearing, and ways to process the data using interpolation technique involving two methods which are Inverse Distance Weighted (IDW) and Spatial autocorrelation. The final outcomes are then presented using story map where covers all the information of the data collected and using the ArcGIS to create a storymap. The visualization of air pollution offers many advantages over statistical analysis since it is intuitive and less complex mathematical or statistical algorithm hence parameter thus allow other people to understand easily especially in public.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

In this chapter, the results derived from interpolation method and spatial autocorrelation are discussed involves $PM_{2.5}$, CO, SO_2 and O_3 readings at the selected schools in Johor. The objectives for this research are explained and justified in this chapter where the identification and comparison of the most polluted area in selected schools in Johor are analyzed. In addition, the relationship between air pollution and school location using spatial-autocorrelation technique is analyzed in this section according to result of the air pollutant reading and the factor of the air pollution will be explained on each school area. Furthermore, this chapter also discussed about the digitize layer involve in ArcMap for the identification of school surrounding which leads to factor of increasing the level of air pollution. All the analyzed result of the air pollutant concentration in Johor and the charts of daily API values in the six selected school locations within one year (2018) are displayed in the story map.

4.2 Digitization of Landuse from Google Earth

Generally, digitization is one of the processes performed in order to obtain the features of building, road and other features in Google Earth. In this study, the digitization is used to trace features from Google Earth which involve building of school, commercial and industrial building. Based on the selected schools area in Johor which includes Sekolah Menengah Teknik Johor Bahru Larkin, Sekolah Kebangsaan Pasir Gudang (2), Sekolah Kebangsaan Separap Batu Pahat, Sekolah Menengah Kebangsaan Bandar Putra Segamat, Sekolah Menengah Kebangsaan Tanjung Pengelih Pengerang and Sekolah Menengah Kebangsaan Bandar Penawar

Kota Tinggi, the digitization process cover one kilometer radius from school area as shown in the figure 4.1.

Figure 4.1 before digitization process of Pasir Gudang

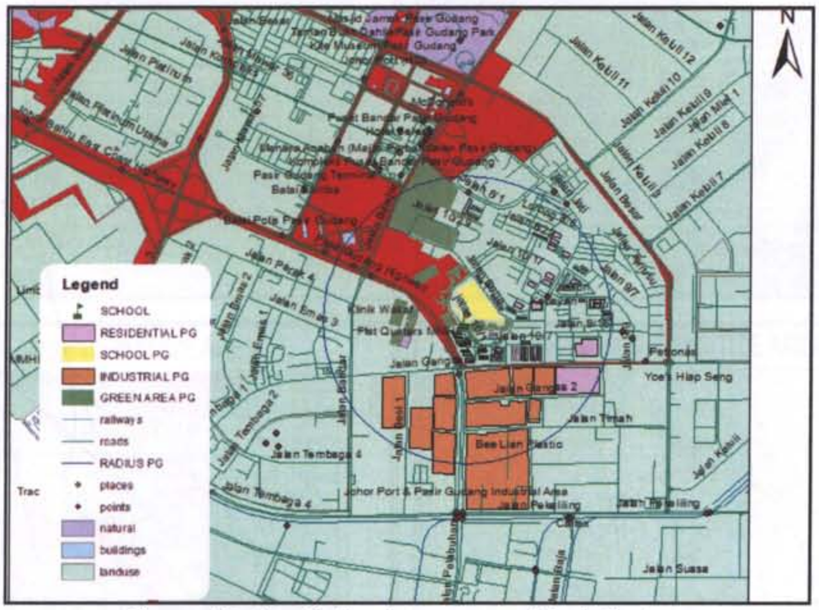

Figure 4.2 after digitization process of Pasir Gudang

Figure 4.1 and figure 4.2 show the before and after output from digitization process except railways, roads, places, natural, buildings and landuse since this layer is obtained from open sources BBBikes. Generally, the digitization output involve general structure only since it is only required to identify the general school surrounding that affect the air pollutant concentration reading which is monitor by the monitoring station. Figure 4.3 shows all the digitization results of the school area in Johor.

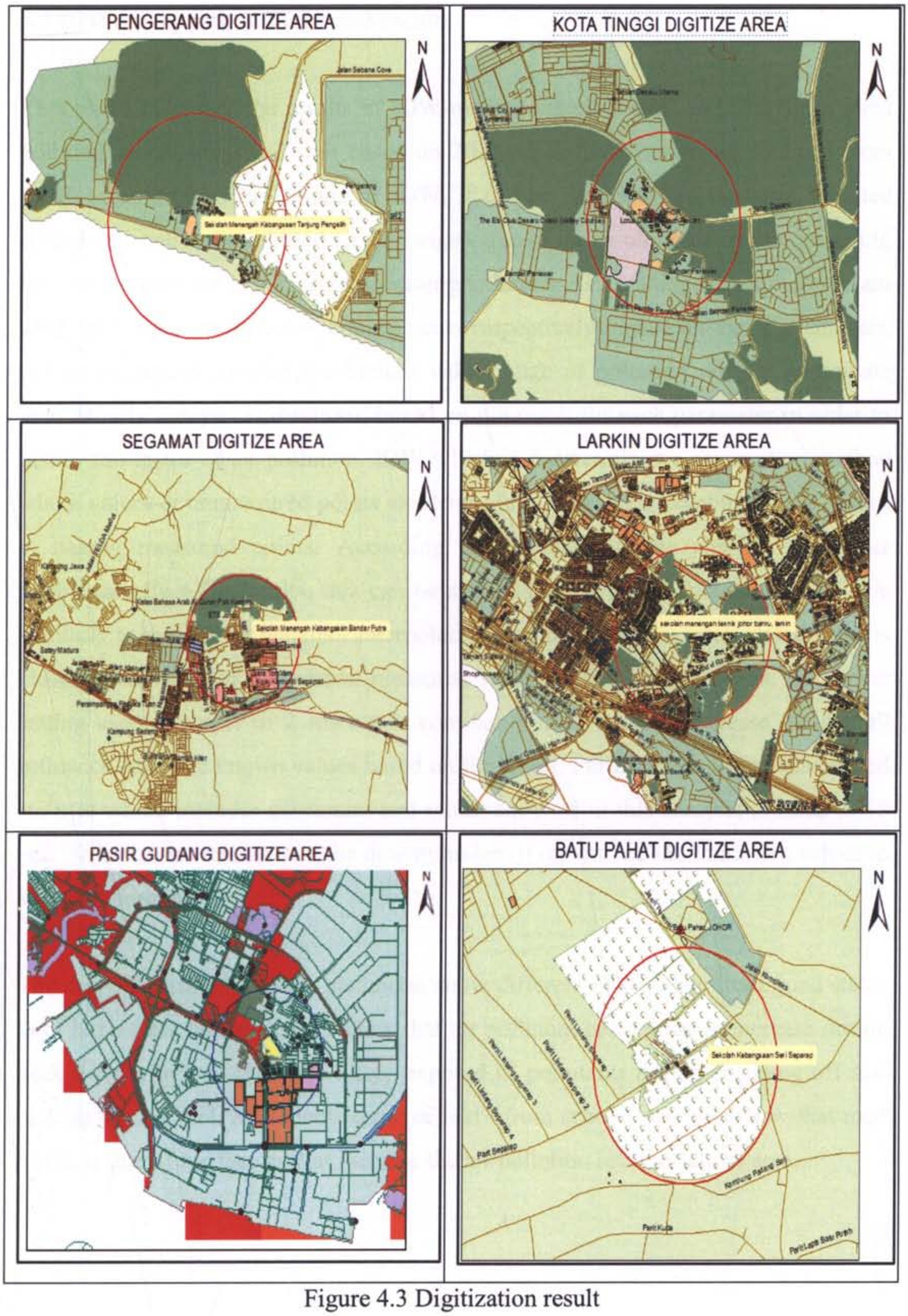

Figure 4.3 Digitization result

4.3 IDW interpolation maps and results

This phase discusses the results of IDW method which is used to identify the most polluted school areas in Johor based on 2018 air pollution readings obtained from DOE. According to the results of IDW, it can be justified that the most polluted school area can be seen based on the range value of the result. Furthermore, mapping for every parameter is displayed according to hourly API reading which is from 7am until 5pm based on school operating hours respectively. Based on the map analysis, red concentration showed the highest value range of pollution on that particulate area. Hourly analysis is discussed based on the result for each parameter in order to justify the factor of air pollution. IDW which is a deterministic assumption method where values at unmeasured points are determined by a linear combination of values at nearby measured points. According to the analysis, the changes of power parameter affect the results, this can be seen when the power increases, IDW acts similarly to the nearest neighbor interpolation method where the interpolated value is close to the value of the nearest measured value. In this IDW analysis, the power setting used is power of 2 since it is commonly used hence it increase the overall influence from the known values based on the result. Furthermore, the neighborhood statistic which includes maximum and minimum used in this analysis is fixed to 15 and 10 which the result show the determination of maximum and minimum values in the neighborhood.

The derived results for every parameter show different color range from good status until hazardous status. Results show that air pollutant concentration increase during peak hour where students are likely exposed to pollutants during dropping off and picking up moment, as students come or leave from school. Analysis show that road traffic is one of the factors that increase the air pollution level in school area.

4.3.1 IDW Interpolation of Particulate Matter 2.5 (PM2.5)

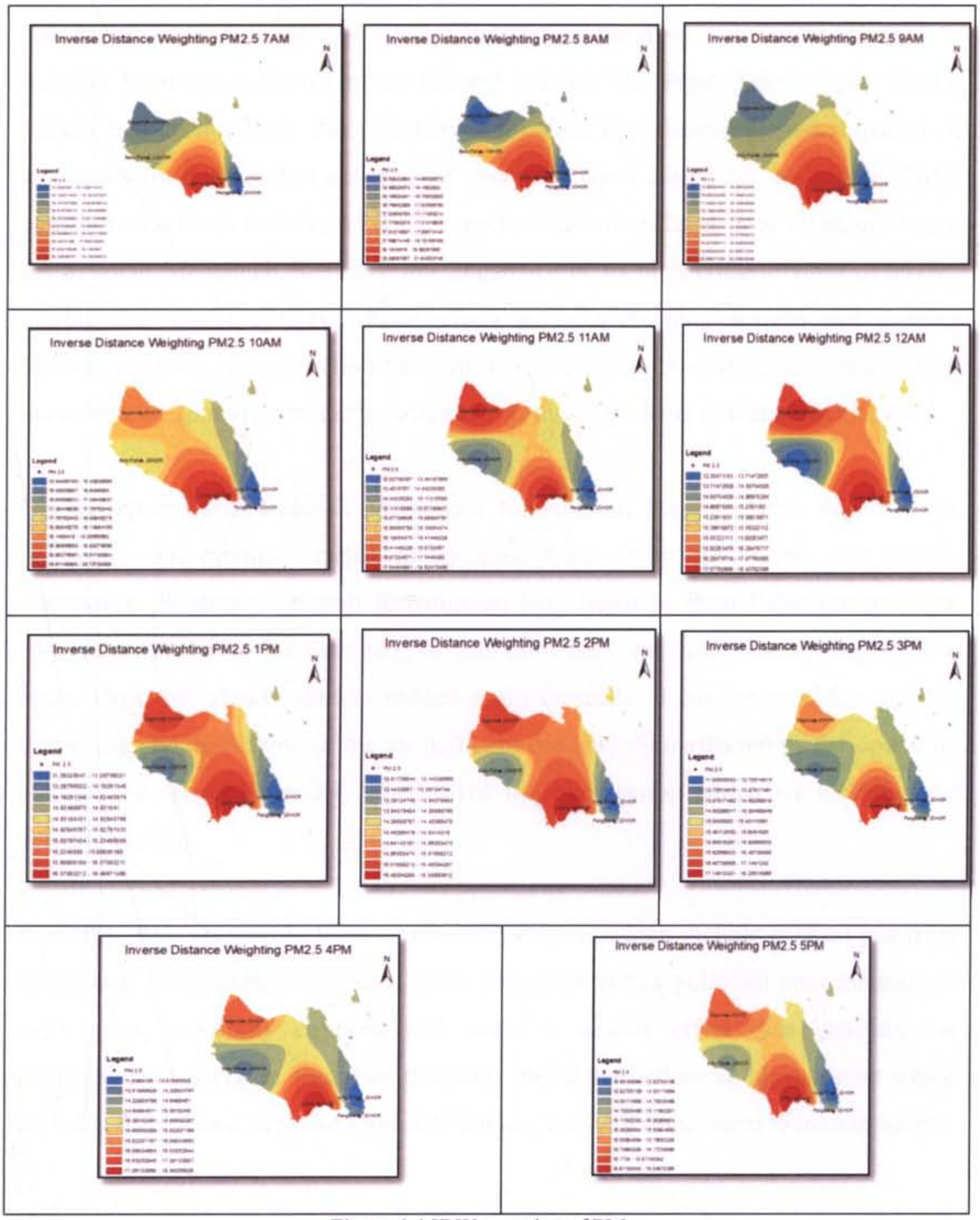

Figure 4.4 IDW mapping of $PM_{2.5}$

Figure 4.4 shows the $PM_{2.5}$ results of IDW mapping where the air pollutant concentration reading changes every hour. It can be observed that the most polluted area is located at Pasir Gudang and Larkin area since it reaches the hazardous status most of the time starting from 7am until 5pm. On the other hand, Pengerang and Kota Tinggi area maintain its good status by showing lower air pollutant concentration reading. It can be concluded that the $PM_{2.5}$ is mostly released in Sekolah Kebangsaan Pasir Gudang (2) and Sekolah Menengah Teknik Johor Bahru, Larkin area during 2018. Pasir Gudang and Larkin experienced the worst quality of air especially during start and end of operating hour. Based on the results, $PM_{2.5}$ concentration tends to increase until it reaches hazardous level from 10am until 2pm for Sekolah Menengah Bandar Putra Segamat due to high concentration of traffic. During the school operation hour which includes morning session and evening session, the $PM_{2.5}$ concentration tends to increase during the changing session which occurred on 12pm to 1pm due to increase volume of students at that particular hour.

On the other hand, Sekolah Menengah Kebangsaan Bandar Putra, Segamat, air pollutant concentration started to increase from 10am until 2pm and slowly decreasing. Whereas, Sekolah Kebangsaan Seri Separap, Batu Pahat air pollutant concentration start to increase early at 7am until 8am and slowly decreasing and rise again 10am but slowly start to reduce again onwards. It can be conclude that the increasing and decreasing of the air pollutant concentration affected by the operating hour of the school especially when involving two session which are morning and evening session.

Basically, $PM_{2.5}$ primarily from combustion sources which include exhaust gas from traffic that occur during operating hour. Exposure to this pollutant concentration at early stage especially children will cause a serious effect thus generate the environmental allergies. Based on the study stated that indoor an air pollutant which includes $PM_{2.5}$ has a negative impact to human thus will bring harm to human health.

4.3.2 IDW Interpolation of Oxides (O_3)

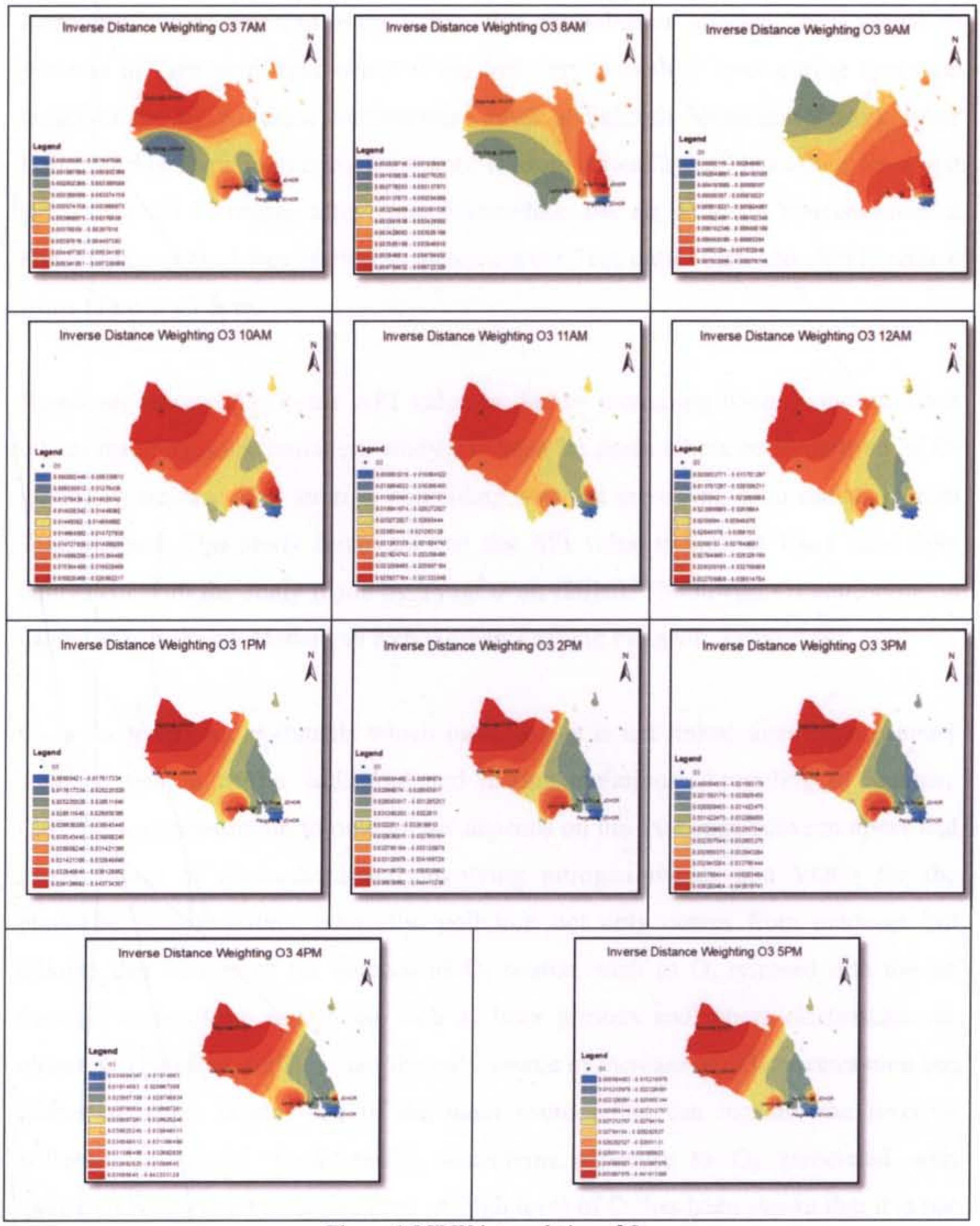

Figure 4.5 IDW interpolation of O_3

Based on the O_3 results in figure 4.5, it can be observed that the O_3 concentration has the highest range value in Sekolah Menengah Kebangsaan Bandar Putra, Segamat and Sekolah Kebangsaan Pasir Gudang (2), Pasir Gudang the air pollutant concentration increase early at 7am until 5pm where it reach hazardous level the entire operation hours compare to other school in Johor. Next, for Sekolah Kebangsaan Seri Separap Batu Pahat, the air pollutant concentration started to increase at 7am until 5pm where it reached very unhealthy level during operation hour. As for air pollutant concentration level at Sekolah Menengah Teknik Johor Bahru Larkin show increasing level until it reach unhealthy and hazardous level and slowly started to reduce after 2pm. Meanwhile, the air pollutant concentration at Kota Tinggi school area started to increase from 7am until 10am and slowly reduce from 11am until 5pm.

Based on research, increase API value is due to increasing ozone concentrations which resulting solar radiation, study has been be made where concentration of O_3 gradually increase after sunrise, coinciding with the increasing solar radiation from 7am onward. This study discovers that the API value is high at 10am until 5pm equivalent with the study made by Tyagi et al, (2016). The lowest O_3 concentration can be seen Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang.

O_3 is secondary air pollutants which mean that it is not linked directly to primary sources such as traffic, industrial and natural emissions. According to Salonen, (2018), O_3 concentration in outdoor air depends on the exchange between upper and lower layers of atmosphere and involving nitrogen oxides and VOCs for the photochemical reactions. Basically, pollution not only comes from outdoors but indoors can be one of the sources of O_3 source, such as O_3 released into the air through some office equipment such as laser printers and others electrostatic air cleaners. Therefore, traffic is not the only source of increase of O3 concentration but indoor activities is also one of the main sources that can increase the level of pollution in school. Significantly, short-term exposure to O_3 associated with increased hospitalization in children. A high level of O_3 has been shown that it is not only contribute to the exacerbation of asthma but also be a cause in the development of asthma.

4.3.3 IDW Interpolation of Carbon Monoxide (CO)

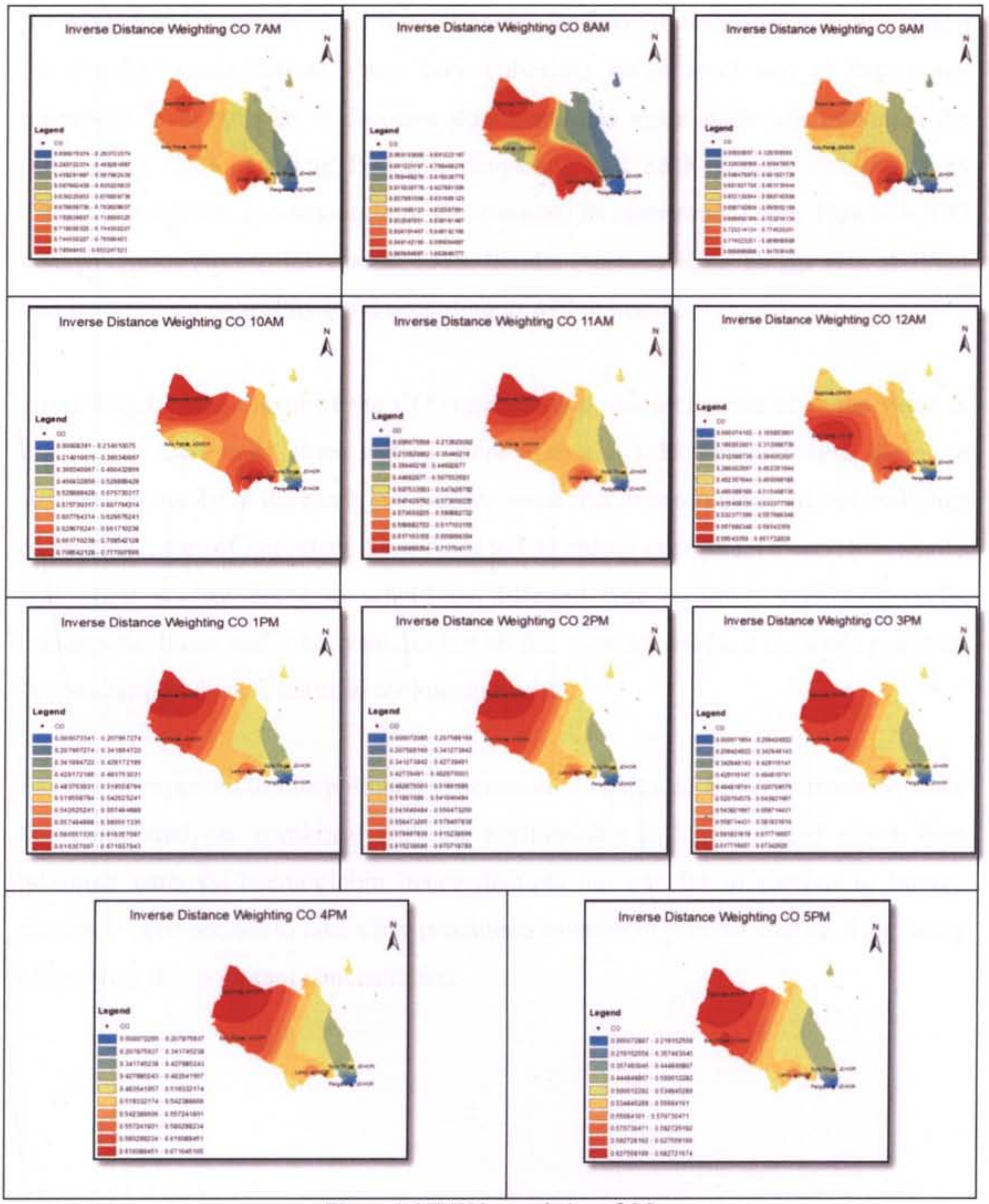

Figure 4.6 IDW interpolation of CO

As referred to figure 4.6, the IDW interpolation results for CO shows in figure 4.5, the concentration of CO started to increase early at 7am in Sekolah Kebangsaan Pasir Gudang (2), Sekolah Kebangsaan Separap Batu Pahat and Sekolah Menengah

Kebangsaan Bandar Putra Segamat compare to other school area. The CO concentration continues to increase for SMK Bandar Putra Segamat area and reach the hazardous level most of the time. Whereas for Sekolah Kebangsaan Pasir Gudang (2) the CO concentration show very unhealthy range level and at 8am reach hazardous level but start to decrease slowly and rise again at the afternoon. On the other hand, SMK Tanjung Pengelih Pengerang and SMK Bandar Penawar Kota Tinggi show lower concentration of CO compare to other school area. However, CO concentrations start to increase at SMK Bandar Penawar Kota Tinggi area at 10am and maintain on unhealthy level according to API indicator.

According to range level of the CO concentration, the increasing of range value is due to the busy road since carbon monoxide is a vehicular pollutant, therefore vehicle exhaust from the roads and parking areas that existed nearby school buildings represents the most important contributor to CO indoor exposure. Observation shows that, most student come to school by different type transport such as bicycle, motorcycle, buses and other vehicles but all this vehicles produce the same pollutant concentration which is harmful for human health.

Excessive exposure to this pollutant concentration can cause acute intoxication since this compound can combined with the haemoglobin in human blood which then produces carboxyl-haemoglobin hence disrupts the transfer of oxygen to human tissues. It is important to take early precaution in order to prevent student from being affected by this pollutant concentration.

4.3.4 IDW Interpolation of Sulphur Dioxide (SO_2)

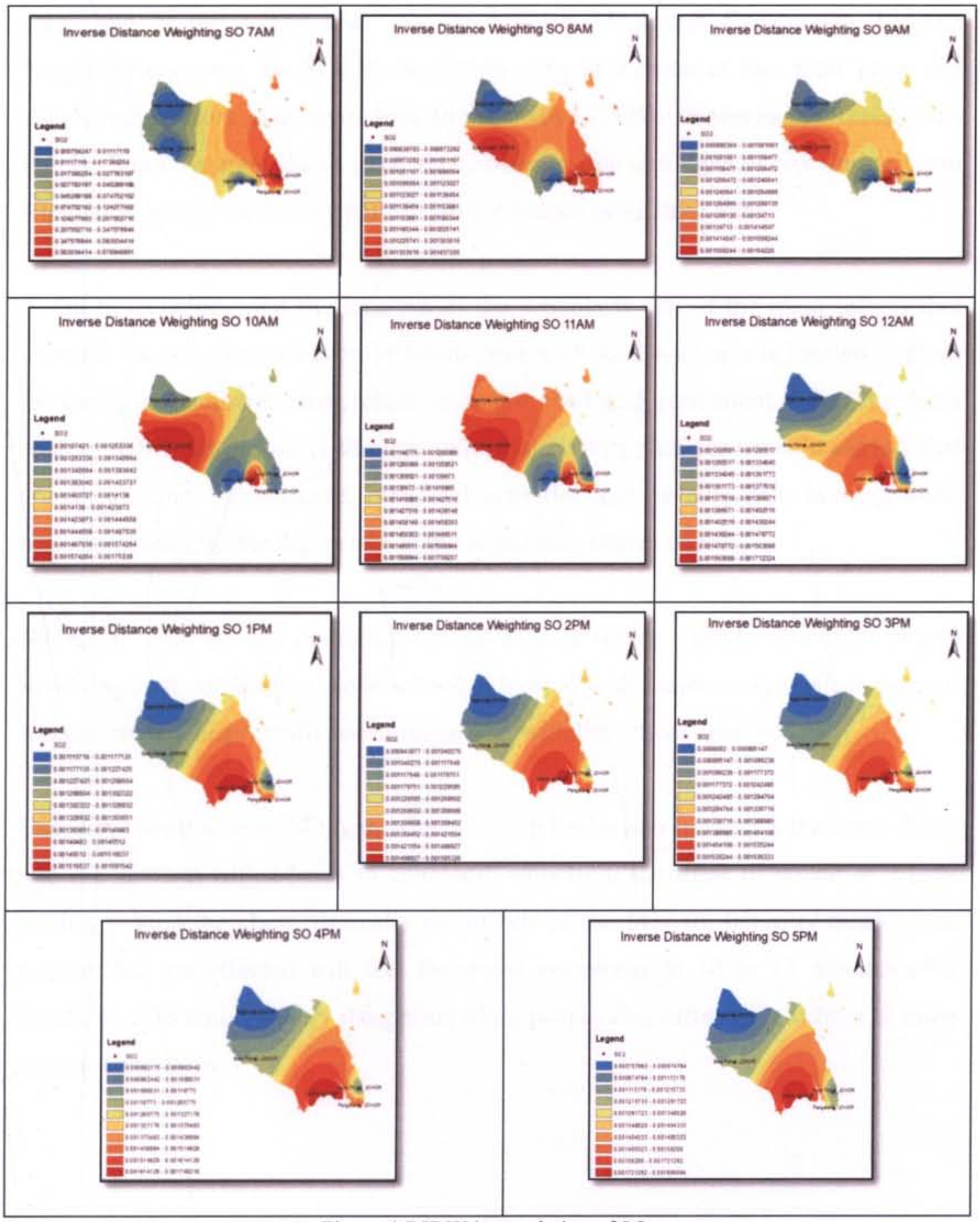

Figure 4.7 IDW interpolation of SO_2

Figure 4.7 shows those IDW interpolation results of SO_2 concentration at the selected school in Johor. Based on the results, Sekolah Menengah Kebangsaan Bandar Penawar Kota Tinggi shows high concentration of SO_2 early at 7am and slowly reduced until 11am and maintained unhealthy status until 5pm. While for the Sekolah Kebangsaan Pasir Gudang (2), the SO_2 concentration started to increase from 7am until 5pm at the school area. As for Sekolah Menengah Kebangsaan Tanjung Pengelih Pengerang, the SO_2 concentration starts to increase at 8am until 11am and slowly reduce from 11am until 5pm. In this analysis, Sekolah Menengah Kebangsaan Bandar Putra Segamat shows good status early in 7am until 5pm except during 10am where it is slowly increasing until 11am but reduce again until 5pm.

It can be conclude that the location of the schools is one of the main factors that increase the SO_2 concentration in school area such as the schools is located in close proximity to industrial area, close to major road and residential area. The main source of SO_2 in the air is through industrial activity that processes materials that contains sulfur. Furthermore, industrial activities also involve with burning fossil fuels containing sulfur that is one of the important sources of SO_2.

Moreover, one of the main sources of SO_2 is motor vehicle emissions where involving fuel combustion since school is located with major road, this can be seen when there is a heavy traffic occurrence near with the school area

Excessive breathe in of SO_2 can affects human health and it irritates the nose, throat and the airways which leads to coughing, wheezing, shortness of breath or a tight feeling around the chest. Basically the effects of the SO_2 are felt very quickly and people that get affected will feel the worst symptoms in 10 or 15 minutes after breathing it in and it is very dangerous when people that suffer with asthma or other similar conditions.

4.4 Comparison of Air Pollution Level

The IDW interpolation results show that different hour shows different reading of air pollution level. Referring to figure 4.8, the air pollutant concentration status, several colors representing the range of API values which is displayed on every IDW map result.

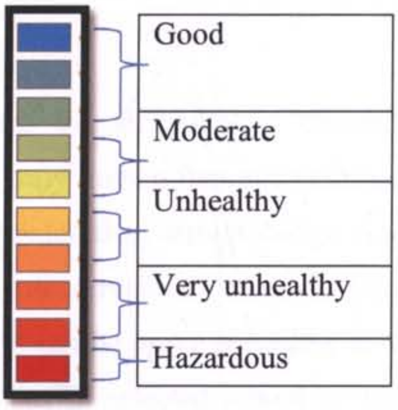

Figure 4.8 API indicator

After the results of $PM_{2.5}$, CO, SO and O_3 are analyzed, it can be concluded that air pollutant concentration increase during peak hour of the school operation hour especially at 7am until 10am and 2pm until 5pm. In addition, changing session between morning and evening session are one of the factor increases of the air pollutant concentration range due to increase of traffic where student come and leave the school. Based on the analysis result, Sekolah Menengah Pasir Gudang (2) located at Pasir Gudang show frequent result of air pollutant concentration reach between very unhealthy and hazardous level compare to other schools area in Johor. On the other hand, Sekolah Menengah Kebangsaan Tanjung Pengelih, Pengerang show frequent result of air pollutant concentration at good until unhealthy range based on the analysis results compare to other schools in Johor.

4.5 Spatial autocorrelation

This section explains about the relationship of air pollutant concentration and the schools surrounding based on the spatial autocorrelation Global Moran's results. The derived spatial autocorrelation Global Moran's I results are in the HTML report. In this analysis, if the Moran's Indices are positive meaning that it rejected the null hypothesis similar with rejecting spatial autocorrelation and the p values is lower than 0.05.

Spatial autocorrelation measures the air pollutant concentrations in relation to schools location in Johor. It is truly known that everything is related to everything else, but near things are more related than distant things. According to the result in this research using spatial autocorrelation method where identification and justification of air pollution level can be prove according to the school surrounding. The reading of air pollution index at selected school in Johor which obtain from DOE can be explained according to the school surrounding. In addition, the closer the school distance with busy road, industrial area or residential area, the higher the level of air pollution.

Study was conducted to justify how the school location interacts or affect the air pollutant concentration. Seven layers which include industrial, residential, school, commercial, green area, road and agriculture area has been digitize from the Google Earth to show the surrounding area of school. The digitization is limited with 1km radius from school area in order to get the details about what really affect the reading of air pollution monitoring system.

4.5.1 Spatial Autocorrelation result

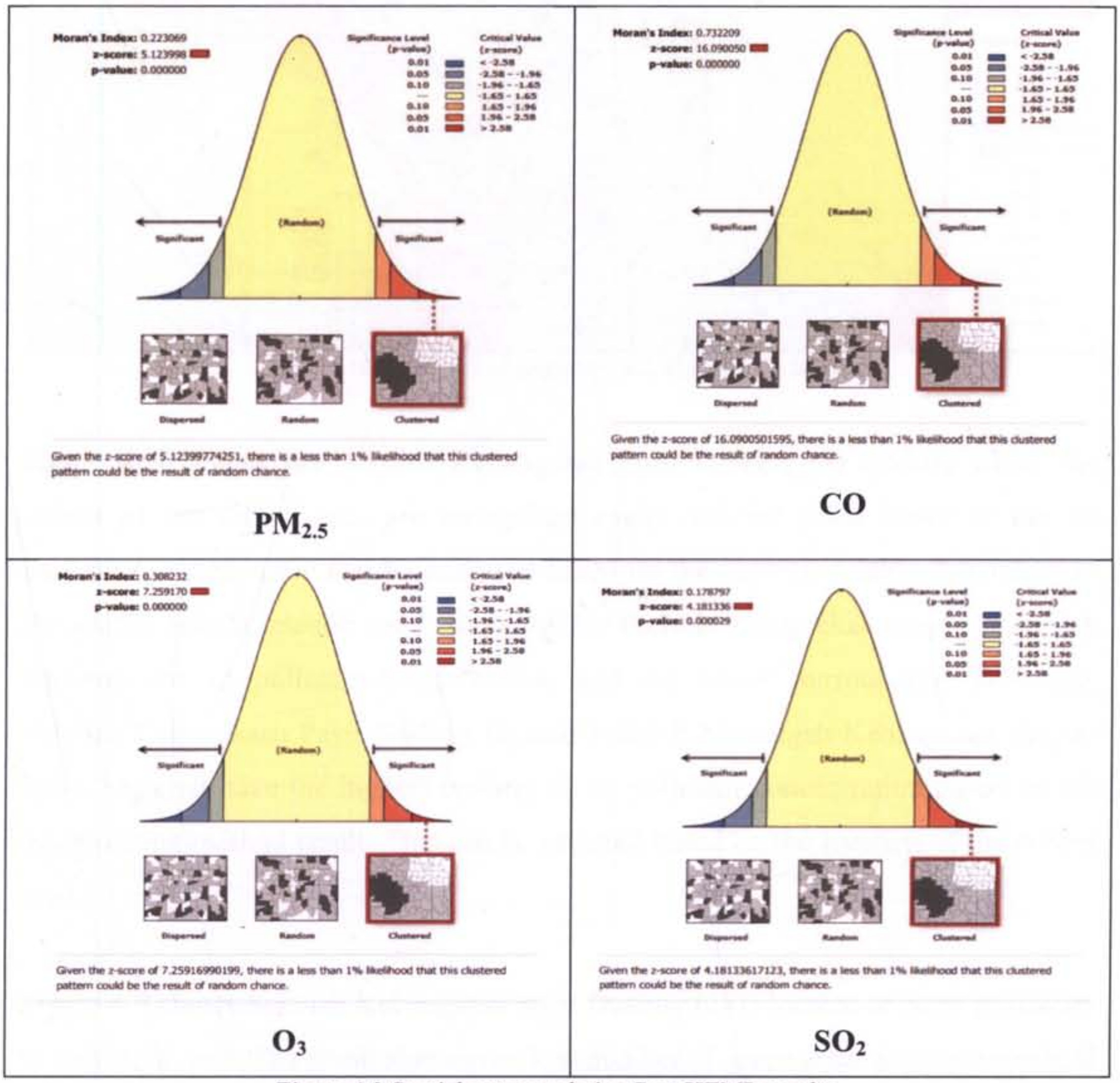

Figure 4.9 Spatial autocorrelation 7am HTML results.

Figure 4.9 shows the air pollutant concentration derived from spatial autocorrelation at 7am hourly. The results show that the Moran's Indices is positive showing strong relationship that it is clustering. All the spatial autocorrelation results show positive clustered and positive Moran's Indices. Based on the result, it can be stated that there is a relationship between air pollutant concentrations with the school locations. More results shown in appendix A, B, C and D.

Figure 4.10 Sekolah Kebangsaan Pasir Gudang (2) landuse

Figure 4.10 shows the Sekolah Kebangsaan Pasir Gudang (2) landuse where the details of the school area are recognized easily and the main factor of the air pollutant concentration can be analyzed based on the activity nearby. According to the spatial autocorrelation result showing that there is strong clustering relationship between the air pollutant concentration and the school surrounding. Basically, Sekolah Kebangsaan Pasir Gudang (2) and Sekolah Menengah Kebangsaan Bandar Putra Segamat have the highest reading of air pollutant concentration based on the interpolation method result. This can be justified based on the location of the school area.

Figure 4.9 shows Sekolah Kebangsaan Pasir Gudang (2) is located in close proximity to industrial area. The result also shows low number of green areas nearby the school which is important to act as a buffer for the industrial areas. Referring to figure 4.9, brown and purple color represents the industrial and residential area respectively. It can be seen that industrial area took out about 50% coverage much more larger compare to residential area which is about 20%, 15% of roads and commercial area and 15% of green area which is not enough to act as a buffer to reduce the range of air pollution. Majority, Sekolah Kebangsaan Pasir Gudang (2) is surrounded with industrial area which then increases the air pollutant concentration range value every single hour especially during school operation hour.

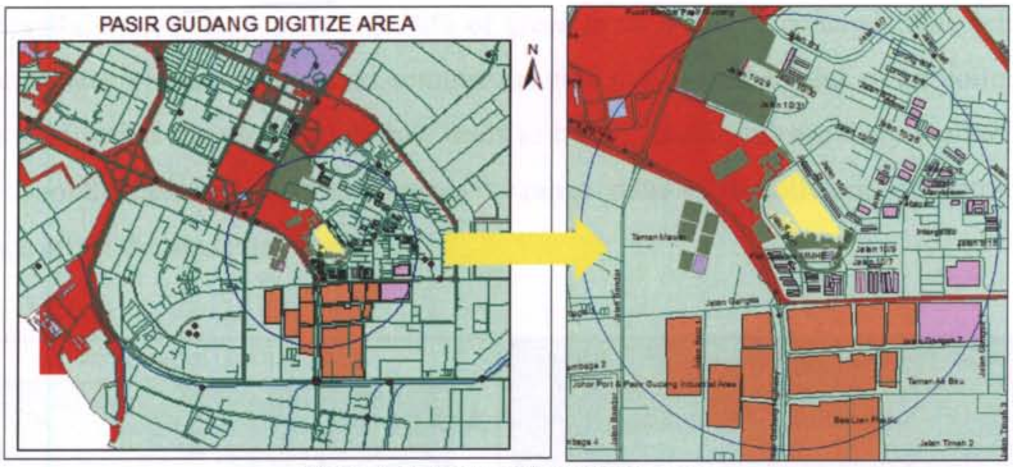

Figure 4.11 Pasir Gudang digitize area

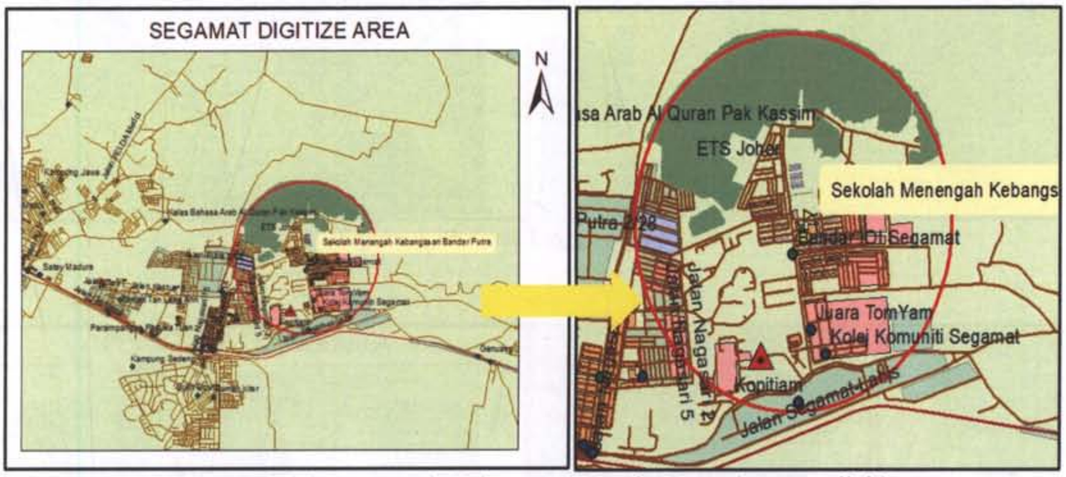

Figure 4.12 Sekolah Menengah Kebangsaan Bandar Putra Segamat digitize area

Figure 4.11 and figure 4.12 show Sekolah Kebangsaan Pasir Gudang (2) and Sekolah Menengah Kebangsaan Bandar Putra Segamat landuse based on Google earth open source. This school located at Segamat area show higher level of air pollutant concentration besides school at Pasir Gudang. It can be concluded that school surroundings has the relationship with the air pollution reading this can be justify based on the figure 4.11 where this school is located near with industrial represented using brown color, residential area represented with blue color, busy roads and commercial area represented using pink color. Residential and commercial areas trigger traffic activities and industrial area release waste smoke into the atmosphere thus more pollutant concentration such as $PM_{2.5}$, SO_2, O_3 and CO are released into the atmosphere which is then breathe in by student. Based on the result shown, the school was cover with 40% of commercial area, 6% of industrial area, 25% of residential area, 6% of roads and 20% of green area. It can be conclude that, school located near with residential and commercial area triggered the value of air pollution due to crowded situation which then leads to traffic, smoke release from the vehicle and from the nearest industrial increase the range value of air pollutant concentration hence affect the students' health.

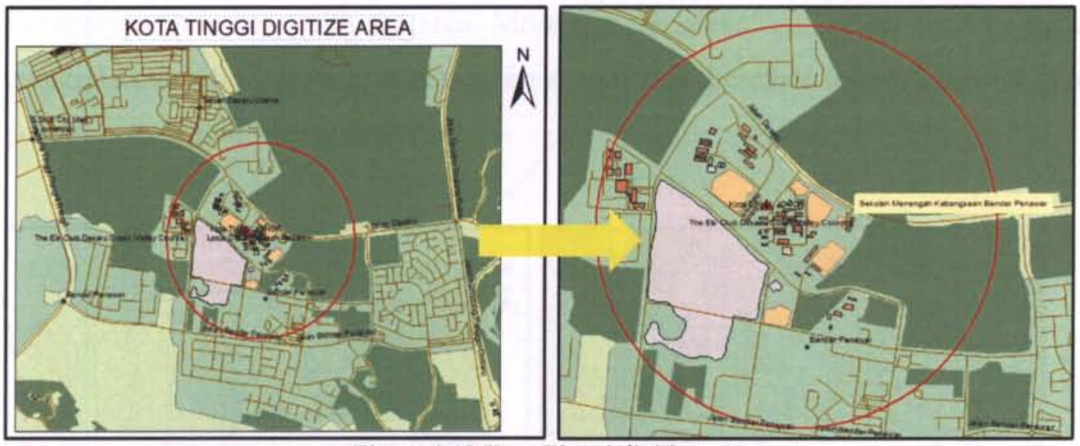

Figure 4.13 Kota Tinggi digitize area

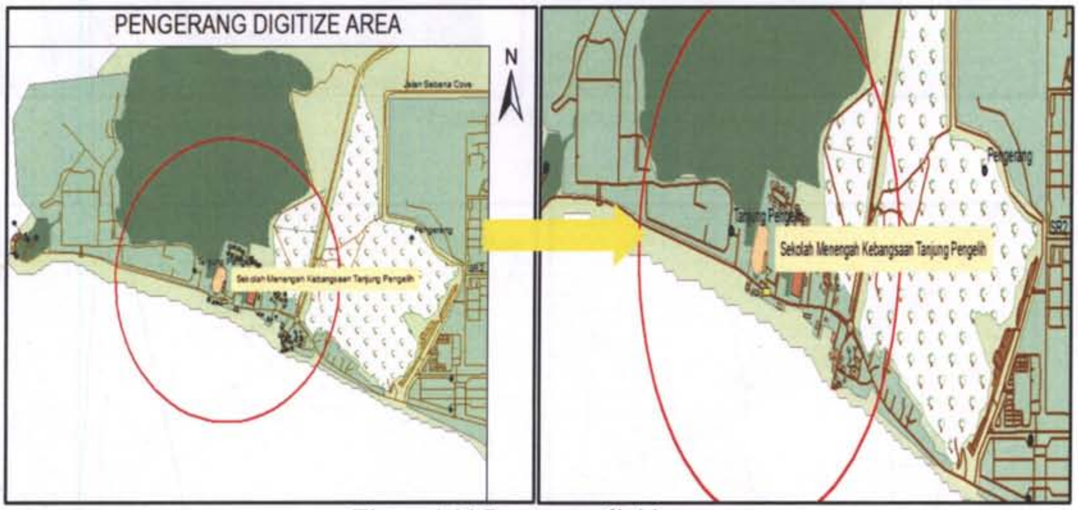

Figure 4.14 Pengerang digitize area

Figure 4.13 and figure 4.14 show Sekolah Menengah Bandar Penawar located in Kota Tinggi and Sekolah Menengah Kebangsaan Tanjung Pengelih located in Pengerang digitize area. Both of this school show low air pollutant concentration level as compared to Pasir Gudang and Segamat area. Observation is made between this two location, even know this school is located near with residential which cover about 30% of the area and commercial that cover 20% of the area, but the number of green area is equal which allow to reduce the air pollution level within that area. This can be explained through the observation made where this two schools area are cover with green area or vegetation which covers about 50% among the radius, that is why the air pollution is lower than Pasir Gudang. As for Sekolah Menengah Kebangsaan Tanjung Pengelih located at Pengerang, basically the school area is located near with oil palm vegetation which cover about 20% and 30% of green area coverage furthermore it is near with sea area. Moreover the green area act as a buffer which penetrate the pollution from affecting the school area therefore reduce the level of air pollution in both of this schools area.

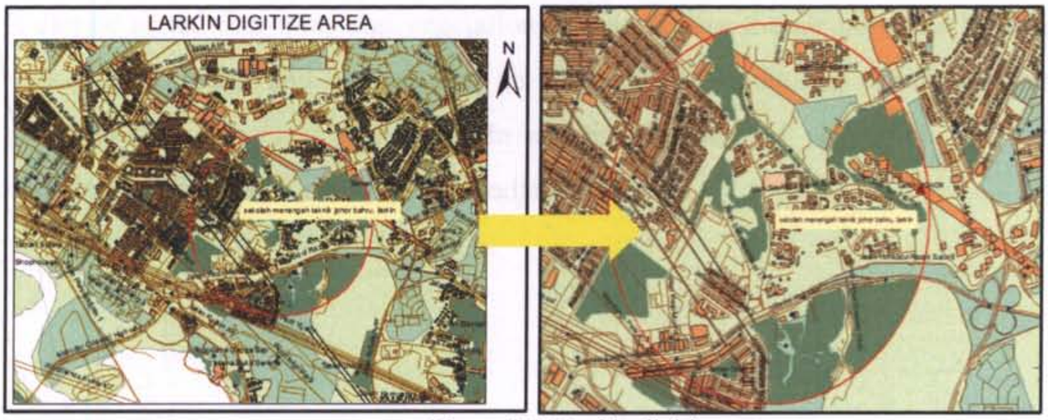

Figure 4.15 Larkin digitize area

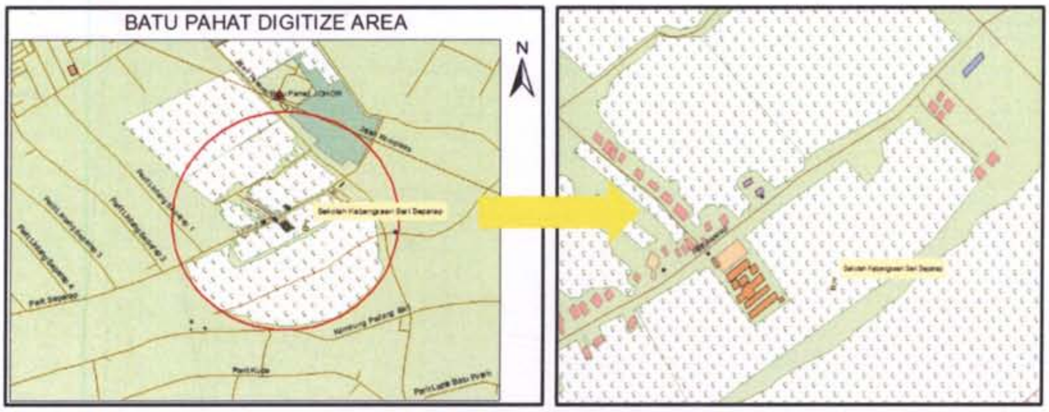

Figure 4.16 Batu Pahat digitize area

Figure 4.15 and 4.16 show the digitize area for Larkin and Batu Pahat schools area where the air pollutant concentration frequently increase and reduce according to time changes. Based on the digitization, Sekolah Menengah Teknik Johor Bahru at Larkin located in urban area consists of residential area and commercial area. Despite the school location in urban area, the air pollution index show that this area is less polluted as compared to Pasir Gudang due the present of green area that cover about 40% of the coverage area which stabilize the pollutant concentration compare to Pasir Gudang area where the buildings are arranged very close with each other hence the coverage of residential area is about 35% and industrial area about 20% of the coverage area. As for Sekolah Kebangsaan Seri Separap at Batu Pahat where the school area is surrounded by oil palm vegetation which cover about 50% of the coverage area. Meanwhile, there is only 20% commercial area, 10% of roads coverage and 20% for residential area.

It can be stated that trees and vegetation able to reduce the air pollution by directly removing pollutant and by reducing air temperature, hence tree effects can reduce pollutant emissions and formation. In addition, present of vegetation can form a barrier between traffic emissions and adjacent areas.

4.6 Story map

This section display the final output of the result in the form of story map. Story map is one of the story maps that allowed people to interact with the result displayed. In this story map, interpolation, spatial autocorrelation method, air pollutant concentration parameter involved, hourly data of each parameter based on 2018 and six selected school in Johor which are Sekolah Menengah Teknik Johor Bahru Larkin, Sekolah Kebangsaan Pasir Gudang (2), Sekolah Kebangsaan Separap Batu Pahat, Sekolah Menengah Kebangsaan Bandar Putra Segamat, Sekolah Menengah Kebangsaan Tanjung Pengelih Pengerang and Sekolah Menengah Kebangsaan Bandar Penawar Kota Tinggi will be display in this story map. Furthermore, information about air pollutant concentration will be explained and videos related with air pollution will be displayed. This is the link for the story.

https://geouitm.maps.arcgis.com/apps/Cascade/index.html?appid=1481b7ca14f44f579327bab79f51b2cf&preview

Figure 4.17 Story map

4.7 Summary

Based on the result analysis done, it can be concluded that the air pollutant concentrations at all the school areas located in Johor are positively correlated with the schools surrounding areas. Sekolah Kebangsaan Pasir Gudang (2) and Sekolah Menengah Kebangsaan Bandar Putra located at Segamat show frequently a very dangerous air pollution range level due to their location which is near with industrial, commercial and residential area. Furthermore, lack of green area in school surrounding is one of the major that triggered the rising of the air pollutant concentration reading. Green areas such as present of forest or tree act as a buffer that penetrate the pollution from directly reach to school area. On the other hand, Sekolah Menengah Kebangsaan Tanjung Pengelih located at Pengerang and Sekolah Menengah Kebangsaan Bandar Penawar Kota Tinggi show much more lower air pollutant concentration reading compare to schools located at Pasir Gudang, Segamat, Larkin and Batu Pahat since the schools area are mostly surrounded with green area, despite the school located near with residential, industrial and commercial area, the air pollutant concentration reading manage to be control due to equal number of green area. Therefore, it can be conclude that there is a relationship between these school locations with the air pollutant concentration reading.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter summarized the aim and objectives of this research based on the result analysis according to the relationship between air pollutant concentration and the school surrounding in Johor. Furthermore, recommendations were made based on the analysis result for early precaution especially for students.

5.2 Conclusion

Air pollution is a momentous global issue and it is the most environmental hazard to human health and it is particular concern in urban areas where elevated pollutant concentration and high risk in getting health problem. It can be conclude that based on the result and analysis of the air pollutant concentration map using IDW method and spatial autocorrelation method, the most polluted school area is located at Sekolah Kebangsaan Pasir Gudang (2) since the school located nearest with industrial area hence, waste smoke release from the industrial area affects the air pollutant concentration level. Therefore, higher volume of air pollutant concentration are released such as $PM_{2.5}$, CO, O_3 and SO_2 into the atmosphere which is then breathe in by the student in that nearer area. Besides industrial area, other sources such as higher traffic activity, residential area and commercial area are one of the factors that lead to rising of air pollutant concentration. Transport emissions constitute a dominant source of urban air pollution.

On the other hand, schools located at Pengerang and Kota Tinggi has lower air pollutant concentration compare to other selected schools in Johor this is due to their location where it is covered with green area despite it is located near with industrial, residential and commercial area. In addition, green area act as a buffer which penetrates the air pollution from being directly reached the schools area. Sekolah Menengah Kebangsaan Bandar Penawar located and Kota Tinggi and Sekolah Menengah Kebangsaan Tanjung Pengelih located at Pengerang which contain larger area of green area which is about 40%-50% of the coverage area. Therefore, it can be conclude that the air pollutant concentration is related with the schools surrounding based on the result analysis made.

5.3 Recommendation

Basically, previous result enable suggestion and recommendations, student daily activity patterns in school are highlights which expose them to air pollution according to the school location. It is important to take early precaution in order to prevent children from getting health problem especially when they are studying at the most polluted area or area with high air pollutant emissions. Thus, identification of the major air pollution problem and raise public awareness of the environmental protection including informing an air pollution abatement policy. Besides, according to the result analysis, school in future should be located away from trafficked roads since the exposure to traffic is based on the distance to road traffic. Moreover, in order to prevent students from being exposed to air pollutants, the road traffic density must be reduced around existing of schools. Most importantly, increase the green and pedestrian spaces surround the schools area since greening the school able to assist in abate exposure to air pollution and green area act as a buffer which penetrate the air pollutant concentration.

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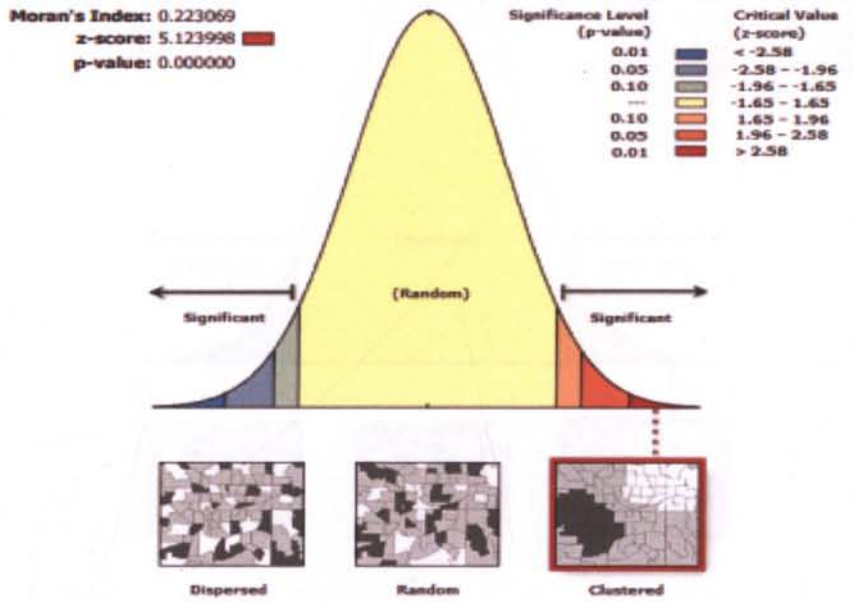
APPENDIX A

($PM_{2.5}$ hourly spatial autoccorrelation results)



Given the z-score of 5.12399774251, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

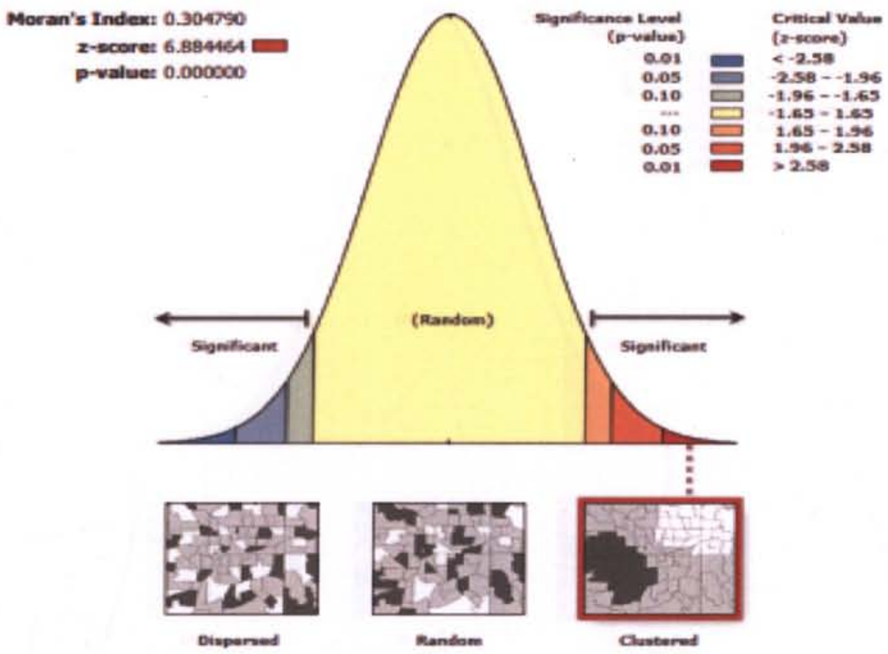
Global Moran's I Summary

Moran's Index:	0.223069
Expected Index:	-0.014085
Variance:	0.002142
z-score:	5.123998
p-value:	0.000000

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	7_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	1000.0000 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 6.8844640873, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

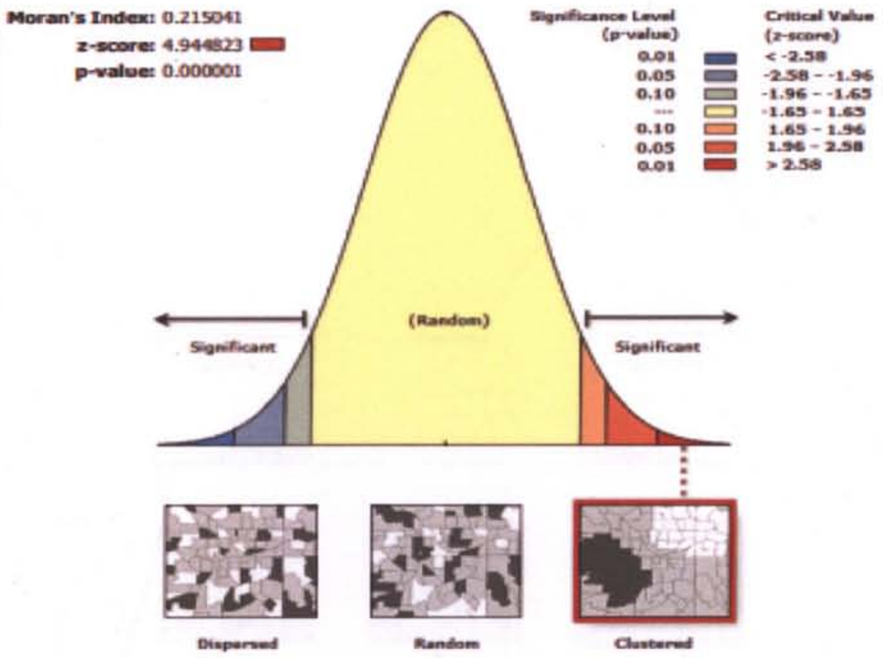
Global Moran's I Summary

Moran's Index:	0.304790
Expected Index:	-0.014085
Variance:	0.002145
z-score:	6.884464
p-value:	0.000000

Dataset Information

Input Feature Class:	PM2.5
Input Field:	8_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.94482300216, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

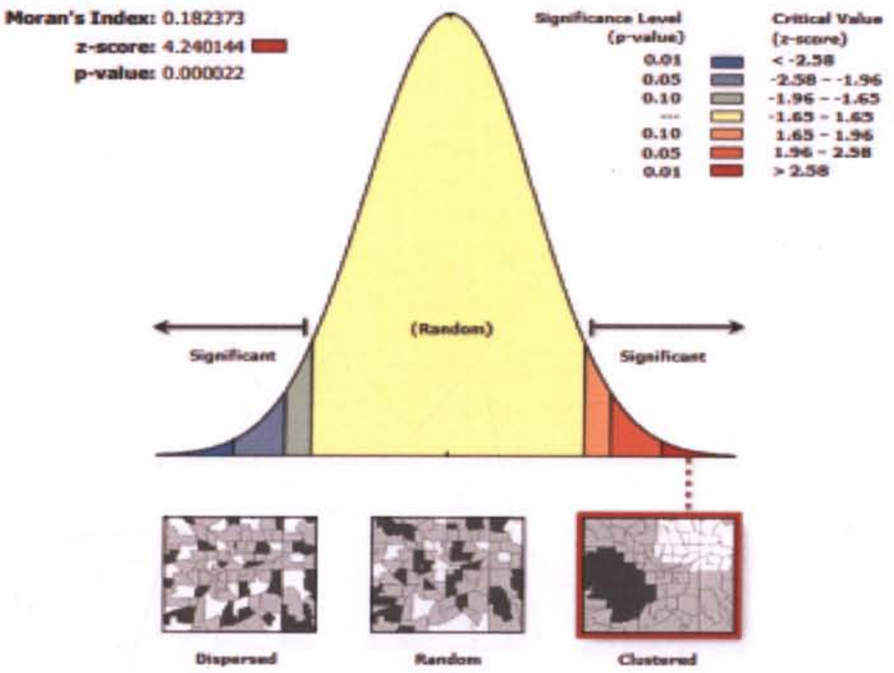
Global Moran's I Summary

Moran's Index:	0.215041
Expected Index:	-0.014085
Variance:	0.002147
z-score:	4.944823
p-value:	0.000001

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	9_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.24014392415, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

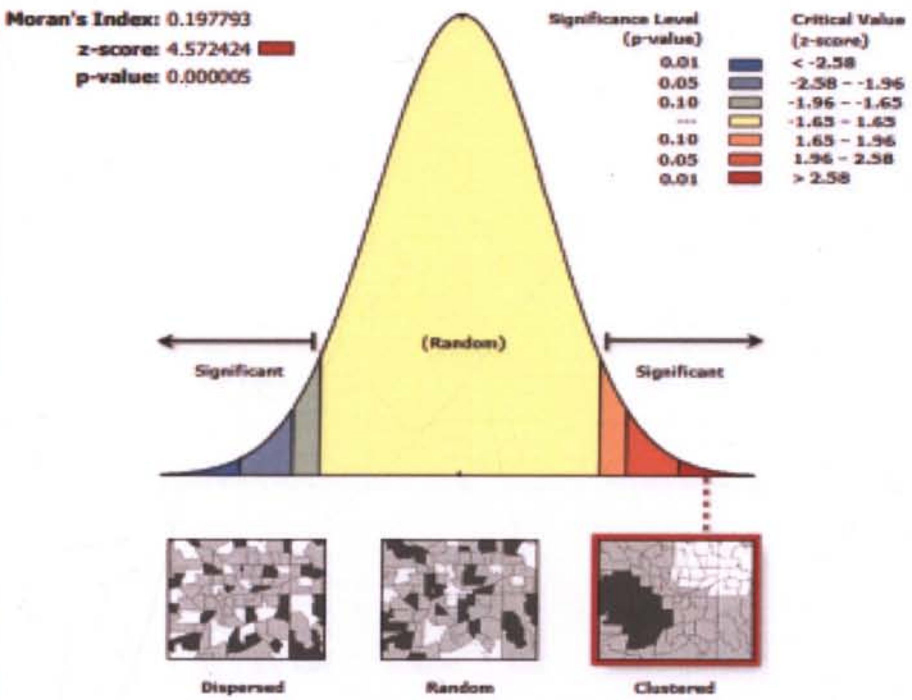
Global Moran's I Summary

Moran's Index:	0.182373
Expected Index:	-0.014085
Variance:	0.002147
z-score:	4.240144
p-value:	0.000022

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	10_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.572424228, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

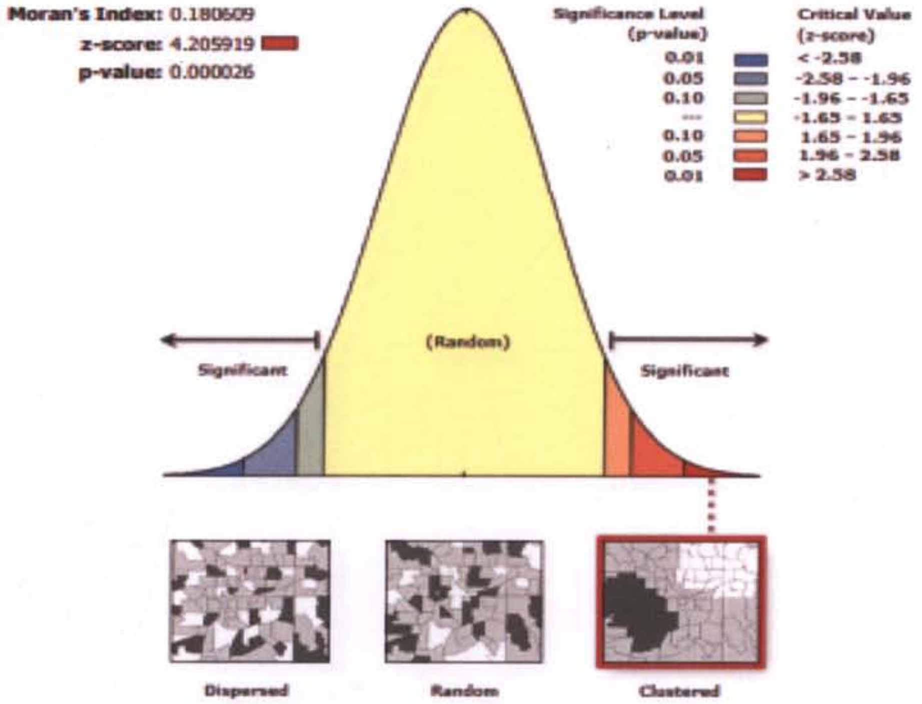
Global Moran's I Summary

Moran's Index:	0.197793
Expected Index:	-0.014085
Variance:	0.002147
z-score:	4.572424
p-value:	0.000005

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	11_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.205918955, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

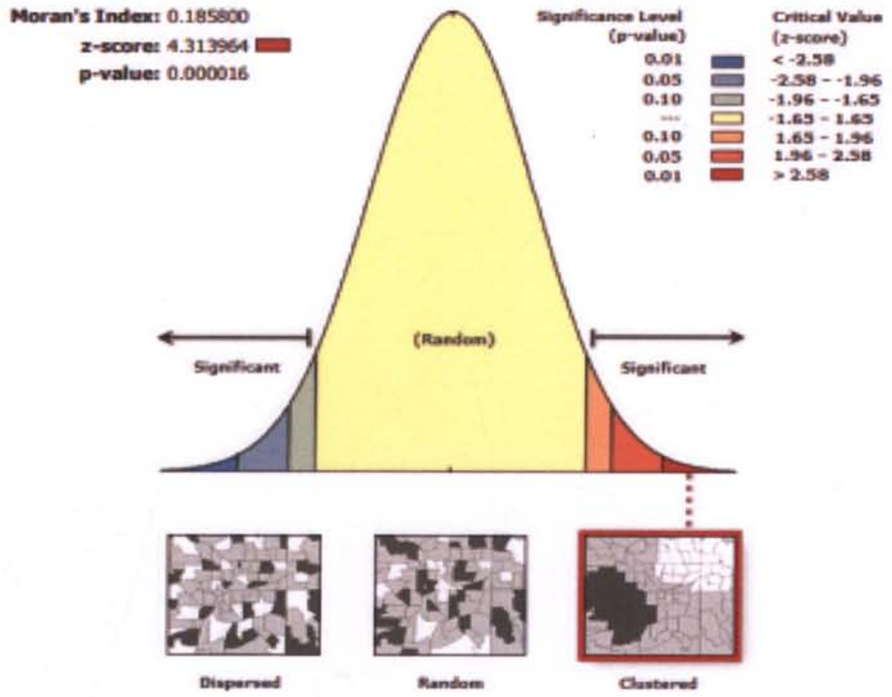
Global Moran's I Summary

Moran's Index:	0.180609
Expected Index:	-0.014085
Variance:	0.002143
z-score:	4.205919
p-value:	0.000026

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	12_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.31396407695, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

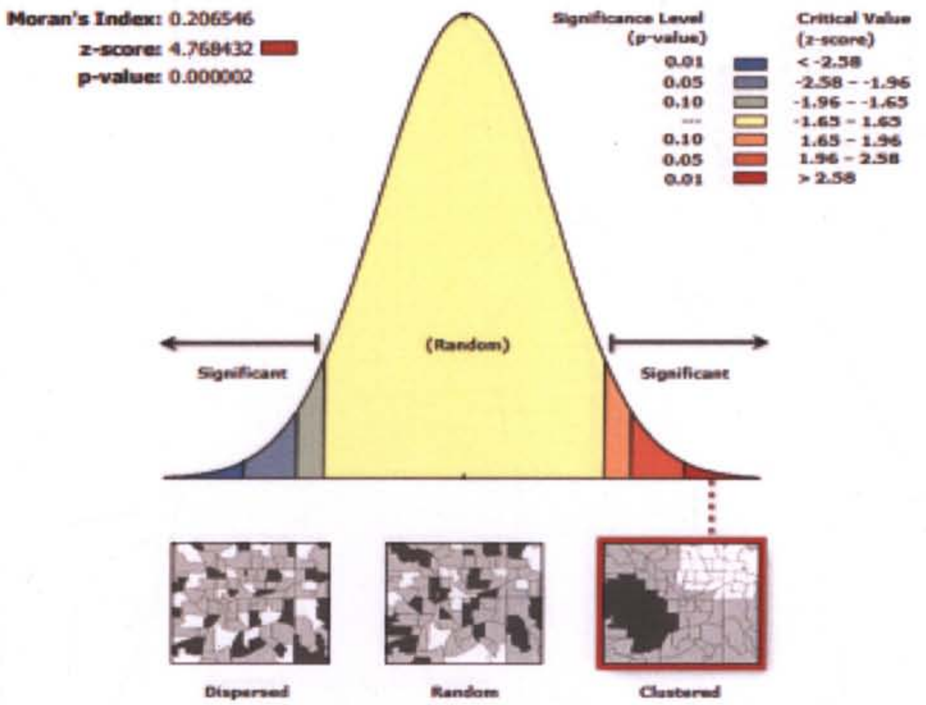
Global Moran's I Summary

Moran's Index:	0.185800
Expected Index:	-0.014085
Variance:	0.002147
z-score:	4.313964
p-value:	0.000016

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	1_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.76843195172, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

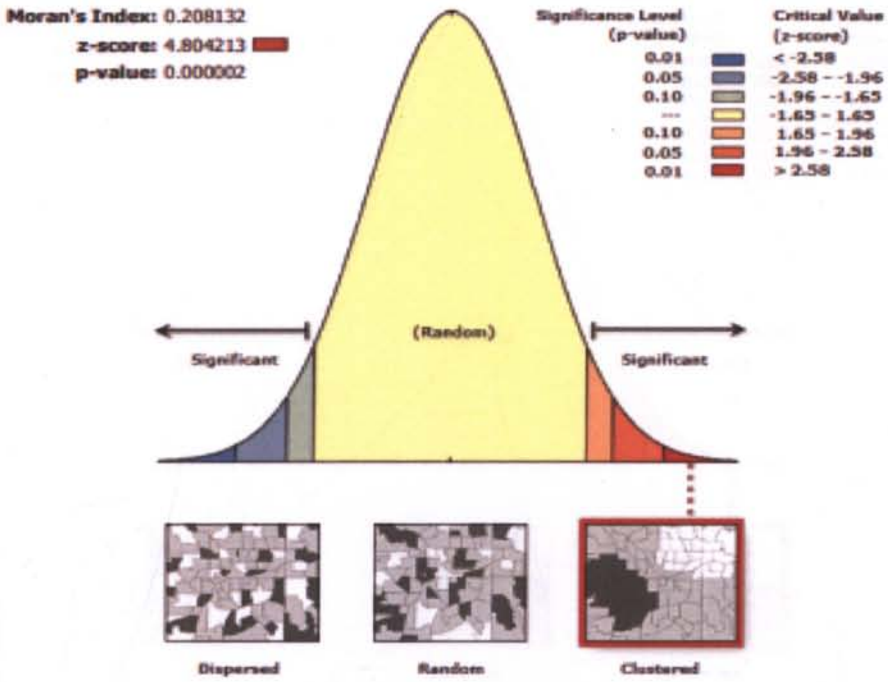
Global Moran's I Summary

Moran's Index:	0.206546
Expected Index:	-0.014085
Variance:	0.002141
z-score:	4.768432
p-value:	0.000002

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	2_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.80421292005, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

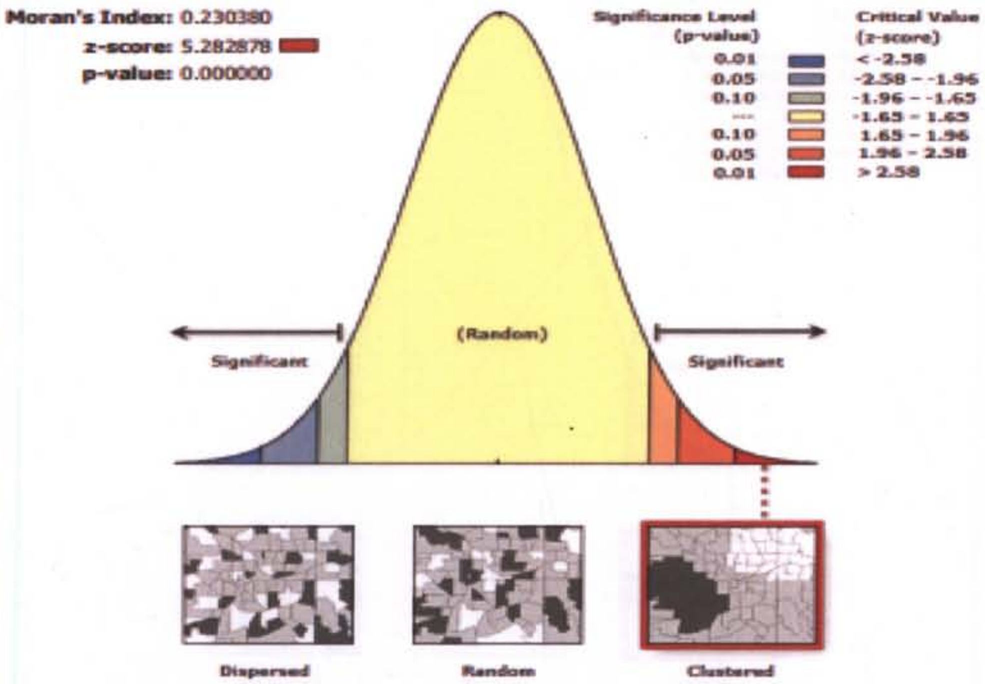
Global Moran's I Summary

Moran's Index:	0.208132
Expected Index:	-0.014085
Variance:	0.002139
z-score:	4.804213
p-value:	0.000002

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	3_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 5.28287812855, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

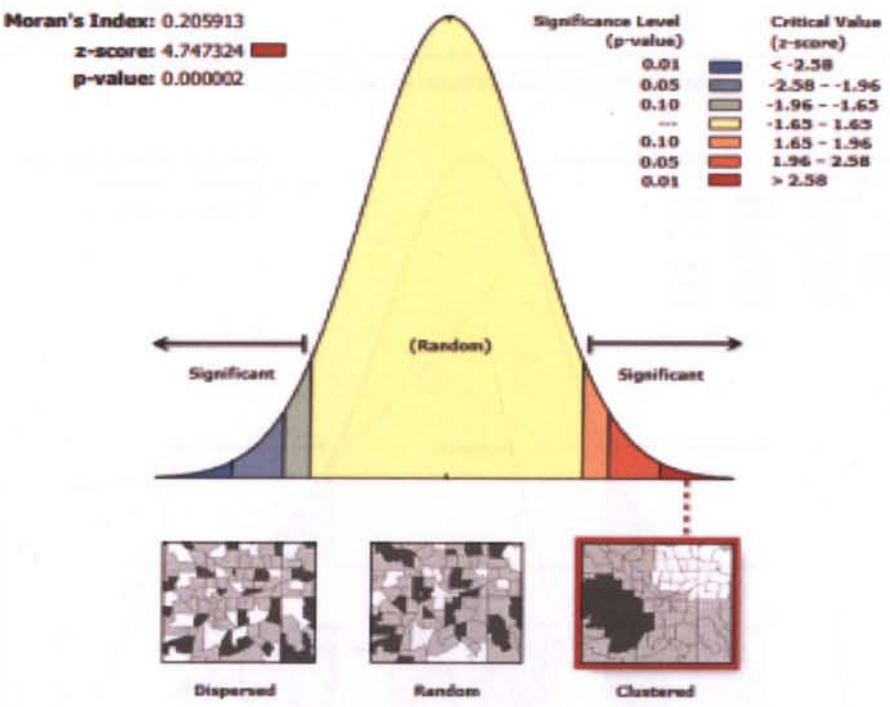
Global Moran's I Summary

Moran's Index:	0.230380
Expected Index:	-0.014085
Variance:	0.002141
z-score:	5.282878
p-value:	0.000000

Dataset Information

Input Feature Class:	PM 2.5
Input Field:	4_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.74732432983, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.205913
Expected Index:	-0.014085
Variance:	0.002148
z-score:	4.747324
p-value:	0.000002

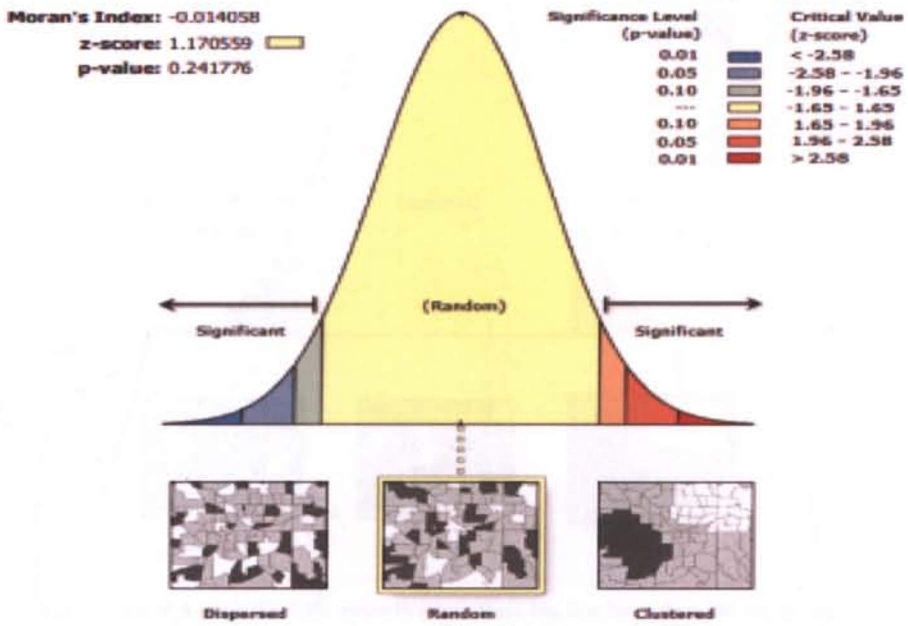
Dataset Information

Input Feature Class:	PM 2.5
Input Field:	5_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

APPENDIX B

(SO_2 hourly spatial autocorrelation results)

Spatial Autocorrelation Report



Given the z-score of 1.1705588364, the pattern does not appear to be significantly different than random.

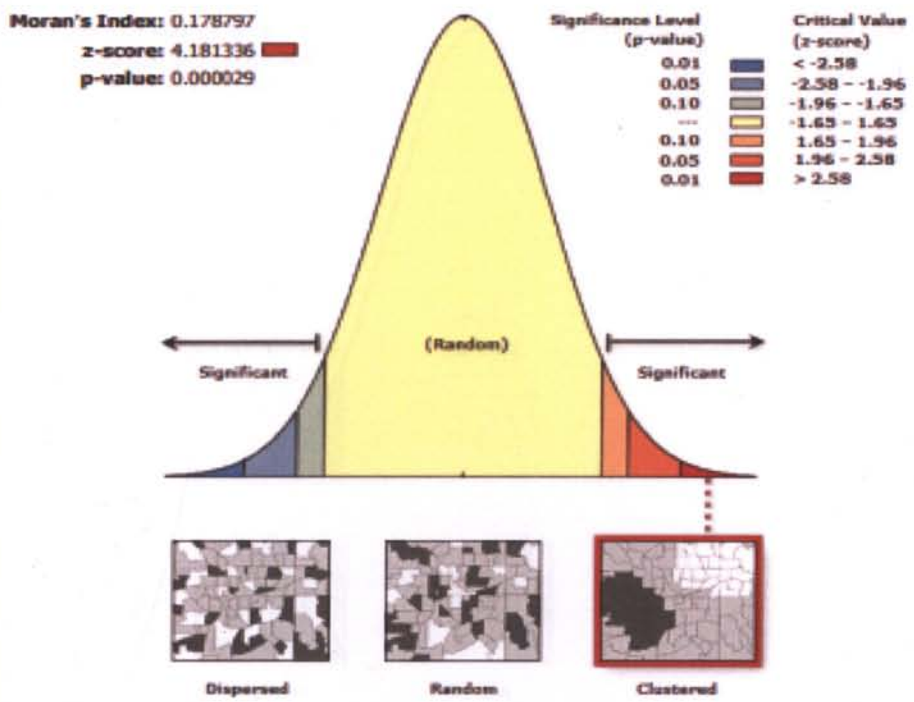
Global Moran's I Summary

Moran's Index:	-0.014058
Expected Index:	-0.014085
Variance:	0.000000
z-score:	1.170559
p-value:	0.241776

Dataset Information

Input Feature Class:	SO2
Input Field:	7_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.18133617123, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

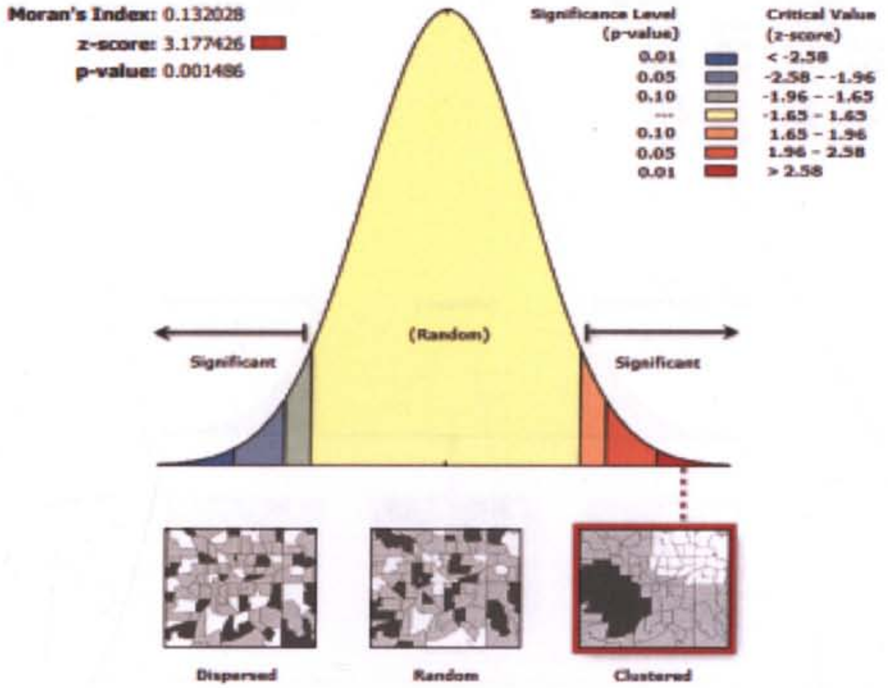
Global Moran's I Summary

Moran's Index:	0.178797
Expected Index:	-0.014085
Variance:	0.002128
z-score:	4.181336
p-value:	0.000029

Dataset Information

Input Feature Class:	SO2
Input Field:	8_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 3.17742599553, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

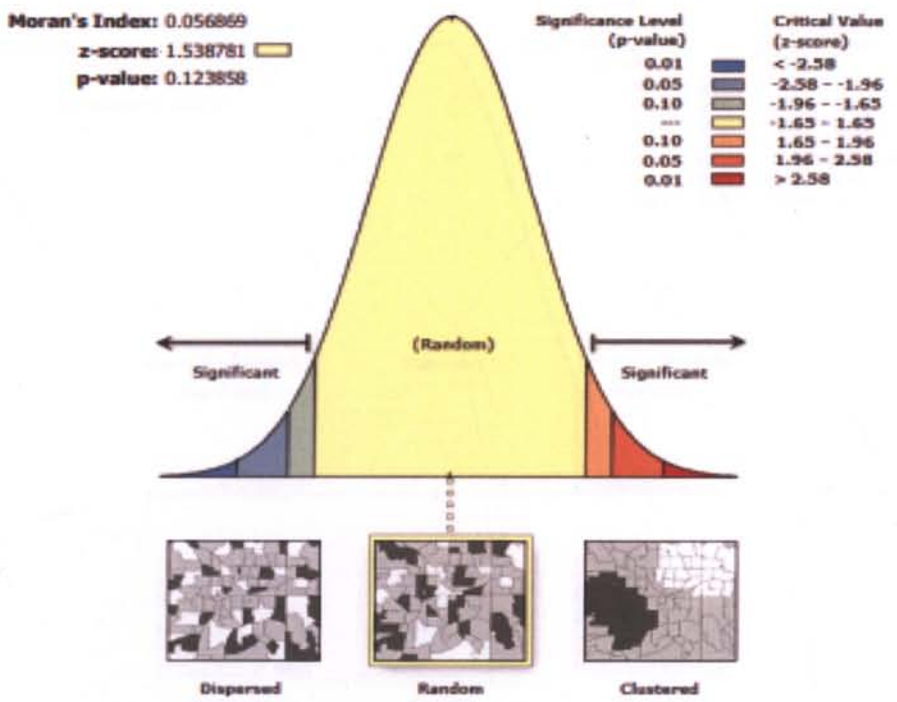
Global Moran's I Summary

Moran's Index:	0.132028
Expected Index:	-0.014085
Variance:	0.002115
z-score:	3.177426
p-value:	0.001486

Dataset Information

Input Feature Class:	SO2
Input Field:	9_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 1.53878140725, the pattern does not appear to be significantly different than random.

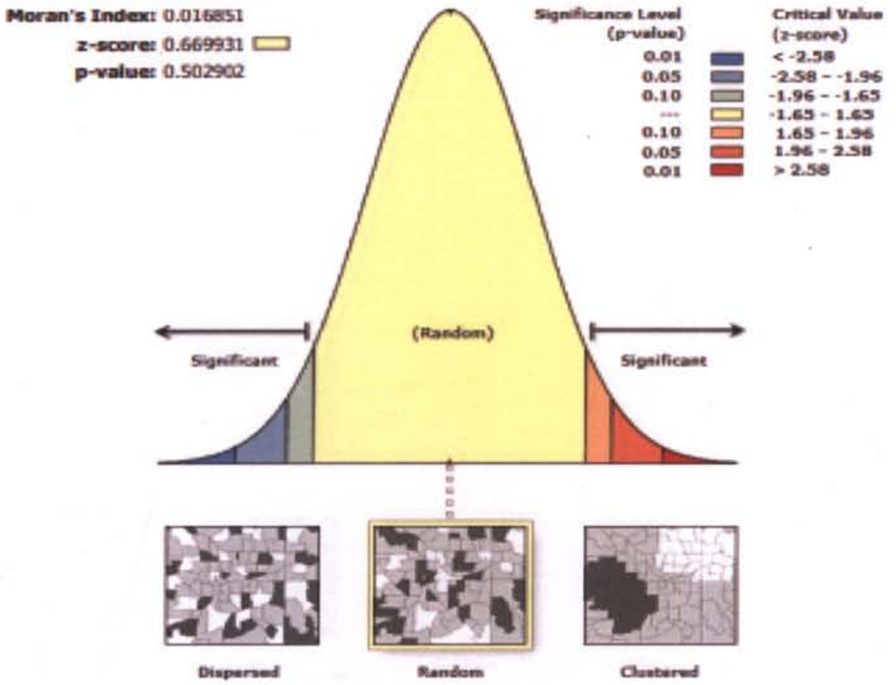
Global Moran's I Summary

Moran's Index:	0.056869
Expected Index:	-0.014085
Variance:	0.002126
z-score:	1.538781
p-value:	0.123858

Dataset Information

Input Feature Class:	SO2
Input Field:	10_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 0.6699308888433, the pattern does not appear to be significantly different than random.

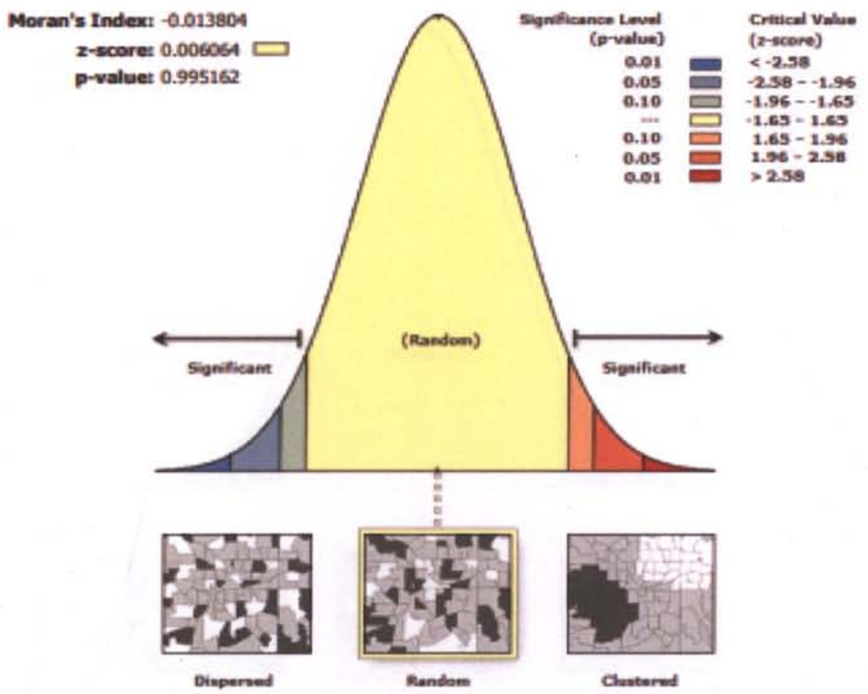
Global Moran's I Summary

Moran's Index:	0.016851
Expected Index:	-0.014085
Variance:	0.002132
z-score:	0.669931
p-value:	0.502902

Dataset Information

Input Feature Class:	SO2
Input Field:	11_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 0.00606366667647, the pattern does not appear to be significantly different than random.

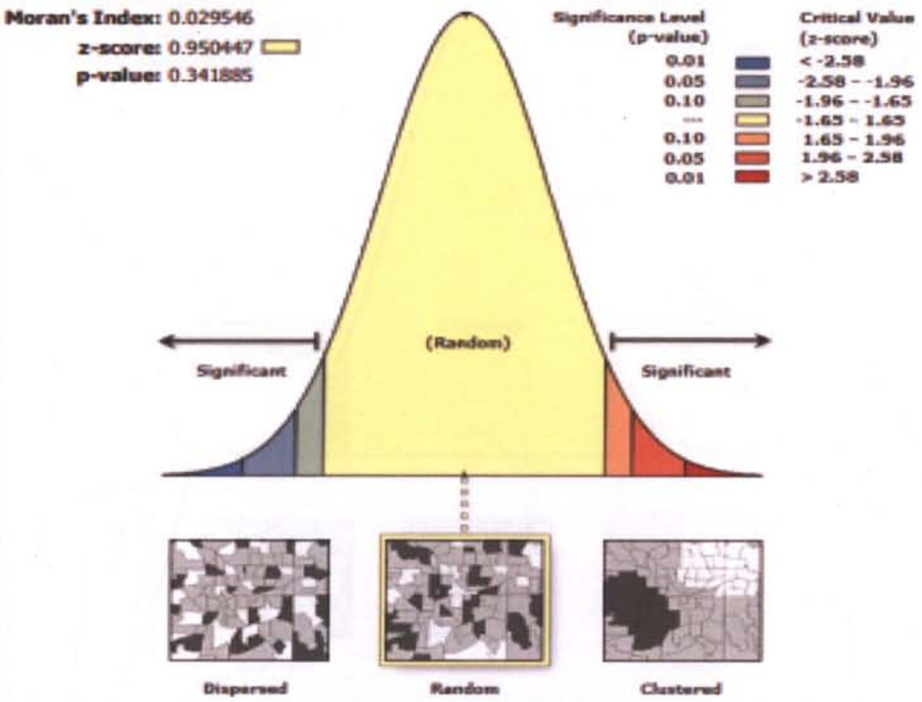
Global Moran's I Summary

Moran's Index:	-0.013804
Expected Index:	-0.014085
Variance:	0.002147
z-score:	0.006064
p-value:	0.995162

Dataset Information

Input Feature Class:	SO2
Input Field:	12_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 0.950447257323, the pattern does not appear to be significantly different than random.

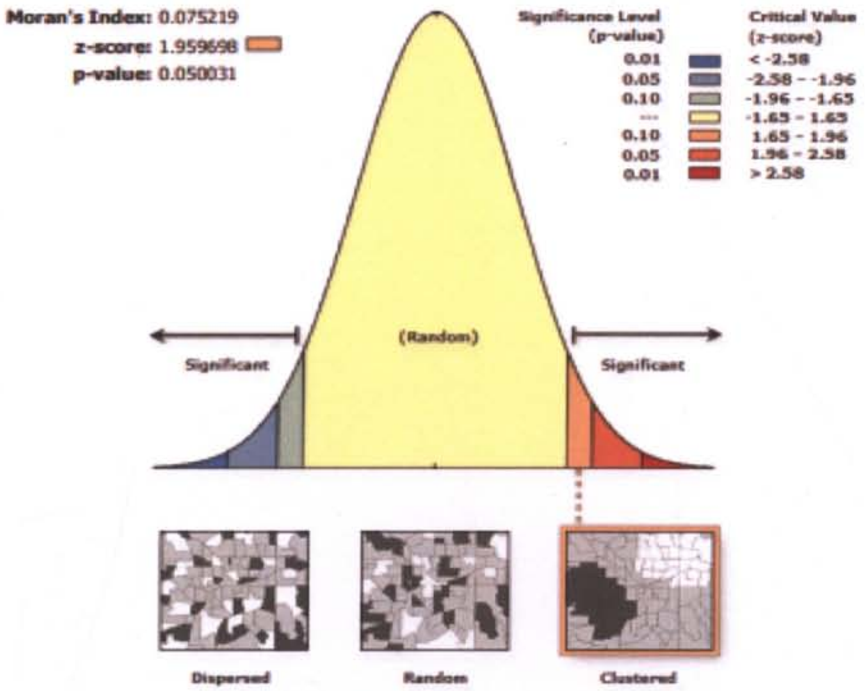
Global Moran's I Summary

Moran's Index:	0.029546
Expected Index:	-0.014085
Variance:	0.002107
z-score:	0.950447
p-value:	0.341885

Dataset Information

Input Feature Class:	SO2
Input Field:	1_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 1.95969819129, there is a less than 10% likelihood that this clustered pattern could be the result of random chance.

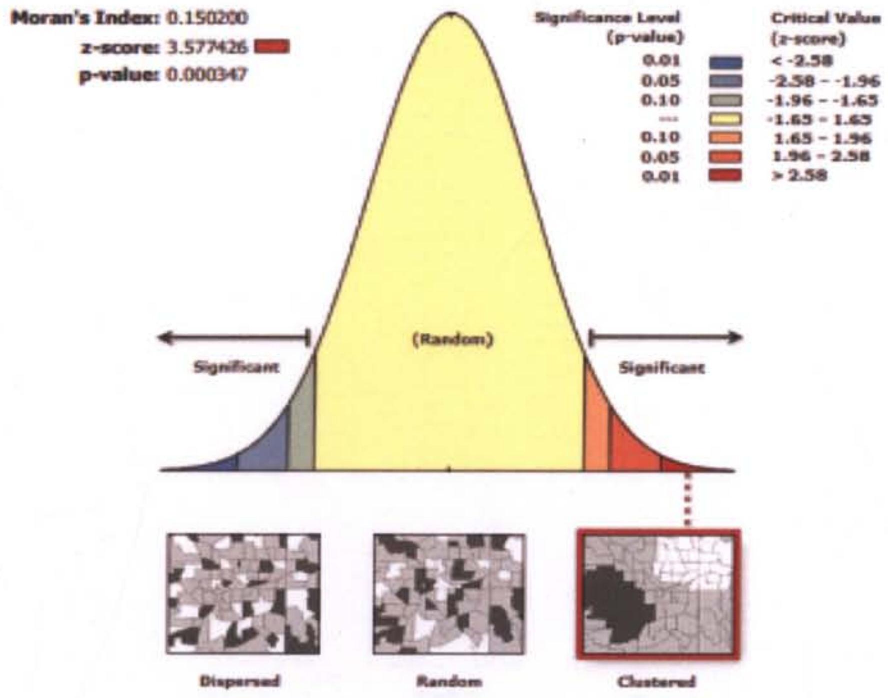
Global Moran's I Summary

Moran's Index:	0.075219
Expected Index:	-0.014085
Variance:	0.002077
z-score:	1.959698
p-value:	0.050031

Dataset Information

Input Feature Class:	SO2
Input Field:	2_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 3.57742635043, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

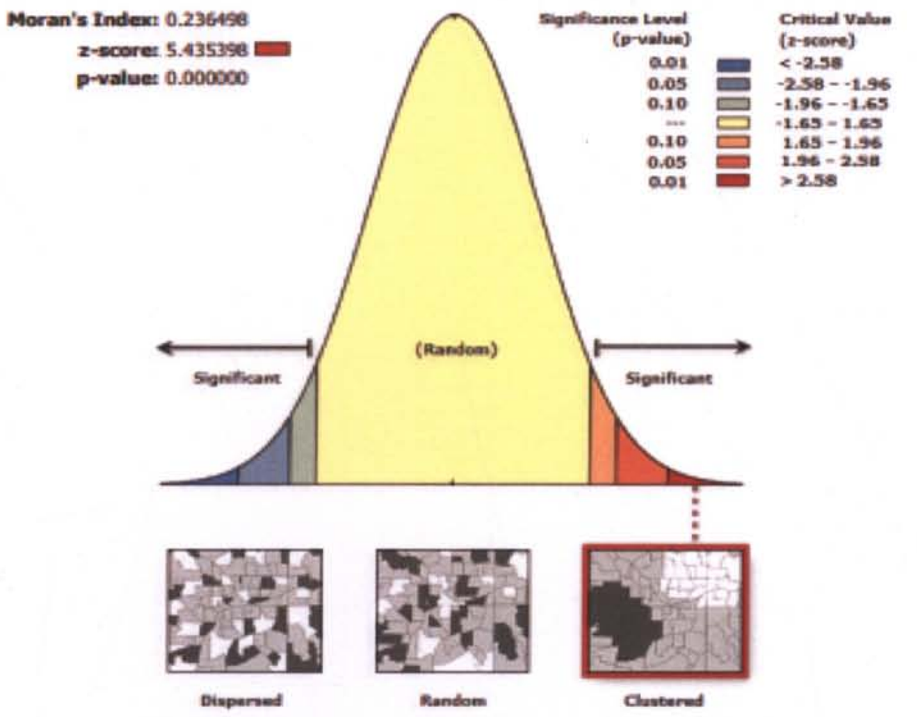
Global Moran's I Summary

Moran's Index:	0.150200
Expected Index:	-0.014085
Variance:	0.002109
z-score:	3.577426
p-value:	0.000347

Dataset Information

Input Feature Class:	SO2
Input Field:	3_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 5.43539819992, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

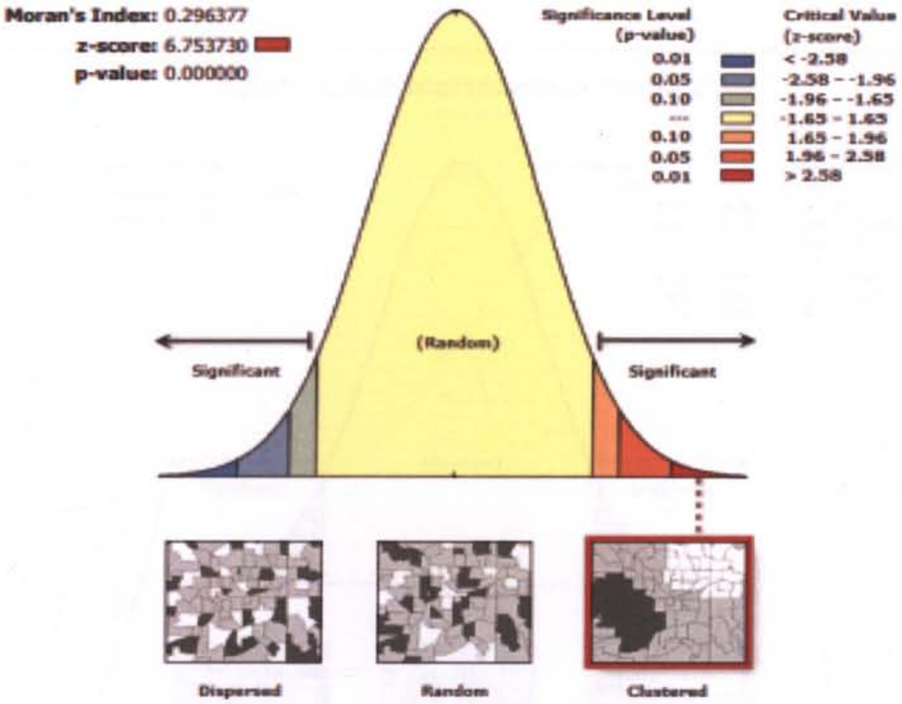
Global Moran's I Summary

Moran's Index:	0.236498
Expected Index:	-0.014085
Variance:	0.002125
z-score:	5.435398
p-value:	0.000000

Dataset Information

Input Feature Class:	SO2
Input Field:	4_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 6.75373011576, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.296377
Expected Index:	-0.014085
Variance:	0.002113
z-score:	6.753730
p-value:	0.000000

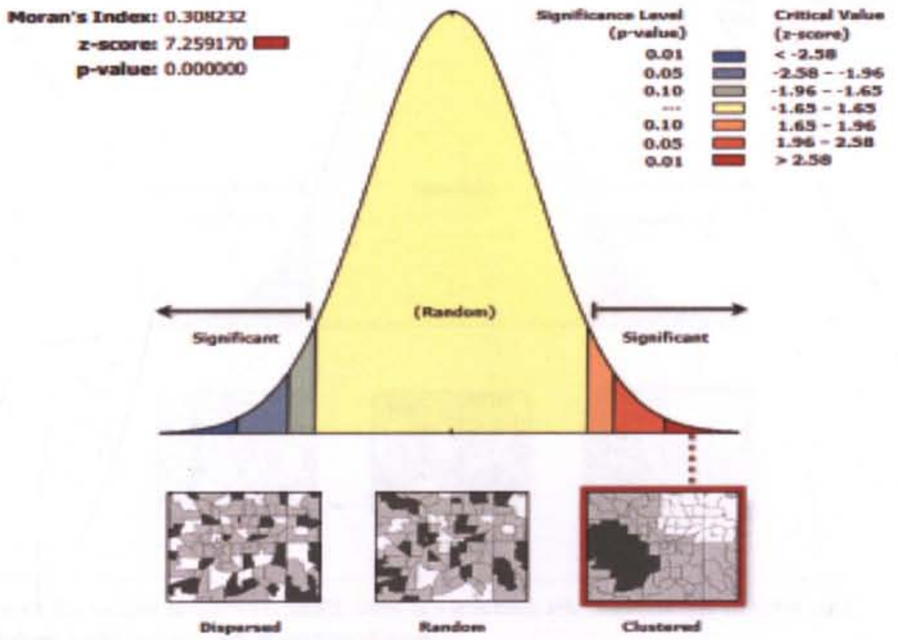
Dataset Information

Input Feature Class:	SO2
Input Field:	5_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

APPENDIX C

(O_3 spatial autocorrelation results)

Spatial Autocorrelation Report



Given the z-score of 7.25916990199, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

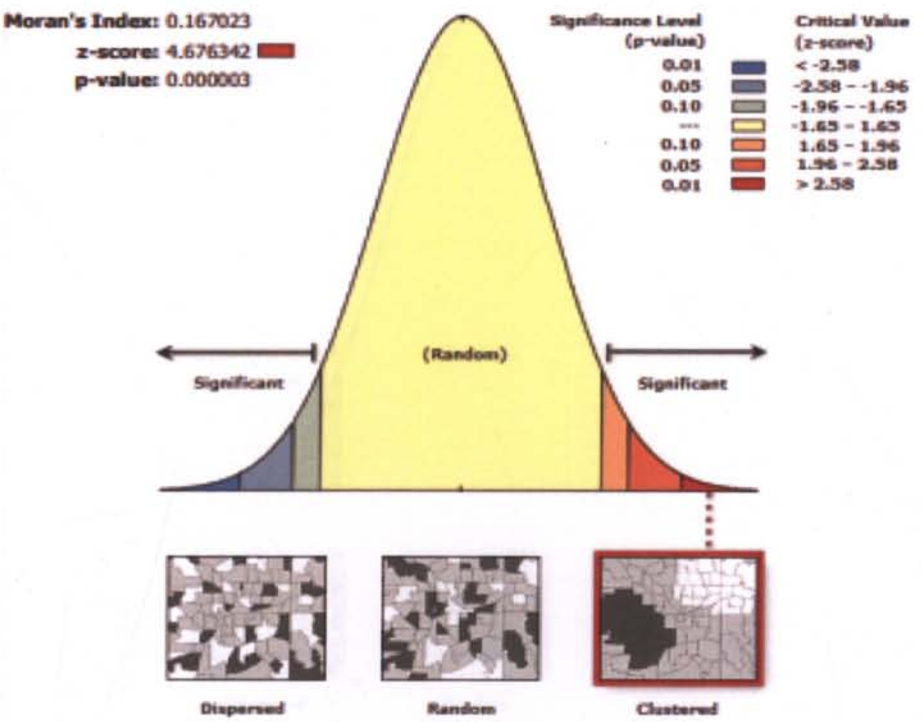
Global Moran's I Summary

Moran's Index:	0.308232
Expected Index:	-0.014085
Variance:	0.001971
z-score:	7.259170
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	7_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 4.67634158095, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

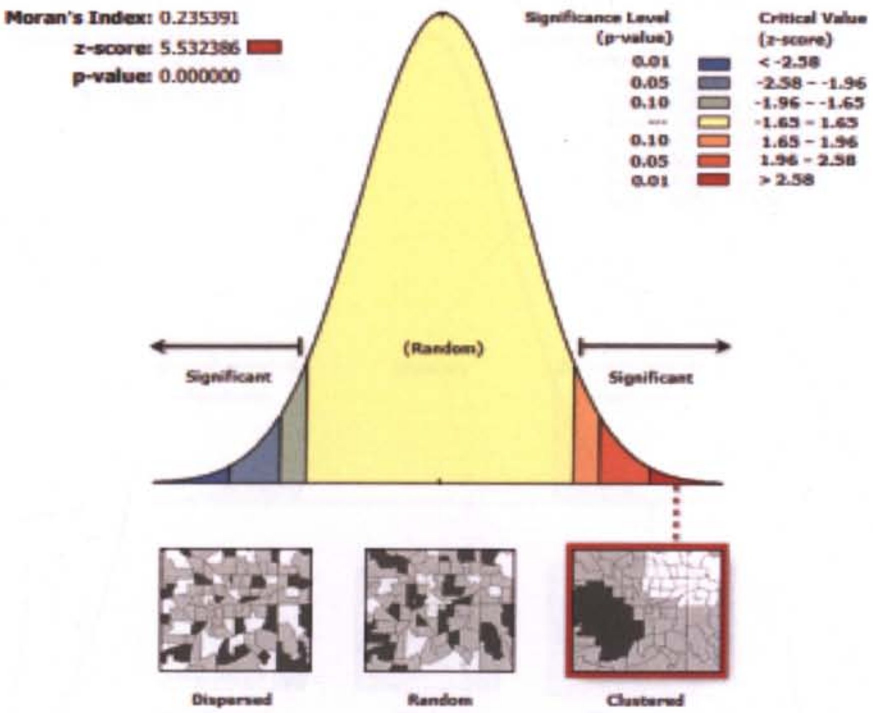
Global Moran's I Summary

Moran's Index:	0.167023
Expected Index:	-0.014085
Variance:	0.001500
z-score:	4.676342
p-value:	0.000003

Dataset Information

Input Feature Class:	O3
Input Field:	8_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 5.53238565125, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

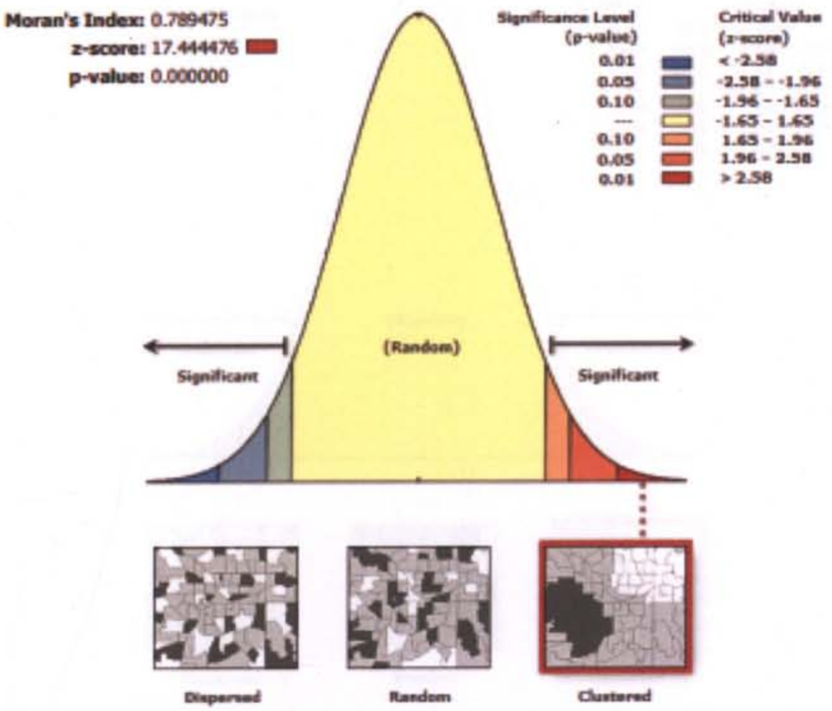
Global Moran's I Summary

Moran's Index:	0.235391
Expected Index:	-0.014085
Variance:	0.002033
z-score:	5.532386
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	9_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 17.4444763328, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

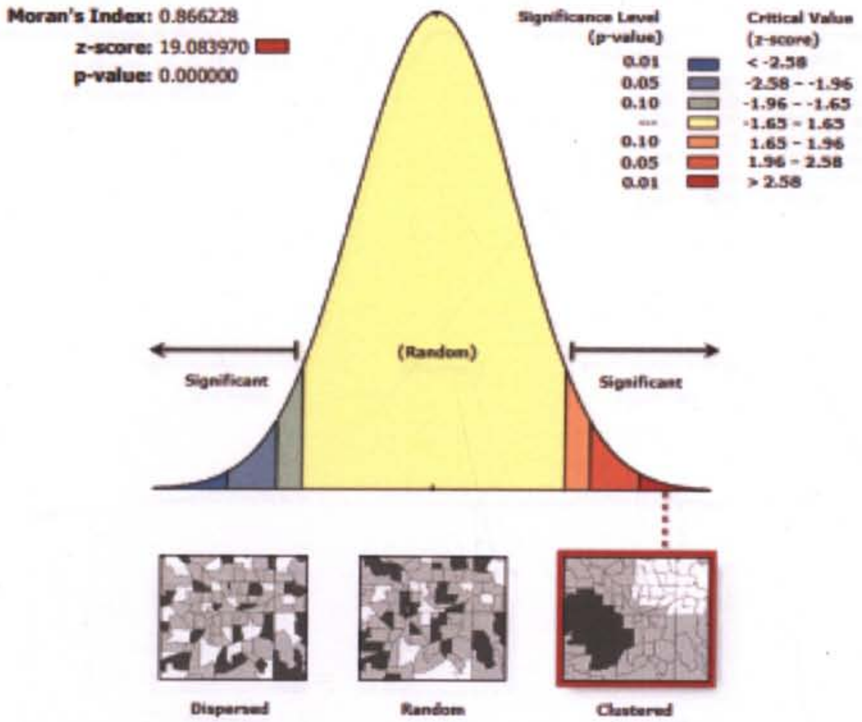
Global Moran's I Summary

Moran's Index:	0.789475
Expected Index:	-0.014085
Variance:	0.002122
z-score:	17.444476
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	10_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.0839703225, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

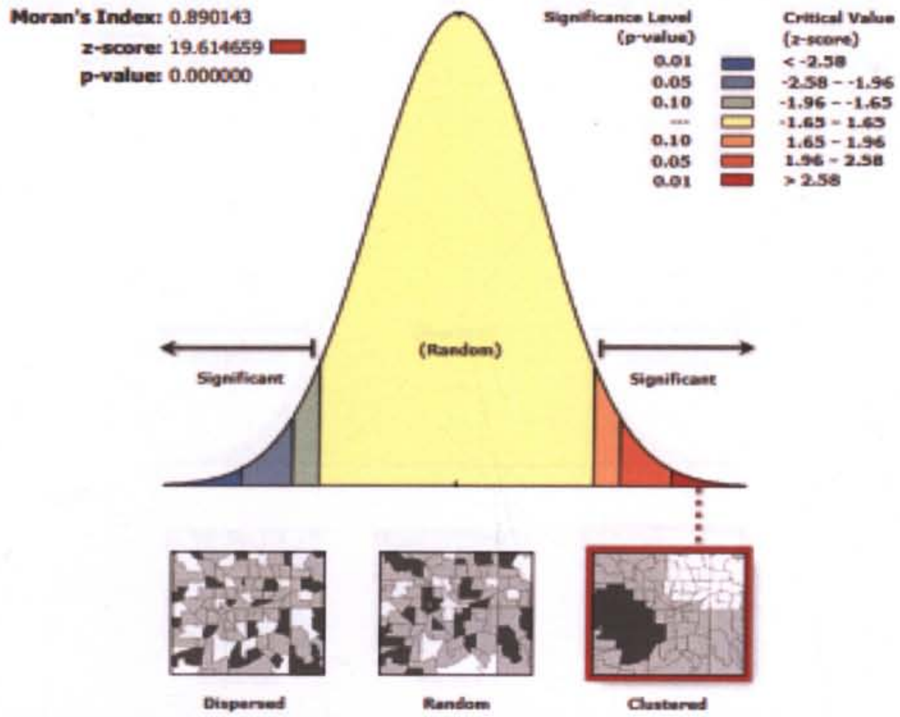
Global Moran's I Summary

Moran's Index:	0.866228
Expected Index:	-0.014085
Variance:	0.002128
z-score:	19.083970
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	11_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.6146588114, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

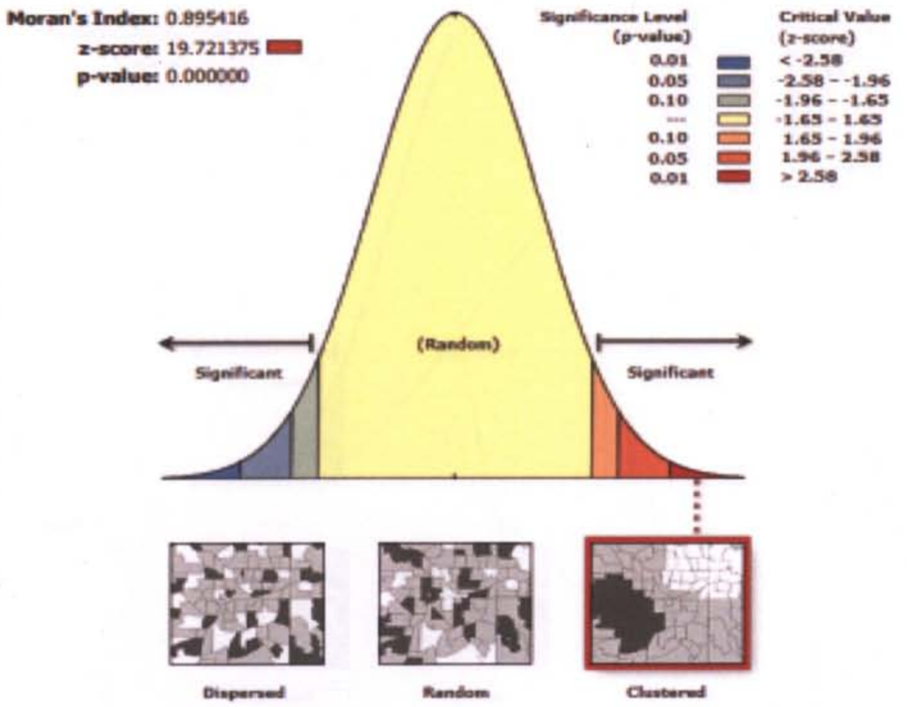
Global Moran's I Summary

Moran's Index:	0.890143
Expected Index:	-0.014085
Variance:	0.002125
z-score:	19.614659
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	12_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.7213746912, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

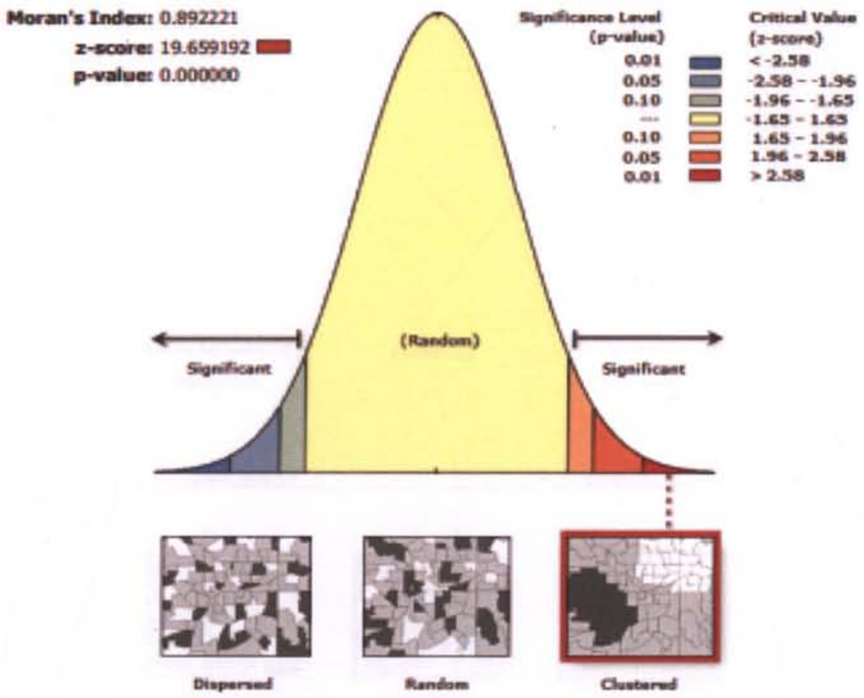
Global Moran's I Summary

Moran's Index:	0.895416
Expected Index:	-0.014085
Variance:	0.002127
z-score:	19.721375
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	1_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.6591920891, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

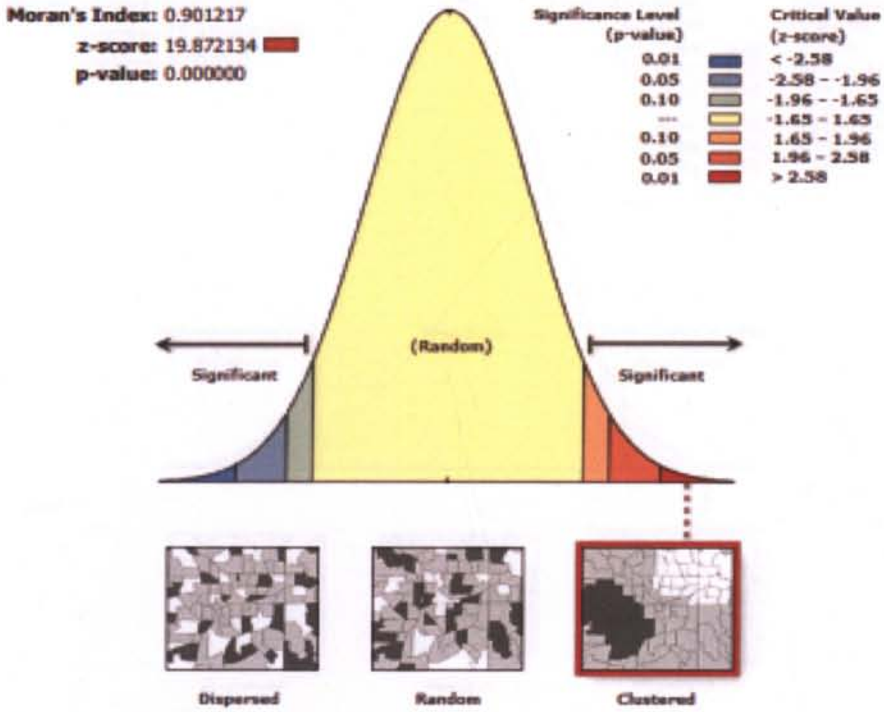
Global Moran's I Summary

Moran's Index:	0.892221
Expected Index:	-0.014085
Variance:	0.002125
z-score:	19.659192
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	2_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.8721342377, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

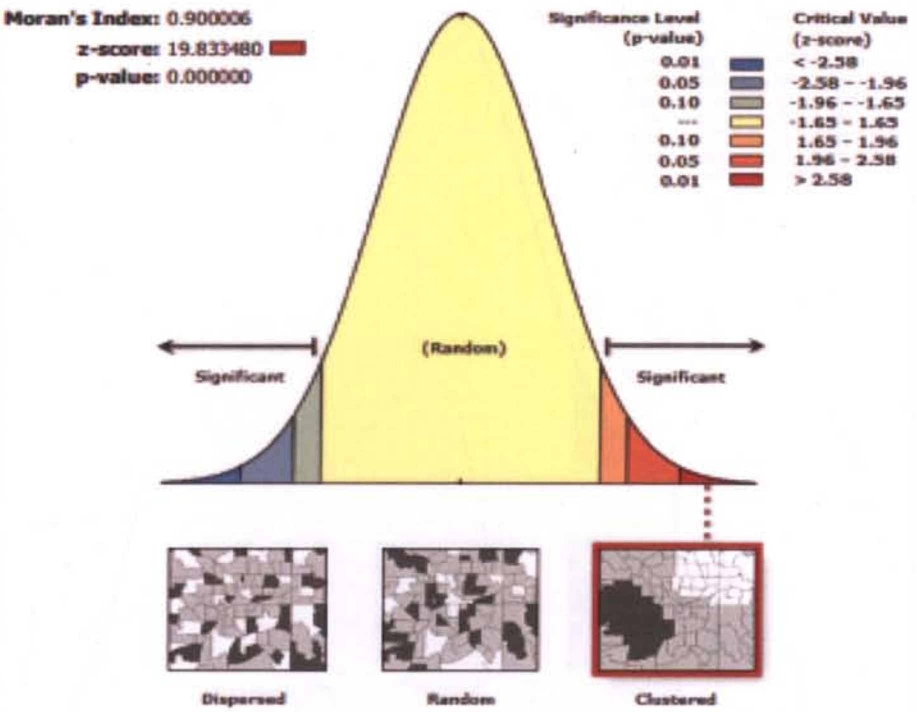
Global Moran's I Summary

Moran's Index:	0.901217
Expected Index:	-0.014085
Variance:	0.002121
z-score:	19.872134
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	3_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.8334801786, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

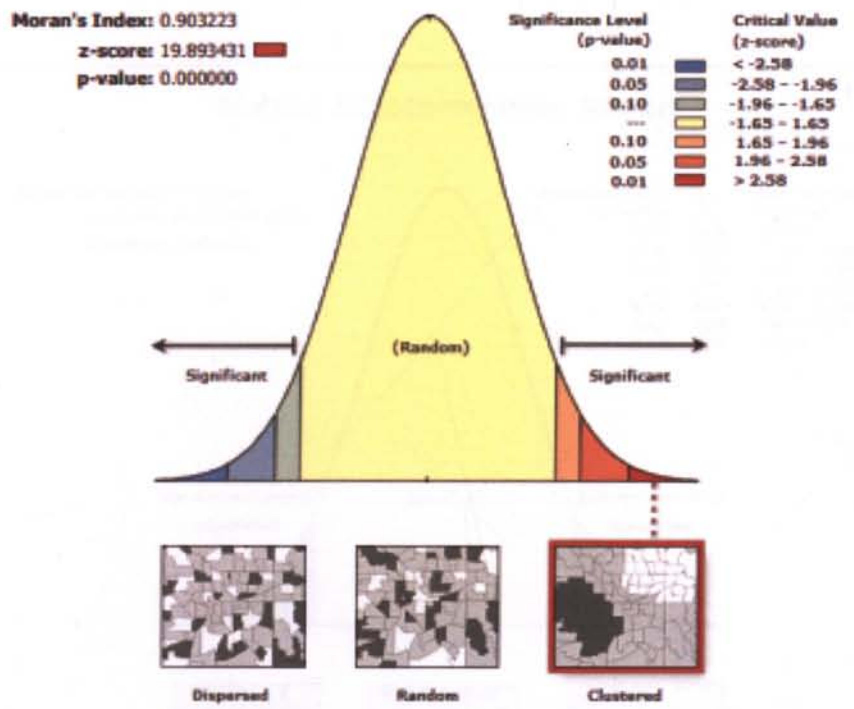
Global Moran's I Summary

Moran's Index:	0.900006
Expected Index:	-0.014085
Variance:	0.002124
z-score:	19.833480
p-value:	0.000000

Dataset Information

Input Feature Class:	O3
Input Field:	4_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

Spatial Autocorrelation Report



Given the z-score of 19.8934312588, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.903223
Expected Index:	-0.014085
Variance:	0.002126
z-score:	19.893431
p-value:	0.000000

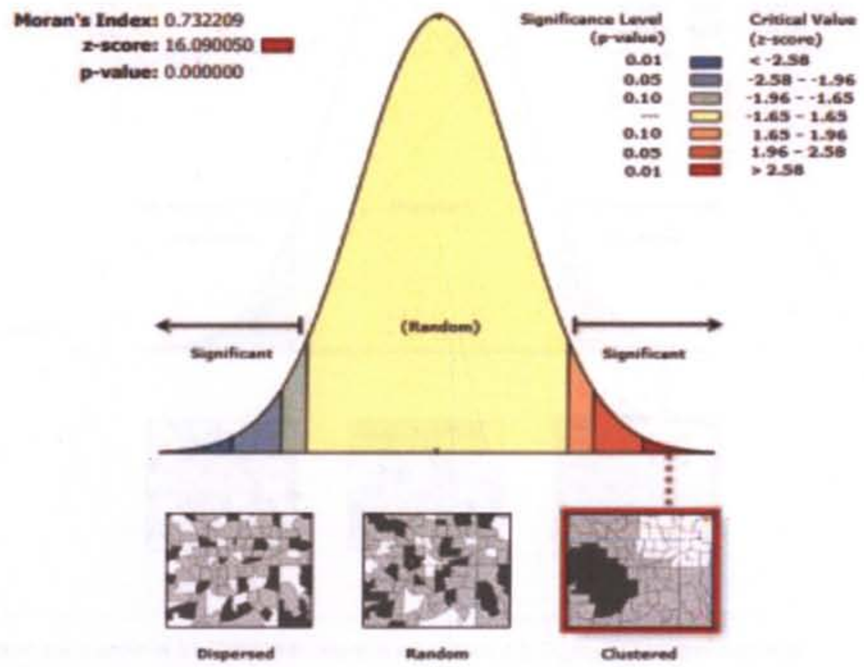
Dataset Information

Input Feature Class:	O3
Input Field:	5_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters
Weights Matrix File:	None
Selection Set:	False

APPENDIX D

(CO spatial-autocorrelation results)

Spatial Autocorrelation Report



Given the z-score of 16.0900501595, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

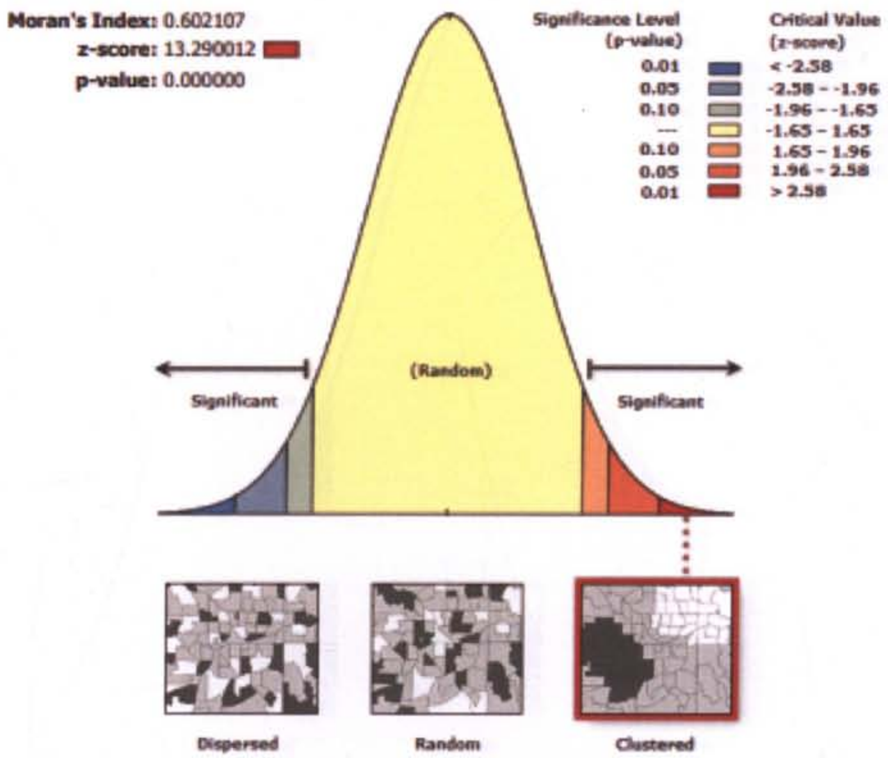
Global Moran's I Summary

Moran's Index:	0.732209
Expected Index:	-0.014085
Variance:	0.002151
z-score:	16.090050
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	7_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 13.290011807, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

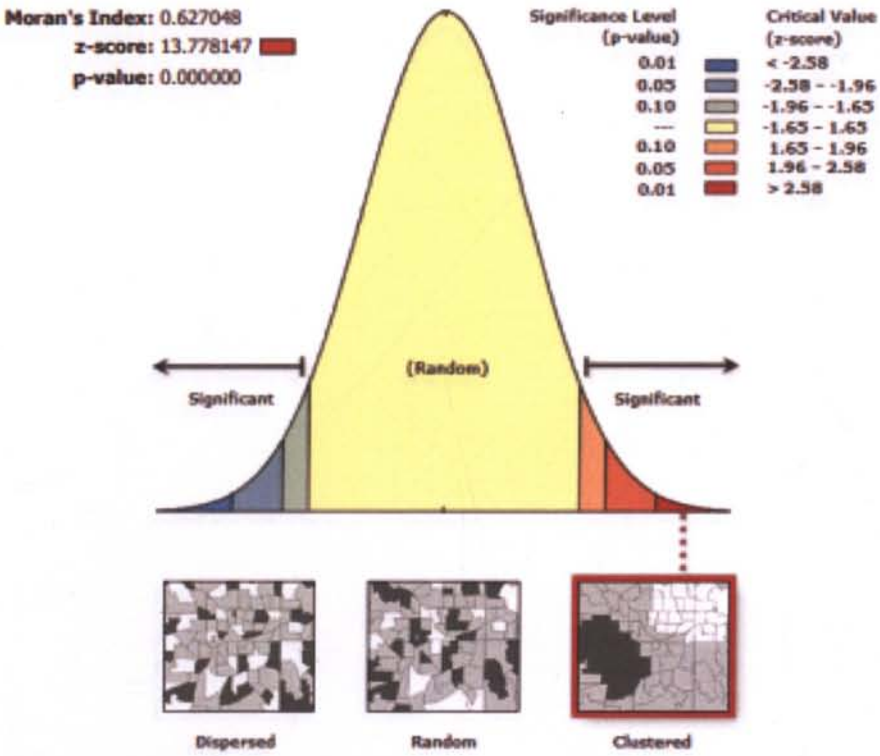
Global Moran's I Summary

Moran's Index:	0.602107
Expected Index:	-0.014085
Variance:	0.002150
z-score:	13.290012
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	8_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 13.7781471204, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

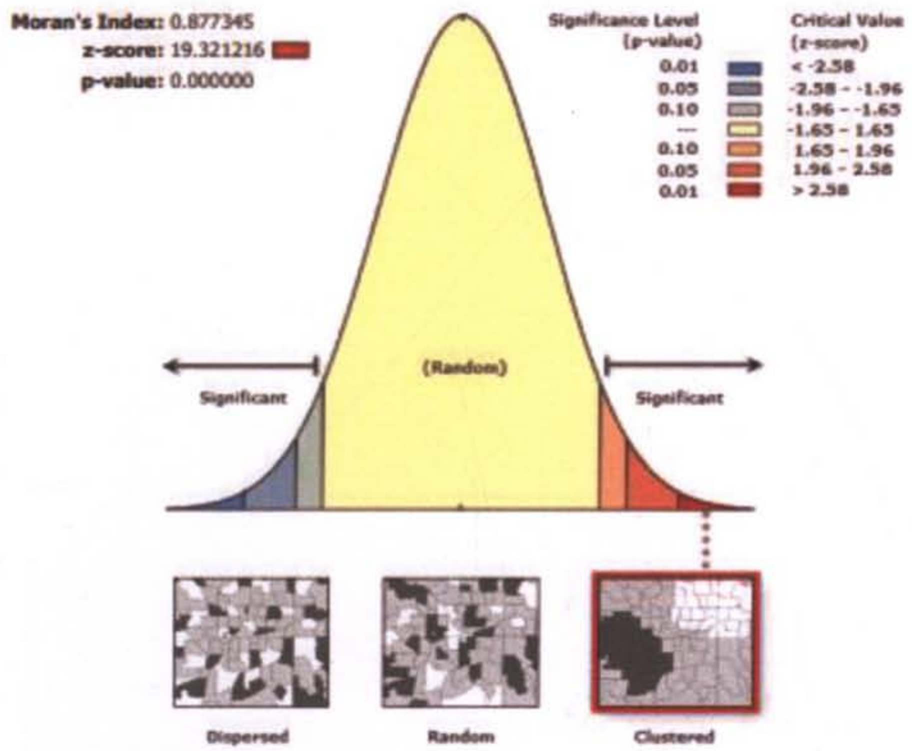
Global Moran's I Summary

Moran's Index:	0.627048
Expected Index:	-0.014085
Variance:	0.002165
z-score:	13.778147
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	9_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 19.3212160951, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

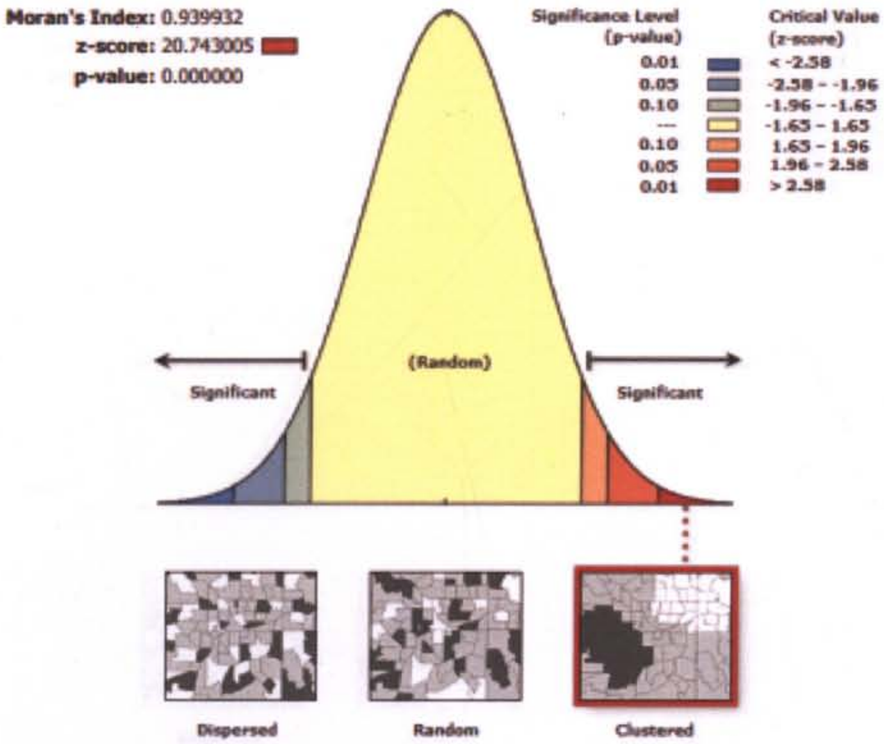
Global Moran's I Summary

Moran's Index:	0.877345
Expected Index:	-0.014085
Variance:	0.002129
z-score:	19.321216
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	10_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.74300479, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

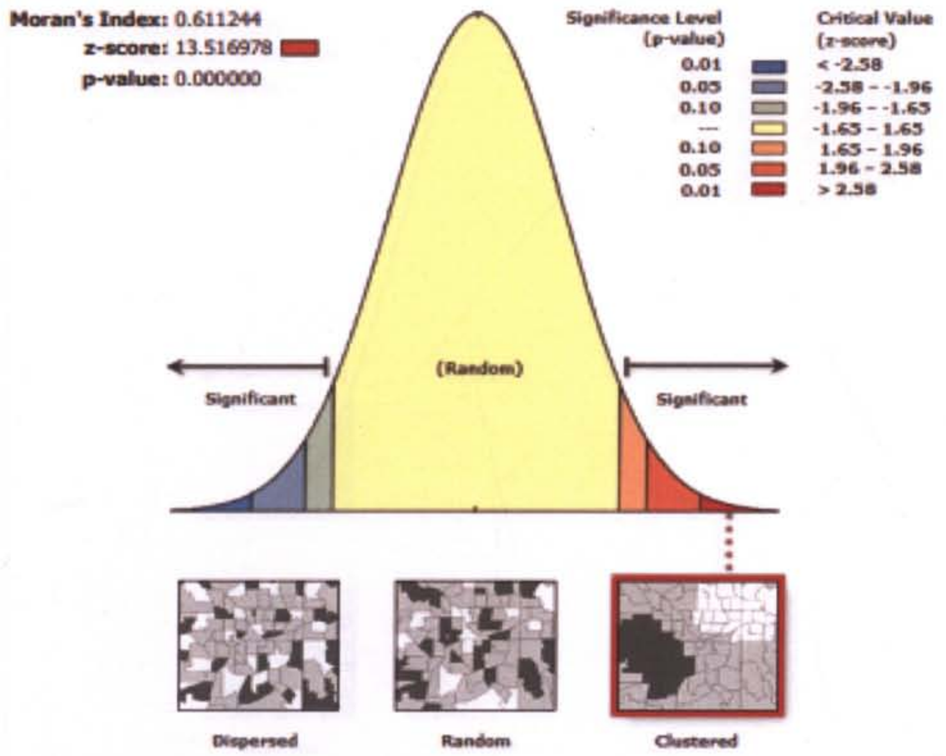
Global Moran's I Summary

Moran's Index:	0.939932
Expected Index:	-0.014085
Variance:	0.002115
z-score:	20.743005
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	11_00_AM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 13.5169783464, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

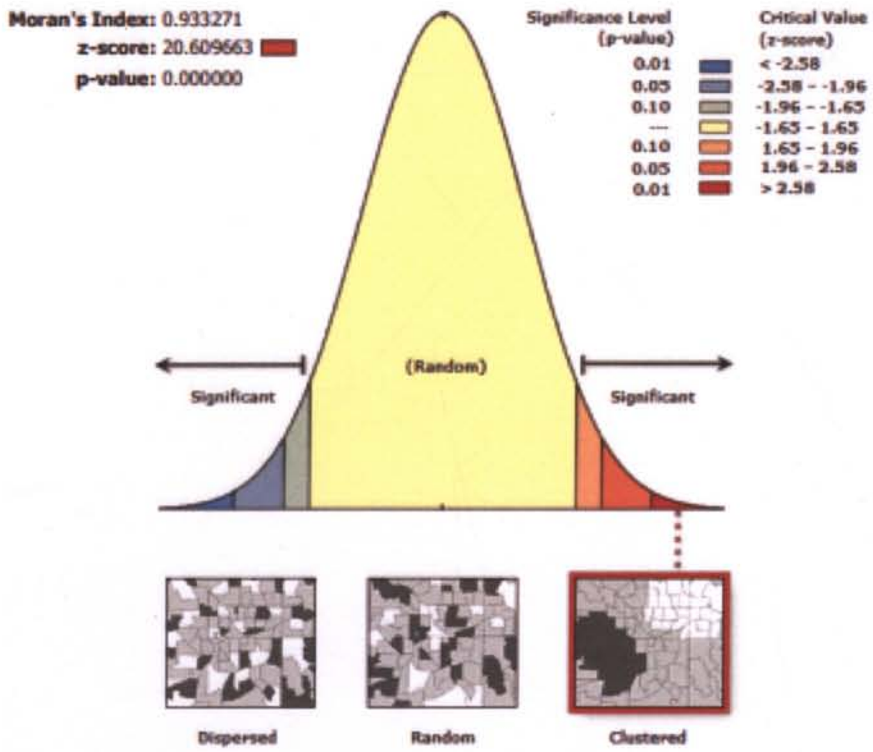
Global Moran's I Summary

Moran's Index:	0.611244
Expected Index:	-0.014085
Variance:	0.002140
z-score:	13.516978
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	12_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.6096626096, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

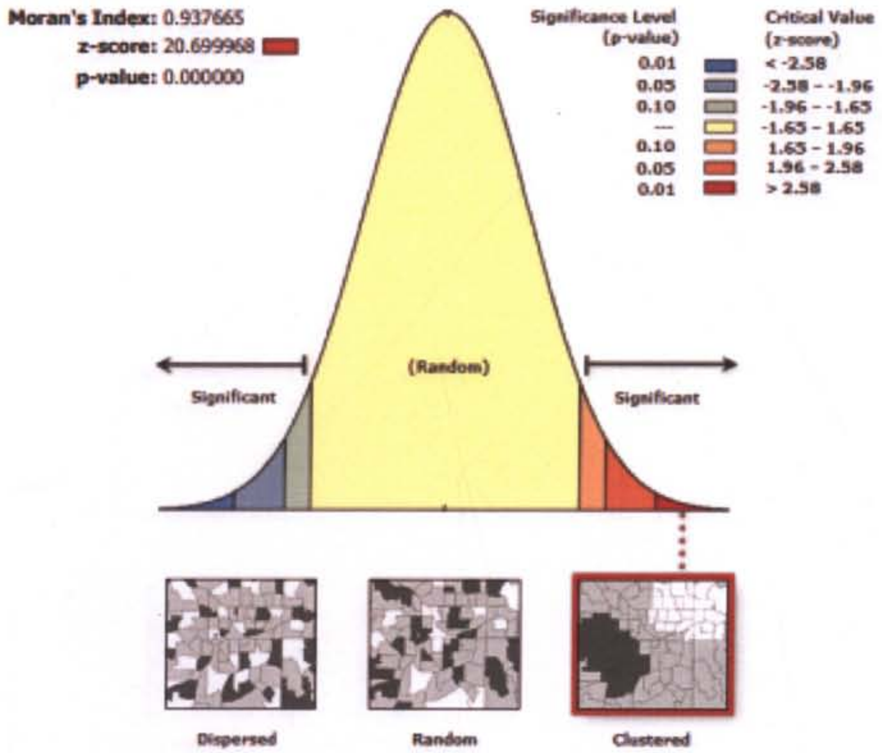
Global Moran's I Summary

Moran's Index:	0.933271
Expected Index:	-0.014085
Variance:	0.002113
z-score:	20.609663
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	1_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.6999678209, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

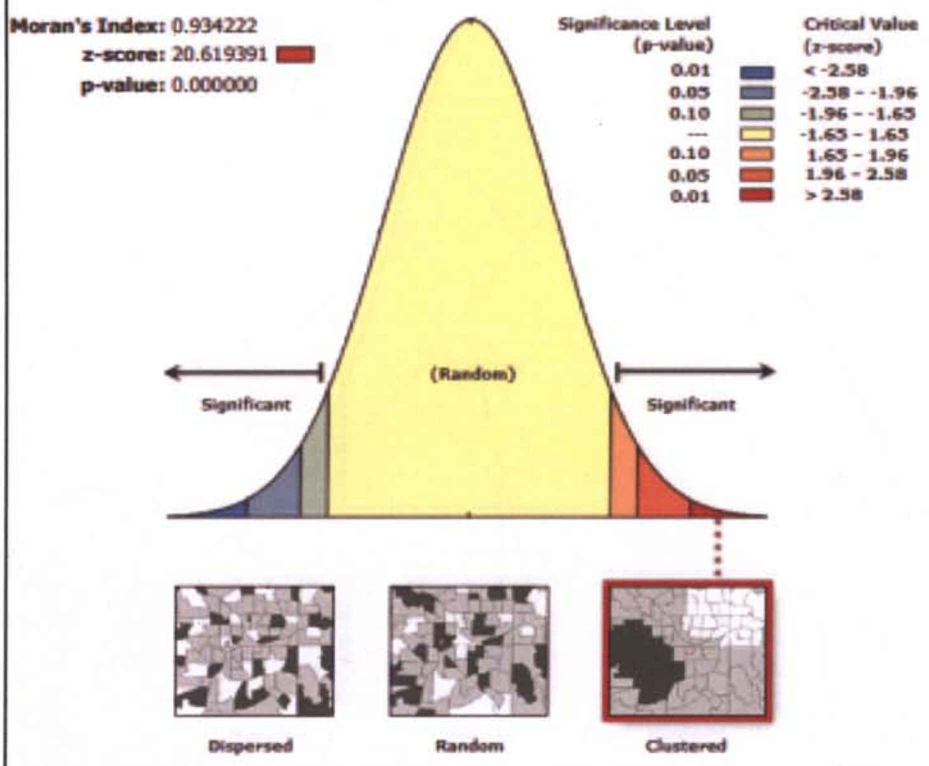
Global Moran's I Summary

Moran's Index:	0.937665
Expected Index:	-0.014085
Variance:	0.002114
z-score:	20.699968
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	2_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.619391451, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

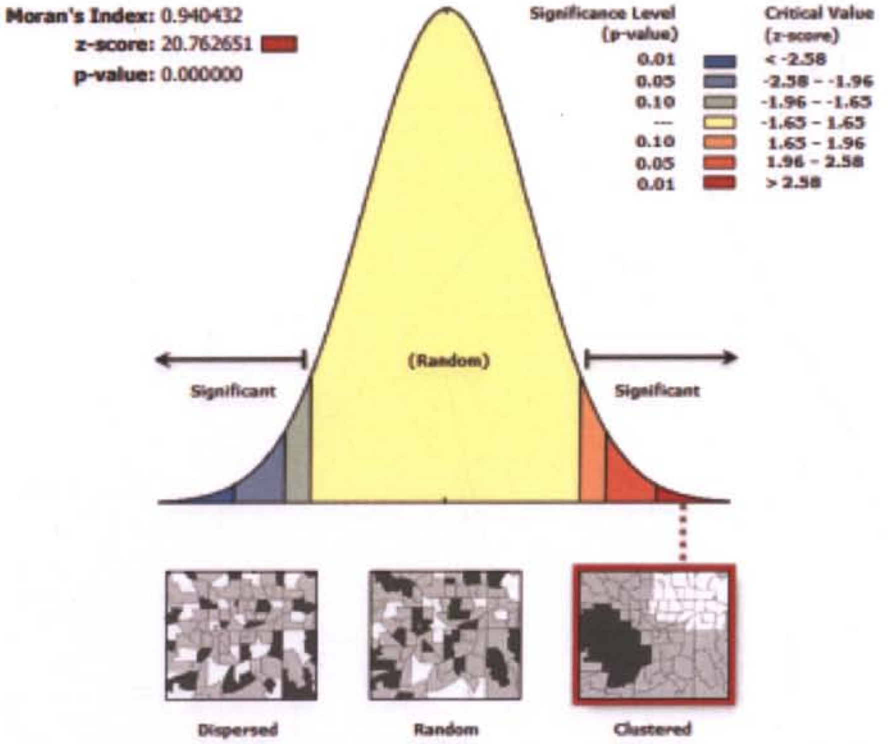
Global Moran's I Summary

Moran's Index:	0.934222
Expected Index:	-0.014085
Variance:	0.002115
z-score:	20.619391
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	3_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.7626509135, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

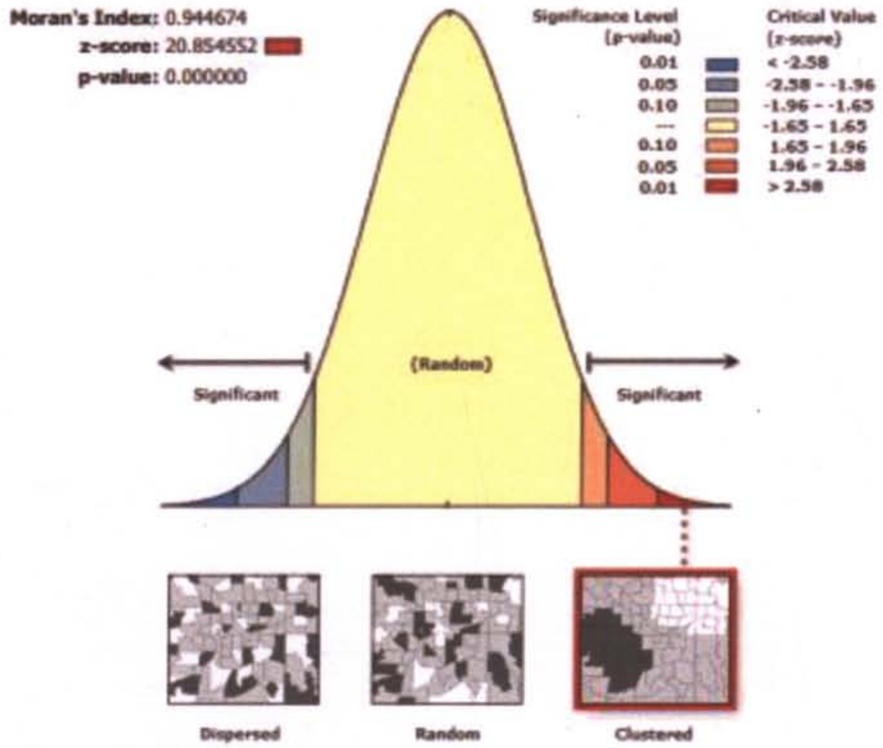
Global Moran's I Summary

Moran's Index:	0.940432
Expected Index:	-0.014085
Variance:	0.002113
z-score:	20.762651
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	4_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters

Spatial Autocorrelation Report



Given the z-score of 20.8545517427, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Global Moran's I Summary

Moran's Index:	0.944674
Expected Index:	-0.014085
Variance:	0.002114
z-score:	20.854552
p-value:	0.000000

Dataset Information

Input Feature Class:	CO
Input Field:	5_00_PM
Conceptualization:	INVERSE_DISTANCE
Distance Method:	EUCLIDEAN
Row Standardization:	False
Distance Threshold:	151802.5757 Meters