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Chapter 3

Spatial statistical techniques for measuring the control and management of epidemics in urban environmental neighbourhood

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Abstract: Urban areas have been ravaged with diverse kinds of epidemics of disease in the past. Some of these diseases are associated with the urban environmental factors which aid in its spread. Several efforts have been made by governments, non-governmental organizations and individuals to curb some of the disease epidemics but not much has been achieved. This research explored the spatial statistical techniques that can be adopted in the management and prevention of epidemics of disease in urban areas. Getis and Ords hot spatial analysis was used to identify locations that have a high occurrence of the disease. Since most of the disease epidemics are associated with the urban environmental factors, geographically weighted regression model (GWR) which has the capability to investigate the relationship of the disease with the factors that aid its spread was used. Results show that the locations that have statistically significant high and low occurrence of the disease spread stood out. Geographically weighted regression model further reveals the specific factors that aid in the spread of the disease at various locations with the statistical level of significance. The study recommends that the spatial statistical methods are significantly appropriate in the management and preventions measures for disease epidemics in urban areas.

Key Words: Epidemics, Spatial, Meningococcal, Meningitis, Statistical techniques

Introduction

Meningococcal meningitis bacteria resides in human beings at different levels of dosage. It resides mostly in people that are living in the *Meningococcal meningitis* endemic regions of the world due to the fact that the bacteria reproduces and thrives very well under a favourable condition (WHO, 1998).

Most people that are living in the *Meningococcal meningitis* endemic region have the bacteria living in them, as carriers but they can never fall sick as a result of it, but they can transmit it to others when the condition is favourable to the bacteria (Moore *et al.*, 1988; Steinhoff 2007).

Environmental factors play a major role in influencing the spread of the disease as the disease is associated with poor housing condition, deprived settlements and household overcrowding (Baker *at al.*, 2000; Fone *et al.*, 2003; Olowokure *et al.*, 2006; Tully *et al.*, 2006). Other studies by Fone *et al.* (2003) and Davies *et al.* (1996) also confirmed that overcrowding and poor housing conditions are significant factors in influencing the spread of the disease. Other environmental factors like high temperature, rainfall and relative humidity play a role in the spread of the disease. Studies by Thomson *et al.* (2006); Yaka *et al.* (2008); Teyssou and Rouzic (2007) all proved that temperature, rainfall and relative humidity influences the spread of the disease.

Studying the spatial pattern of *Meningococcal meningitis* has become very critical because of the havoc that it has caused to humanity; the disease has affected every region of the world with severe cases in the developing countries, especially West Africa (WHO, 2003; Tobias *et al.*, 2011) and also northern Nigeria to be specific (Mohammed *et al.*, 2000; Sawa and Buhari, 2011). The pattern of the spread of *Meningococcal meningitis* is still very unclear to public health practitioners, epidemiologists and urban health planners, even though some of the factors that facilitate the spread are known (Bharti *et al.*, 2012). The combination of factors that could aid the spread pattern of the disease in a particular location may be different across geographical locations.

Due to Nigeria's location, within the Sub-Saharan Africa's "*Meningitis* Belt", seasonal epidemics expectedly occur in a cyclic pattern. High temperature, dusty winds, poor distribution of services in the towns and people living in an overcrowded condition has made people vulnerable to the respiratory disease and are among some of the reasons behind the *meningitis* belt's high burden of *Meningococcal* disease (Greenwood, 2006). A study carried out by Mohammed *et al.* (2000) reported that five major epidemics of *Meningococcal meningitis* occurred in the northern part of Nigeria within 30 years, in 1970, 1975, 1977, 1986, and 1996. According to that study, the epidemic of 1996 was the worst among all of them. It was followed by comparable epidemics in Chad in 1988, and that of Niger Republic in 1991 and 1994 which share their borders with Nigeria. At least 1,650 people in Nigeria have died as a result of the *Meningitis* epidemic in the northern part of the country in 1996 (Sawa & Buhari, 2011).

In spite of the nearly annual occurrences of this disease, governments do not seem to be winning the battle posed by the epidemic. Most often, outbreaks take governments unaware despite the fact that the period in which the disease is frequent is very well known. Little or no effort is made to check the spread until there is an outbreak. During epidemics, interventions are limited to the provision of vaccines to areas under attack. Thus, actions are usually taken when it is already too late and many lives have been lost. There is always a challenge in predicting the epidemics of *Meningococcal meningitis* and it normally results in the late commencement of preventive strategies, like the vaccination, which does not produce a good outcome (Greenwood *et al.*, 1984). The conventional statistical approach used in detecting and measuring the spread of diseases has not yielded much result; instead, it gives a general overview of factors responsible for the spread of diseases. This study explores some of the spatial statistical techniques that can be adopted in the management and prevention of epidemics of disease in urban areas.

Epidemics of Meningococcal Meningitis

The *Meningococcal meningitis* attack usually begins with an intense headache, vomiting and stiff neck and progresses to a coma within few hours (Varaine *et al.*, 1997). The fatality of typical untreated cases is about 80 percent. With early diagnosis and treatment, case fatality rates have declined to less than 10 percent. According to Greenwood *et al.* (1984), developing countries have accounted for a high number of the occurrences of *Meningococcal* disease with a proportion of those carrying the disease and the ones that have been attacked fluctuating between 1:100 when there are epidemics to 1:1,000 in areas that are endemic. It suggests that people are able to evolve immunity, naturally to this disease in areas that are prone to the bacteria that causes it. There might be little level of natural immunity in regions of little endemicity. Most of the people travelling from regions of low endemicity to regions of high endemicity especially the residents of Europe travelling to some areas in Africa, the Indian sub-continent and some other areas in Asia, parts of Middle East and the South America would therefore be susceptible to *Meningococcal* disease (LaForce *et al.*, 2007).

Harrison *et al.*, (2011) pointed out that the epidemics of *Meningococcal meningitis* is evident everywhere in the world (Figure 3.1), and it is observed in some countries like Europe, America and Asia that there is an increase in the spread of the disease and also a display of the epidemiological impression which is described with the consistent outbreaks and frequent endemic occurrence of the disease in a sporadic manner. From 1970 to 1971, the cases of the disease were witnessed in Italy, Spain, Yugoslavia, and Portugal and in between 1971 to 1972 in Belgium. It was 1974 in Argentina, 1974 to 1975 in the United Kingdom and with a rapid increase in the cases in France between 1973 and 1978. There were reported cases of *Meningococcal meningitis* from Cuba between 1982 and 1984, Chile was in 1986 and 1993 (Jafri et al., 2013).

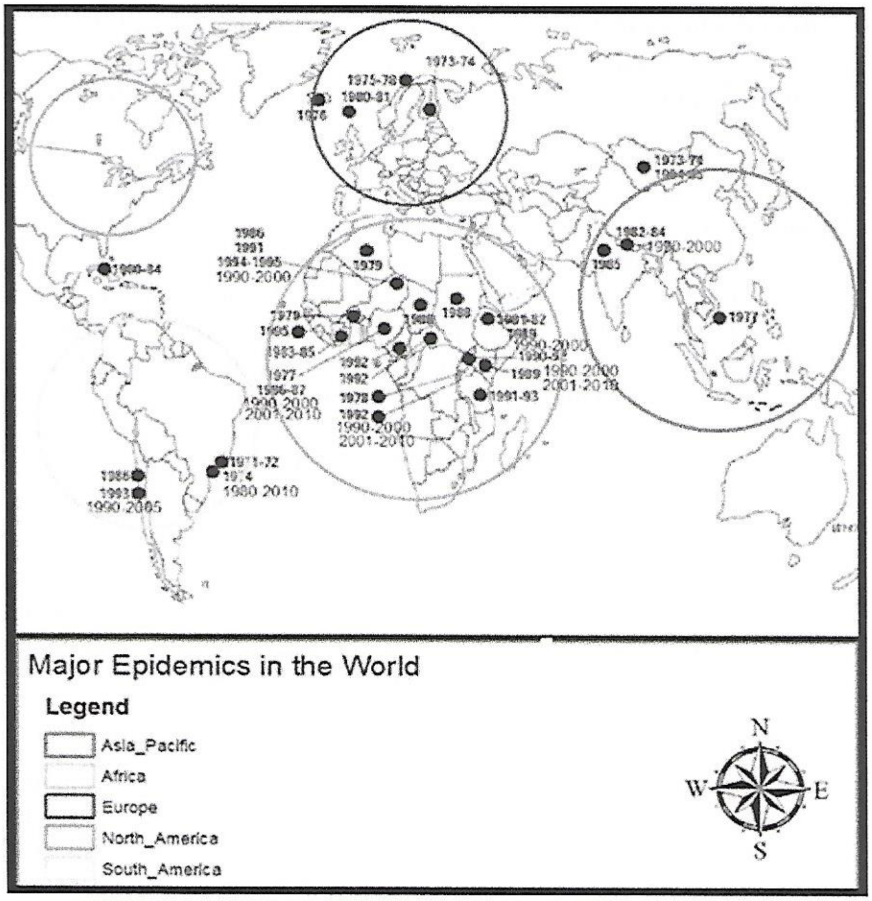

Figure 3.1 Adapted Map of the world showing locations of *Meningococcal meningitis* (Source: WHO 2003)

Spatial Epidemiology

Spatial epidemiology deals with studying the spatial spread of incidences of disease and the relationships with factors that contribute to the disease spread. Having an understanding of the spatial and temporal changes of the disease and categorizing the spatial structure is very important for the health planners to have a clear knowledge of the population's interaction with the immediate environment. The source of spatial epidemiology is John Snow and dates back to 1855 with the study he conducted on the spread of cholera in London (Osie, 2010).

Buyong (2007) defined spatial data analysis as the statistical study of phenomena that manifests them in space. This makes location, area, topology, spatial arrangement, distance and interaction the focus of attention. Spatial data analysis focuses mainly on the spatial aspects of the data in the area of spatial dependence and spatial heterogeneity. The techniques' main objective is to describe spatial distributions, discover patterns of spatial association (clustering), suggest different spatial regimes or other forms of spatial instability (non-stationary) and identify typical observations (Anselin, 1988).

In the conventional statistics, the methods developed are only applicable to the attributes components of the spatial data, but different methods are required for the treatment of the spatial components of spatial data. Waller and Gotway (2004) pointed out that in health research; spatial analysis is used to detect and quantify patterns of disease distribution that may offer insights into disease epidemiology. Spatial analysis is designed to detect clusters of health events and demonstrate significant areas of either high or low disease risk. The concept tends to look at how observations that are located near each other are influenced by each other and it is not distributed in space or time by random chance alone (Meade and Earickson, 2000). The advantage of detecting clusters is to identify spatial patterns that are unique and different than what could be expected in the absence of the phenomenon being studied and this makes clustering to be the measure of an areas abnormality relative to a null expectation (Fotheringham *et al.*, 2002).

Spatial Pattern Analysis in Epidemiological Studies

A number of studies conducted using the spatial pattern analysis show that it is helpful in determining the locations of high and low incidence of diseases. A study by Zhang *et al.* (2008) investigated the spatial pattern of malaria in a province in China because it was the most affected in the whole of China from 2005 – 2006. It was very critical to understand the pattern of spread so as to identify those locations that have high cases for future public health planning and resource allocation. Spatial cluster analysis using spatial scan statistics techniques was used. The result shows that some particular counties were at high risk for malaria.

Similarly, a study by Yeshiwondim *et al.* (2009) also investigated the spatial and temporal pattern of malaria incidence at a village in Ethiopia. Global moran's I and the anselin local spatial autocorrelation statistics were used to analyse the malaria data. The anselin local spatial autocorrelation statistics reveals clustering or hotspots within five and ten kilometres distance from the villages in the study area. It was observed that there were temporal; variations in the malaria incidence. The study could not identify those environmental factors that influence the incidence of malaria. In the same line, Srivastava *et al.* (2009) conducted a study on the identification of malaria hotspots for focused intervention in India. The purpose of the research was to identify the location of the high spot so that the authorities will focus their attention on such areas. Hot spot analysis was conducted and those areas with high cases of the disease were identified and more attention was to be given to them in order to mitigate the high cases of the disease. However, identification of factors that influence the spread of the disease was not considered by the study.

The spatial pattern analysis method was also applied to the schistosomiasis disease in China. The study was conducted by Hu *et al.* (2013), on the spatial pattern of schistosomiasis in Xingzi in the province of Jiangxi in China. Xingzi is a location where the disease of schistosomiasis had been a threat to public health. Logistic regression model and variogram techniques were used in the study. The results revealed that in those locations the disease was common and it had a spatial pattern. This finding helped in giving an insight on the characteristics of the epidemiology of the disease and would assist in the long term sustainable strategies for schistosomiasis control. Further studies were conducted on the spatial pattern of schistosomiasis in Yangtze river valley by Hu *et al.* (2014) between the years of 1991 – 2001 and 2007 – 2008. Luc anselin local spatial autocorrelation and Kuldorf spatial scan statistics were used in the study. The result showed that the magnitude and number of clusters varied from 1999 – 2001. The finding specifically showed those locations that have consistent cases which the public health planners and authorities concerned were expected to direct their attention towards. However, the limitation of the study is its inability to identify factors that were influencing the high cases of the disease.

There were also studies on spatial pattern analysis conducted for the epidemiology of *Meningococcal meningitis.* Hoebe *et al.* (2004) used space time cluster analysis to investigate the invasive *Meningococcal* disease in the Netherlands. The cluster analysis method that was used is the space-time nearest neighbour analysis. It was discovered that the clustering which was beyond chance took place between the neighbours in close range with each other. The study was able to locate those areas where higher cases of the disease were more apparent, but it could not quantify the extent of the clustering. A similar study was conducted by Greene *et al.* (2005) to investigate the Spatio-temporal pattern of viral *meningitis* in Michigan. The research showed that blacks and infants were found to be the risk group. The cases of the disease were found to be concentrated on the southern part of the study area. Spatio-temporal clusters were identified from 1998-2001. Similarly, the study could not identify those local and socio-demographic factors that influenced the spread of the disease. Philippon *et al.* (2009) in a study to investigate the spatial pattern of *Meningococcal meningitis* in Mali could also not identify the potential factors that influence the spread of the disease.

To further buttress the applicability of spatial pattern analysis in the epidemiology of *Meningococcal meningitis,* another study by Maïnassara *et al.* (2010) on spatial cluster occurrence and spatio-temporal evolution of the *Meningococcal* disease in Niger was conducted. Satscan using Poisson model was used to calculate the relative risk of occurrence of spatial clusters. Spatial clusters were detected at the south-eastern part of the country in the year 2002-2003. Clusters were found in the following years at the exact location as those detected in 2002-2003. Statistically significant Spatio-temporal patterns were discovered within the study years. This study too only identified the location of high clusters and the pattern of transmission of the disease but could not show any relationship between the factors that influence the spread of the disease and those locations.

In the same country (Niger), Paireau *et al.* (2012) conducted another study on the spatio-temporal clustering of *Meningococcal meningitis.* The study was conducted with the hope of gaining an understanding of the epidemiology of the disease in the whole country so as to improve the control strategies. Anselin local Moran's I test for spatial autocorrelation and Kuldorf's spatial scan statistics were used to identify the spatial and spatio-temporal clusters of cases. It was observed that there were spatial clusters every year (2003-2004) and the consistent cases were more on the southern districts of Niger. The study has shown the strength of spatial pattern analysis in detecting the clusters of *Meningococcal meningitis,* but it also could not show the relationship between the clusters and the factors that may be responsible.

Geographically Weighted Regression Modelling in Epidemiological Studies

A study by Lin and Wen (2011) investigated if spatial heterogeneity exists in the relationship of dengue mosquito and dengue-human relationship within a certain area. Ordinary least square (OLS) and geographically weighted regression (GWR) models were used to analyse the spatial relationship and also to identify the spatial heterogeneities through the use of some data of entomology and the cases of dengue in Kaohsiung and Fengshan in 2002. The findings in the study showed that dengue-mosquito and dengue-human relationship were significantly spatially non-stationary. This infers that in some areas, higher dengue incidence was related to higher vector/host densities, while in some areas higher incidences were associated with lower vector/host densities. The study shows clearly how GWR model can be used to spatially differentiate the relationships of dengue incidence with immature mosquito and human densities.

Gilbert and Chakraborty (2011) conducted another study in the application of GWR for environmental justice analysis. The past research on environmental justice was narrow with very simple assumptions in measuring health risk and also the traditional regression methods failed to clearly discern spatial variation in the statistical variation of the statistical relationship. The objective of the study was to assess if the potential health risk as a result of exposure to hazardous air pollutants is related to race/ethnicity with socio-economic level. And also, to check how the significance of the statistical relationship between health risk/ethnicity or socio-economic status vary across the state. The findings in the study showed that race and ethnicity are significantly related to cancer risk in Florida. The study also discovered that conventional regression can cover critical local variation in the statistical relationship that is relevant to the environmental justice analysis.

Chen and Truong (2012) examined the extent to which the relationship between city disadvantages and the disease of obesity varies over geographic space. Multi-levels models were integrated with geographically weighted regression so as to examine the spatially varying relationship of obesity and area disadvantages. Body mass index was used as the dependent variable while the explanatory variable was the disadvantage index which is made up of minority composition, poverty level, and social disorder. Included also is the individual socio-demographic characteristics which accounted for the compositional effect. The result showed that the relationship between township disadvantages and high obesity was discovered to be area specific. Heterogeneity of place-level determinants of obesity was discovered across the geographical area.

Another study was undertaken by Chalkias *et al.* (2013) on the geographically heterogeneity of the relationship between obesity in childhood and the socio-environment. In the study, GWR model showed that areas that were defined by high population density, low education level, low family income and a narrow coverage of recreational areas represented an "obesogenic" environment. The benefit derived from using this model is its help to identify the causal factors.

Procedures and Methods

The data utilised in this study includes locations of the refuse dump and locations of hospitals. The total number of all the refuse dumps and the hospitals (primary health care and secondary healthcare) for each of the neighbourhoods were collected, aggregated and recorded in the polygon. Based on the literature reviewed, poor housing condition was found to influence the occurrence of *Meningococcal meningitis*. Consequently, housing condition information sought was categorized into four parts in which the buildings within the study area falls into any of the four.

I. Housing condition 1, structure is fit for purpose

II. Housing condition 2, structure is fit for purpose with sign of deterioration

III. Housing condition 3, structure is not fit for purpose, can be fixed

IV. Housing condition 4, structure not fit for purpose, needs to be demolished

Based on the documents reviewed on the factors that influence urbanization sourced from the Ministry of Economic Planning Kaduna, Nigeria, the following were considered for this research.

I. Population density for the neighbourhoods

II. Housing ownership for each neighbourhood

III. Percentage of occupation in each of the neighbourhoods

Data on *Meningococcal meningitis* cases were collected from the hospitals and clinics that are within Kaduna Urban Area between the months of January to December from 2007 to 2011.

The research was conducted in Kaduna Urban Area located within Kaduna, the capital of Kaduna state in Nigeria, which also falls within the "Africa Meningitis Belt". Kaduna Urban Area is made up Kaduna north and Kaduna south local governments, part of Chikun local government and part of Igabi local governments. The extent of Kaduna Urban Area (KUA) is approximately a rectangle measuring 40km by 30km lying roughly northeast/southwest with the heart of Kaduna in its centre (Lock, 2010). Figure 3.2 is the map of Kaduna Urban Area showing the four local governments and the twenty-four districts under the study area.

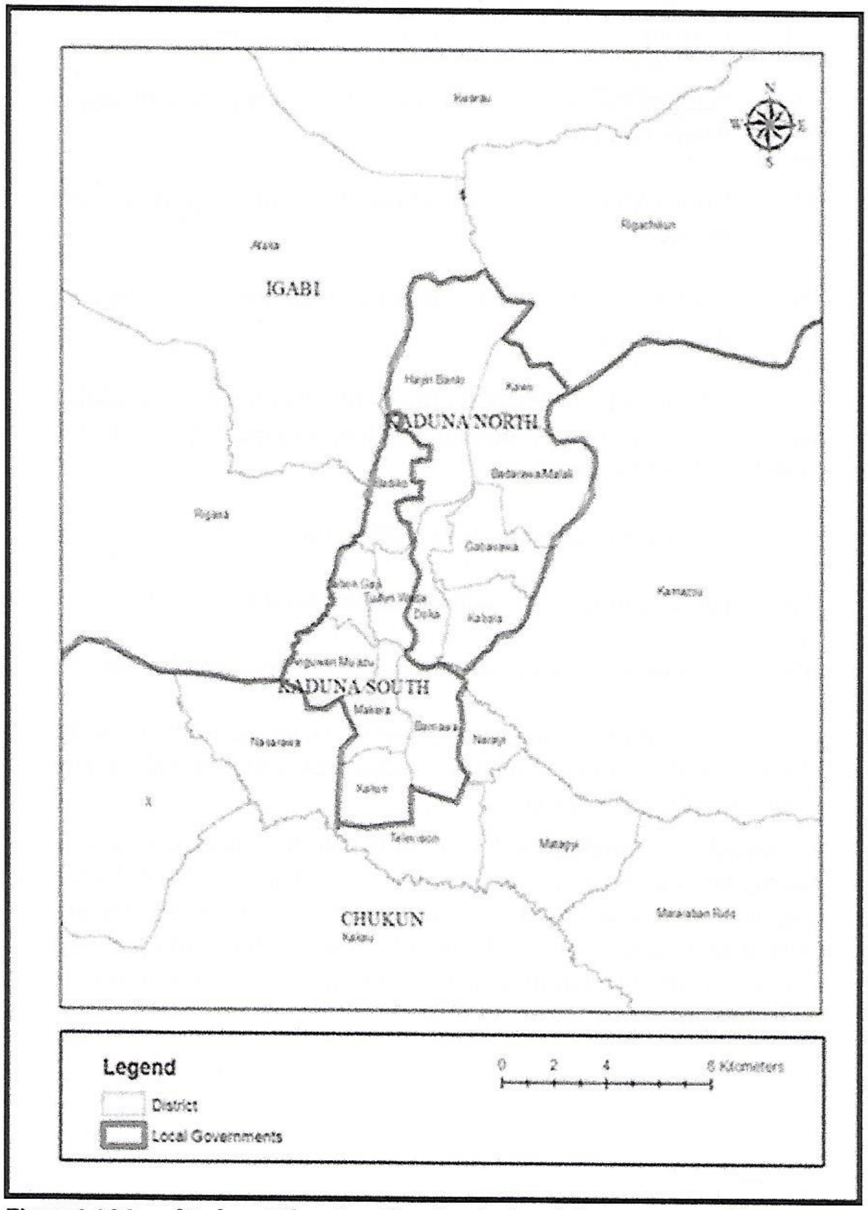

Figure 3.2 Map of Kaduna Urban Area Showing the Local Governments and 24 Districts

Spatial Pattern Analysis

Spatial pattern analysis was used in this study to determine if the incidence of *Meningococcal meningitis* in KUA conforms to a particular pattern which can either be clustered, dispersed or random and the statistical level of significance of the pattern was also identified. The spatial pattern analysis method used is the local spatial autocorrelation. Getis and Ord Local Gi* Statistics was used because it revealed the neighbourhoods that had high and low concentration of the incidence of *Meningococcal meningitis*. And also, to show the clusters' statistical significance level of the concentration either high or low. Spatio-temporal pattern analysis was conducted to determine the trend of the incidence of *Meningococcal meningitis* in KUA. Figure 3.3 shows the model of the spatial pattern analysis used for the study.

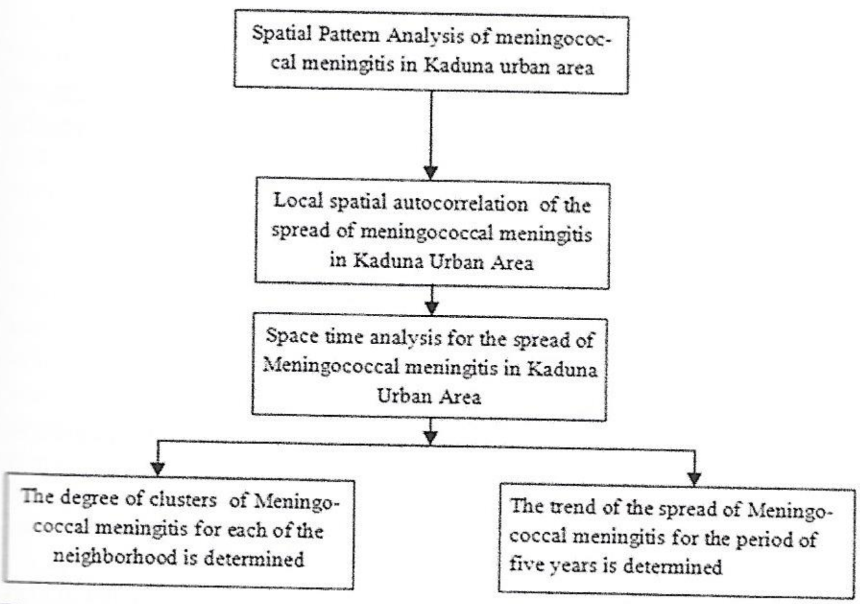

Figure 3.3 Flow chart for the Spatial Pattern Analysis Methods

Modelling the Spatial Relationships of *Meningococcal Meningitis* in Kaduna Urban Area

Geographically weighted regression (GWR) is among the various techniques of spatial regression that is being used in spatial statistics. GWR gives the local model of the variable that is being investigated or that is to be predicted by having a regression equation for each feature in the set of data. Each of the equation is put together by GWR, both the dependent and explanatory variable of the features that fall within the bandwidth of the targeted feature. Such a technique of GWR has the capacity to estimate the relationship between dependent and independent variable locally. Thus, determining the risk factors that influence the spread of *Meningococcal meningitis* peculiar to Kaduna Urban Area was easily achieved. The technique was also used to investigate the relationship of each of the factors that influence the incidence of the disease on each neighbourhood. The outcome showed the extent to which each of those factors influenced the incidence of the disease in each of the neighbourhoods. Figure 3.4 is the flow chart for the spatial relations modelling of *Meningococcal meningitis* in KUA.

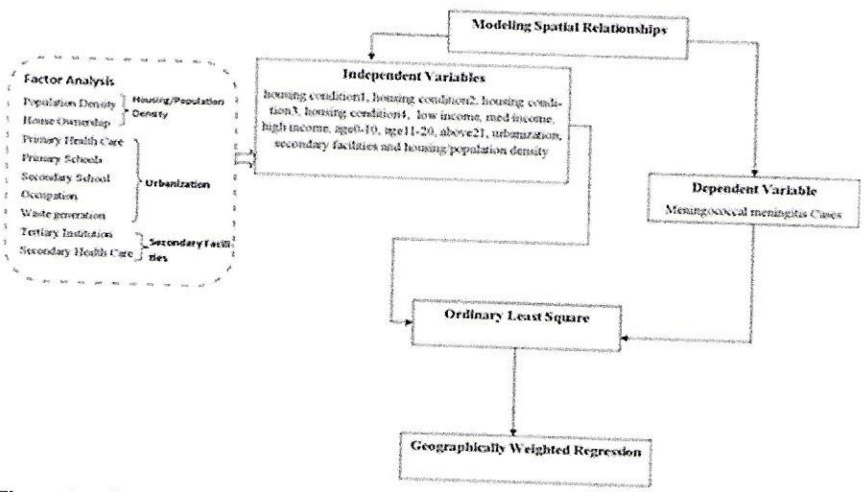

Figure 3.4 Flow chart for modelling spatial relationship for *Meningococcal meningitis* in KUA

Spatial Pattern and Temporal Analysis

Getis and Ord Gi* local spatial autocorrelation analysis was conducted in KUA with the 106 neighbourhoods. The map in Figure 3.5 (a) shows that there is a cluster of neighbourhoods with high incidences of *Meningococcal meningitis* in the neighbourhoods that are located at the south-western part of Kaduna Urban Area for year 2007. Some of the neighbourhoods with the clusters fell on the high cluster region with a standard deviation of 1.65-2.58 indicating that the clusters of high concentration of *Meningococcal meningitis* in those neighbourhoods are statistically significant. Those neighbourhoods with the z score greater than 2.58 were considered significant at 99% confidence level (p <0.01) and they are placed under the hotspot category. Neighbourhoods with z score between 1.65-1.96 and 1.96-2.58 are significant at 90% and 95% confidence level (p<0.10 and 0.05) respectively were categorized as neighbourhoods with a high risk of *Meningococcal meningitis*. The other neighbourhoods fell within the z score of -1.65 to 1.65 indicating that there was no statistically significant spatial association of neighbourhoods with the high or low *Meningococcal meningitis* incidence. Therefore, there is a pattern for the incidence of *Meningococcal Meningitis* in KUA.

Some of the neighbourhoods especially the ones that fell on the locations where there is a statistically significant pattern of the incidence of *Meningococcal meningitis* have inadequate urban facilities and services. Such neighbourhoods include Tudun-Wada, Sabon-Gari, Nasarawa, Tudun-Nupawa and Kakuri which all fell on the central and towards the south-western part of KUA. Other characteristics of such locations include high density residential neighbourhoods and poor housing conditions.

In 2008 there was a shift of the high concentration of neighbourhoods with *Meningococcal meningitis* incidences from south-western part of KUA to south-eastern part of the study area as it is shown in Figure 3.5 (b). In Figure 3.5 (c) there was a twist in the spatial pattern of the incidence of *Meningococcal meningitis* in Kaduna Urban Area for the year 2009. Unlike the other years that had only hotspot clusters, there were cold spot clusters on the spatial pattern of *Meningococcal meningitis* for year 2009. The possible reason is because 2009 was the year that the incidence of *Meningococcal meningitis* was high in the whole of West Africa and there was a reflection of that in KUA. These results match those observed in the earlier studies conducted by Jafri *et al.* (2013) and WHO (2013) which pointed out that 2009 *Meningococcal meningitis* epidemic was the highest between 2007 and 2011. Another reason could be the fact that the built environmental factors and socio-economic factors like the poor development of the urban area as a result of inadequate facilities and services, poor housing condition, high density residential neighbourhoods and low-income level were fully in existence in those locations.

The neighbourhoods that fell under the category of low clustering values are located on the south-eastern part of the study area with z score of -1.96 to -1.65 and -2.58 to -1.96 are termed as cold spot. The other neighbourhoods that fell within the z score of -1.65 to1.65 indicating that there was no statistically significant spatial association pattern of the *Meningococcal meningitis* incidence. In the year 2010, the clustering of high values of *Meningococcal meningitis* incidence was observed in the central part of KUA as shown in Figure 3.5 (d). Those neighbourhoods with a z score of >2.58 were considered significant at 99% confidence level ($p<0.01$) and they are under the category of hotspot. The Figure 3.5 (e) shows the incidence of *Meningococcal meningitis* in KUA for the year 2011. The neighbourhoods with a high value of clusters are located at the central part and it extends towards the south-western part of the study area.

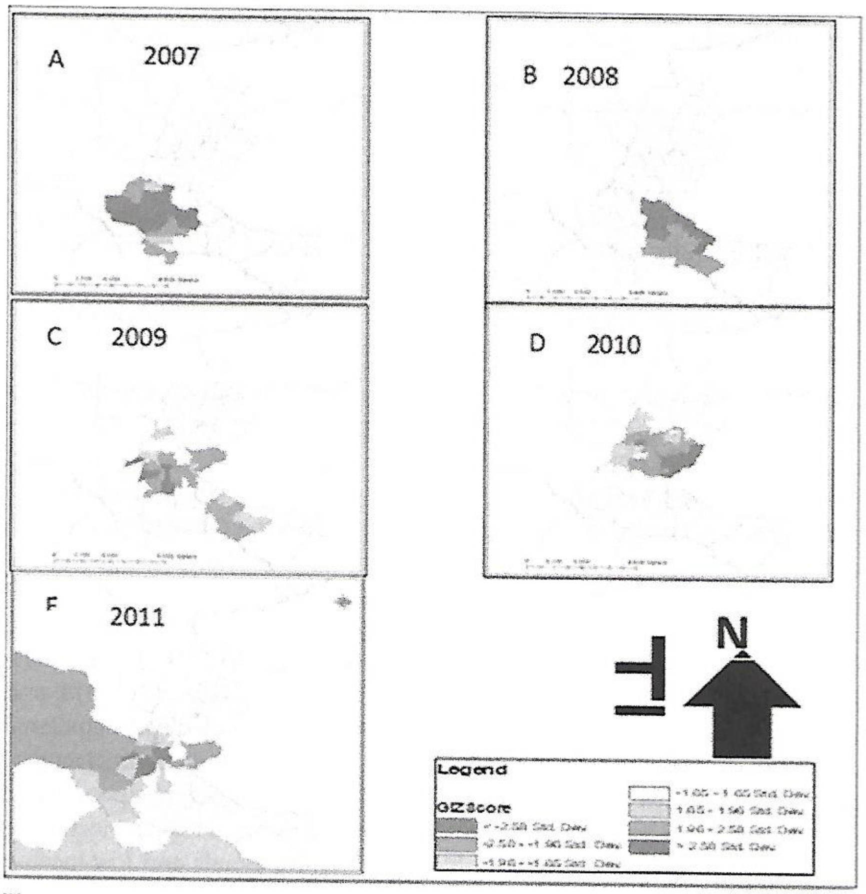

Figure 3.5 Getis and Ord Gi* Local Spatial Analysis for *Meningococcal meningitis* for KUA from year 2007 to 2011

The result of the spatial pattern analysis for the five-year period revealed that there is a pattern of the incidence of *Meningococcal meningitis* in KUA. Therefore it showed a 95% statistical confidence that the result patterns was not by chance. The findings in this study revealed the spatial pattern of *Meningococcal meningitis* incidence in KUA and the specific locations that have high and low concentrations of the disease. It was observed that in some locations there was a consistently high incidence of the disease. The consistent high concentration in the incidence of the disease was observed in neighbourhoods that are located in the central parts and also southern parts of the study area.

Comparison between OLS and GWR Models

The purpose of comparing GWR and OLS models was to identify the model with better performance. This was done by relating the model R^2 and the AICc value for both the GWR and OLS models. Recording higher R^2 means that the independent variables explain more variance in the dependent variable (Tu and Xia, 2008). While a lower AICc value indicates a closer approximation of the model reality, inferring that lower AICc means having a better model performance (Wang *et al.*, 2005). As a general rule, according to Fortheringham *et al.* (2002) and Mathews and Yang (2012), the differences of AICc between the OLS and GWR models must not be less than 3, and the model that has the lower number of not less than 3 is accepted as the better fit model. In other words, any of the models (OLS and GWR) with lower AICc value which is not less than 3 is more reliable. Supposing OLS and GWR model is ran, and the values of the AICc for the OLS is less than that of the GWR with at least (3), it is then accepted as the better fit model.

The result of the calibrated GWR indicated that there was an improvement on the OLS model. Analysing the two models together with their various AICc values revealed a drop in the value from 254.32 for the OLS model to 249.48 for the GWR model. There was a difference of about five (5) which implies that the local model fitness is greater when the spatial datasets of the incidence of *Meningococcal meningitis* is explained. The R^2 for the GWR model with an improvement of about 4 percent as shown in Table 3.1 also suggested that there was an improvement in the GWR model. About 4 percent explanation made by the GWR model was not accounted for in the OLS model which is significant in the relationship between the incidence of the disease and the variables. A study by Binbin *et al.* (2011) also had an improvement of GWR over OLS through the AICc and the R^2 because the GWR model has a better fit than the OLS model when an experiment to investigate the varying spatial relationships between house price and floor area with sample house prices in London was conducted. The study discovered that a particular locality in the study area had a strong effect on the parameter estimate.

Figure 3.6 is the map showing the local R^2 spatial smoothing of the GWR model pointing out those neighbourhoods where the model's prediction and strength of the relationship is better. The map indicates that there is a variation in the strength of the relationship in the whole of Kaduna Urban Area (KUA). The local R^2 map shows that those neighbourhoods located from some parts of the central parts towards the southern parts of KUA are having a higher R^2 which incidentally are the neighbourhoods that are more affected by *Meningococcal meningitis* disease compared with those on the northern parts of KUA. It was also observed that the spatial variation in the relationship patterns displays the intensity of relationship increasing from the northern parts to the southern parts of KUA. Hence, the variation indicates that there are local fluctuations in the relationship (non-stationary). Nonetheless, the best fit was observed in the neighbourhoods located from the central parts towards the southern parts of KUA.

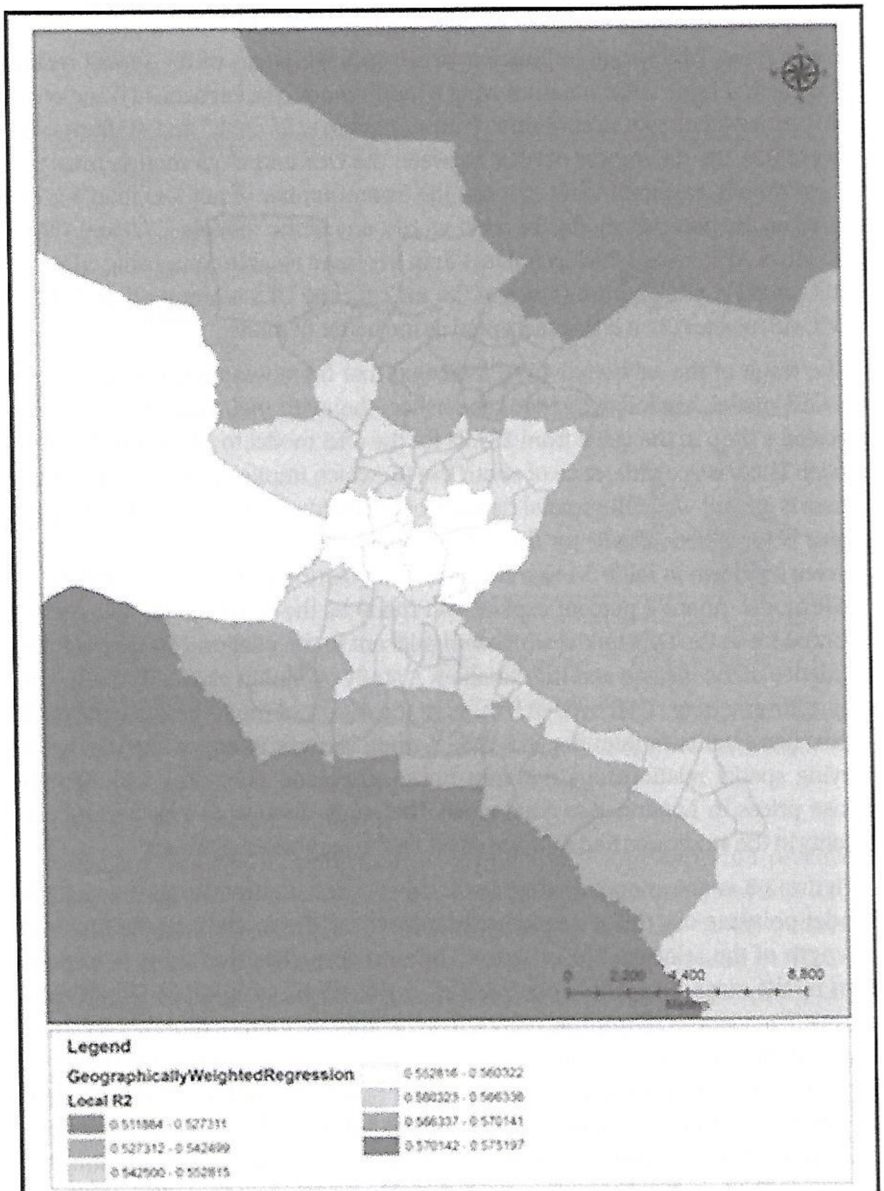

Figure 3.6 Local R^2 Smoothing for GWR Showing Model's Fitness Spatial Variation

Table 3.1 Summary of GWR Results

Neighbours	106
Residual Square	43.92
Effective Number	16.51
Sigma	0.69
AICc	249.48
R^2	0.57
R^2 Adjusted	0.49

Table 3.2 Comparison between GWR and OLS

	GWR	**OLS**
AICc	249.48	254.32
R^2	0.57	0.53
Adjusted R^2	0.49	0.47

Parameter Estimates (coefficient) and *T*-Values

This section deals with the GWR model results. The result of the parameter estimates reveals that there are variations. These variations are not so much for all the explanatory variables and it is not all the independent variables that show a significant relationship with the incidence of *Meningococcal meningitis* in KUA. Some of the variables show variations in the relationship with some recording significant t-values. Yet some are without any significant value which gives a deeper insight into the existing local relationship of *Meningococcal meningitis* and the independent variables which OLS model could not give within KUA. The spatial varying relationship existing is known through the parameter estimates and the t-values for each of the variable. Among the eleven explanatory variables, 4 are statistically significant; these are urbanization, housing density age 0-10 and housing condition 3. These variables are the most important with respect to explaining the incidence of *Meningococcal meningitis in* KUA. This result is consistent with the fact that in Nigeria squatter settlements, overcrowded neighbourhoods and age are major determinants in the transmission of communicable diseases like *Meningococcal meningitis* (Federal Ministry of Health, 2010).

On the other hand, housing condition 4 even though was significant in OLS but was not significant in GWR is another determinant in the transmission of

Meningococcal meningitis. Good housing condition is not associated with *Meningococcal meningitis*, probably that is the reason why it fails to return a significant t-values for housing condition 1 and 2 in the OLS model. Another explanatory variable that returned an insignificant t-value is the medium income level and high-income level.

In view of the methodology of this research which indicated that the spatial variation in the relationship for dependent and independent variable and the level of significance for GWR model can be detected with the results of the parameter estimates and t-values, the result for urbanization variable in Figure 3.7 shows the result with a parameter estimates from a low value of -0.289654 to a high value of 0.179541. The neighbourhoods that have a low value for the parameter estimates are located on some parts of the central KUA and also in the north-western parts. The neighbourhoods with low value for the parameter estimates returned significant t-values. Also, the neighbourhoods with negative parameter estimates are in the areas with significant t-values which indicate the influence of urbanization. This is because the influence of urbanization on *Meningococcal meningitis* is on the inverse, implying that the less the urbanization, then the more the influence of the disease in those neighbourhoods.

The neighbourhoods that returned a significant t-values are located on the central parts of KUA and it moves towards the western parts. The parameter estimates kept decreasing as it goes towards the western parts of KUA indicating that there is variation in the spatial relationship which is due to the urbanization variable. The neighbourhoods that have inadequate facilities, poor services, absence of any physical plan and overcrowded are the ones with the negative parameter estimates which invariably influences the incidence of *Meningococcal meningitis*. The neighbourhoods within these locations include Rigasa, Tudun Wada, Anguwan Mu'azu, Nasarawa, Kakuri and Tudun Nupawa. The reason why parameter estimates are low may be connected with the fact that, it is in the low developed locations which are characterized with poor housing conditions, low income level, deprived neighbourhoods in terms of facilities and services and overcrowded environment. According to Olowukure *et al.* (2006), deprived neighbourhoods and low income are associated with the incidence of *Meningococcal meningitis*.

The result of the OLS model for housing condition 3 and 4 parameter estimate returned a significant value. The reason for this kind of result is because OLS model takes into consideration the whole study area (106 neighbourhoods) unlike the result of GWR model which is localized to each of the neighbourhoods. This implies that houses that fell under this category of housing condition 3 and 4 at the OLS model are more susceptible to the incidence of *Meningococcal meningitis* in KUA. However, the GWR model revealed that there was no significant contribution that housing condition 4 variable is making in the incidence of *Meningococcal meningitis* disease in the neighbourhoods. The parameter estimates are higher at the western parts and also in some locations on the eastern parts. These suggest that the influence of the disease even though not significant is more on the western and some parts on the eastern side.

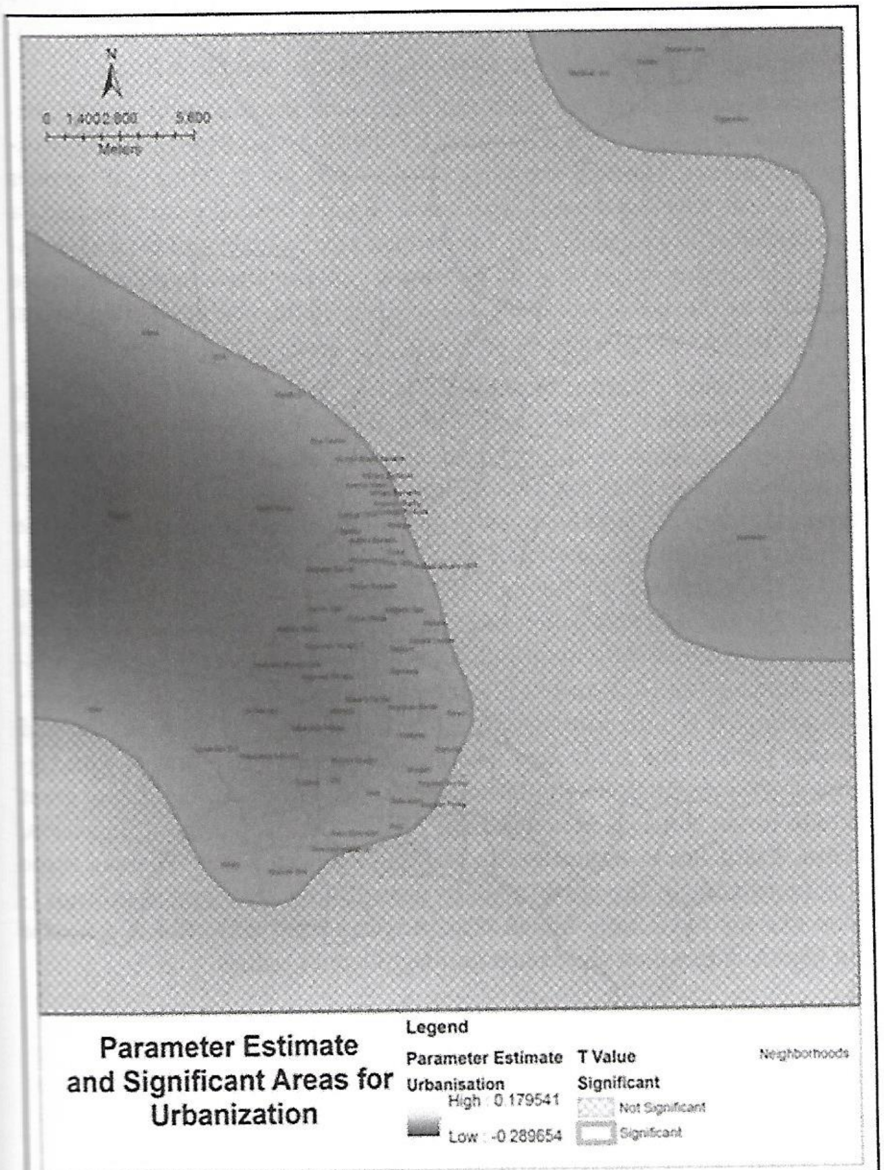

Figure 3.7 GWR Results for Urbanization

In the result of the GWR model, it was observed that housing condition 3 explanatory variable returned a significant parameter estimate of high value of 0.943612 and a low value of 0.287530 indicating that it made a significant contribution in the incidence of the disease in KUA as shown in Figure 3.7. The neighbourhoods that returned the significant parameter estimate as an indication of the existence of spatial varying relationship include Angwan Sanusi, Sabon Gari, Kabala West, Angwan Mu'azu, Kudandan, Nasarawa, Rigasa, Rigachikun, Maraban Jos, Kamazou and Bakin Ruwa.

It was observed from the result that it is where the urbanization explanatory variable is significant that housing condition 3 and 4 explanatory variables flourishes. The implication is that, inadequate facilities and services exist in "less developed area". This makes it have less value and the people that cannot afford to stay in the "developed area" usually opt for such locations. That is the reason why the housing conditions that are poor are more common in the less developed area and the incidence of *Meningococcal meningitis* is also high there.

The parameter estimates for housing density in the GWR results as shown in Figure 3.8 indicates that it returned a negative parameter estimates for explanatory variable and also, there is a significant relationship existing between *Meningococcal meningitis* and this variable. The results have indicated that there is a significant contribution that this variable makes in the incidence of *Meningococcal meningitis* in some of the neighbourhoods of KUA as it can be seen on the map- the parameter estimates value is having a high value of 0.213754 and a low value of -0.045778. The area where the parameter estimates are high indicates that there is a significant relationship. Drawing from this result, it is clear that the incidence of *Meningococcal meningitis* is influenced by housing density in KUA. The central and western parts of the study area have higher parameter estimates with significant t-values. Such neighbourhoods that fall within the significant areas include Tudun Nupawa, Makera, Doka, Angwan Barde, Barnawa, Television, Rigasa, Bakin Ruwa, Anguwan Mu'azu and Angwan Rimi. Whereas some neighbourhoods in the north-western parts do not have any significant t-value like Air force base, Malali GRA, Angwan Rimi GRA, Murtala square and Rigachukun which recorded a non-significant t-values.

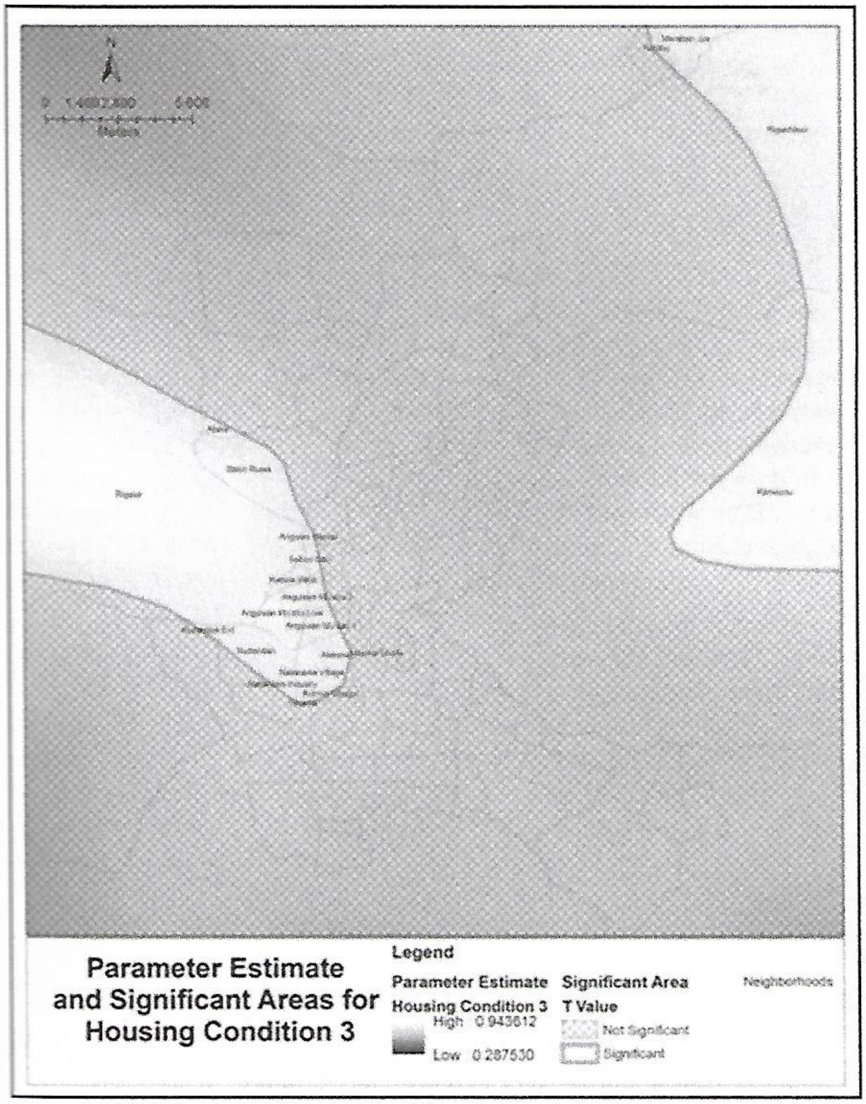

Figure 3.8 GWR Results for Housing Condition 3

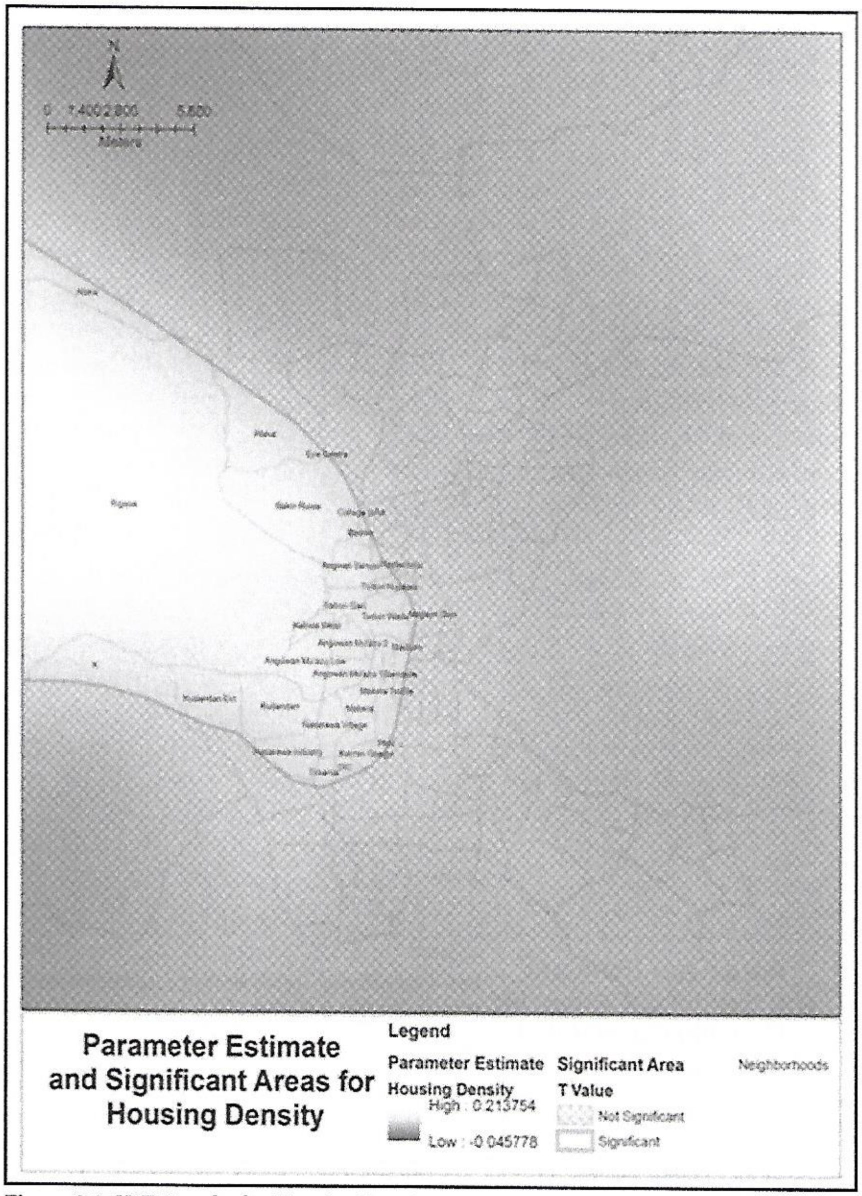

Figure 3.9 GWR Results for Housing Density

Conclusion

The findings in the spatial and temporal pattern analysis have shown the pattern and locations of concentrations of the disease. It revealed those neighbourhoods that have high and low incidences of the *Meningococcal meningitis*. This finding has pointed out the precise locations where there are high and low concentrations of the disease in KUA. Identifying those locations that the disease incidence is high will assist policy makers and health professionals to address the menace of the disease.

Ordinary Least Square (OLS) model only gives the global or general results on the relationship existing between the dependent and independent variable; the model did not specify the exact neighbourhoods where the relationship between the incidence of *Meningococcal meningitis* and all the factors are significant or less significant in KUA. It gave a general outcome showing the existence of a significant relationship between *Meningococcal meningitis* and some of the factors in the whole of KUA. The summary of the OLS means that the relationship is non-stationary because there is a local fluctuation existing in the relationships. This implies that the contribution each of the variables makes in the incidence of *Meningococcal meningitis* in KUA is not the same. It is high in some areas and low in other areas. For this reason, OLS is not the best model for explaining this kind of relationship.

The outcome of this analysis has shown that spatial data also have a non-static relationship across the geographic space when the results of OLS and GWR model fitness are compared through their parameter estimates and the t-value. Due to the potential of identifying specific relationships of dependent and independent variables across the geographic space, Geographically Weighted Regression (GWR) model is the best method. This is the peculiarity of using the local regression model (GWR) because it reveals details that are not displayed when OLS is used.

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