Environmental Technology & Science Journal
Vol. 8 No. 2 December 2017

Digital Mapping of Cholera in Parts of Kaduna State, Nigeria

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Abstract
The focus of this paper is to analyze the spatial patterns and clusters of cholera epidemic in five local government areas (LGAs) of Kaduna State. To achieve this goal, inventories were obtained from Kaduna State Ministry of health on cholera epidemic. The K-function method was used to determine the spatial heterogeneity of cholera epidemic. The identification of clusters and mapping were achieved through the use of digitized and google earth image 2016. The result shows that four among the five local governments were clustered with the exception of Kaduna North for which the disease pattern is random. Moreover, the result revealed that the overall spatial pattern of cholera epidemic in the study area is clustered, and the overall cholera disease risk was more concentrated in Igabi and Kaduna North LGA.

Key words: Spatial Pattern, Cholera, Digitized, K-function and Cluster**.**

Introduction
Cholera is endemic in Nigeria (Falade & Lawoyin, 1999). Nigeria reported an outbreak of cholera in May 2013. Since then and up until October 2014, a total of 40,608 suspected cholera cases have been reported. There have been 898 deaths, giving a case fatality rate (CFR) of 1.95%. The outbreak has experienced a strong upsurge since early 2014, with more than 34,000 cases and 664 deaths reported from January 2014 to October 2014. Suspected cholera cases were recorded in 19 of the country's 36 states (51%). The states affected include; Bauchi, Kaduna, Plateau, Kano, Borno, Adamawa, Katsina, Kebbi and Zamfara States (WHO, 2013).

The threat of cholera rampaging through Nigeria has been a concern. Recent global health reports show a continual vulnerability of large populations to infectious diseases in relation to our environment. Cholera is one of the deadliest disease in Africa (WHO 1993), within 2-3 hours of unset symptoms a previously healthy person may severely become dehydrated and if not treated may die within 24hours (WHO 2010). Cholera is an epidemic and infectious disease which is of global and public health significance, hence the need of this research to recognize and address it accordingly with the aid of geospatial techniques.

Nigeria is a prime area to study spatial patterns associated with diseases because it is a country where millions of people live in close proximity not only to other people but also to open and unsafe water sources. It is also a country that is actively engaged in alteration of its aquatic ecosystems, a process often associated with changed disease ecologies (WHO, 1993).

Spatial statistics is the process of extracting or creating new information about a set of geographic features to perform routine examination, assessment, evaluation, analysis or modeling of data in a geographic area based on pre-established and computerized criteria and standards. Spatial analysis is a technique for analyzing spatial data mostly on human scale. Complex issues arise in spatial analysis, many of which are neither clearly defined nor completely resolved. The most fundamental of these is the problem of defining the spatial location of the entities being studied (Scott & Getis, 2008).

Geographic Information System (GIS) and epidemiological approaches are helpful tools to control the disease spatially and temporally. GIS is a computer system for capturing, storing, querying, analyzing, and displaying geospatial data (Chang, 2008). The general functions of GIS in health studies are disease mapping and modeling, spatio-temporal changes analysis and risk assessment, public health care and hospital management. GIS has the capabilities of analyzing the spatial patterns, cluster and distribution of disease and its influential environments towards creating an innovative cholera control plan in the country. Spatial epidemiology is an essential approach in understanding of spatial disease risk transmission and pattern particularly, disease mapping and descriptive analysis (Chin-Lai, 2009).

Several approaches have been used to study the incidence of cholera. Notably among them are (Osei & Duker 2008) who used spatial regression models to explore the spatial dependency of cholera prevalence on an important local environmental factor (open-space refuse dumps) in kumasi, Ghana. Inhabitants with high density of refuse dumps were observed to their cholera prevalence than those with lower density of refuse dumps.

Ali *et al,* (2001,2002a, 2002b) utilized logistics regression , simple and multiple regression models to study the spatial epidemiology of cholera in an endemic area of Bangladesh. Akyala *et al,(2014)* ,investigated cholera outbreak in an urban north central Nigerian community. They employed descriptive statistics, active case search and un-matched case control study.

Diego *et al,*(2010) examined the spatial clustering of cholera outbreaks using Ripley's K and L indices and bootstrapping methods to evaluate the occurrence of the clustering in the cases during outbreaks using different temporal windows. The spatial location of cases was also against the spatial clustering.

Frank and Alfred (2008) conducted a research on spatial and demographic patterns of cholera in Ashanti region – Ghana. A GIS based spatial analysis and statistical analysis were carried out to determine clustering of cholera, and the result showed that high cholera rates are clustered around Kumasi metropolis.

This study present the application of K-function method to determine the spatial heterogeneity of cholera epidemic in parts of Kaduna State by generating eminent spatial patterns in the data through spatial maps, evaluate the degree of spatial clusters of points and disease risks and creating an inventive cholera control plan by exploring spatial analysis toolset in ArcGIS software for cholera mapping and pattern analysis in the study area.

The Study Area

The study area is Kaduna state and lies between latitudes 10º20'0"N and 11º10'0"N of the equator and between longitudes 7°10'0"E and 8°0'0"E East of Greenwich Meridian. The state shares boundary with Zamfara, Katsina , kano in the North, Bauchi, Plateau in the Eastern part of the Nigeria and to the western part lies Niger state. The state has a projected population of 7, 205,354 with twenty three local government areas. Five Local Government Areas with higher cholera cases were chosen for this research namely; Igabi, Kaduna North, Kaduna South, Sabon-Gari and Zaria (see Figure 1). These Areas were selected because based on the data collected, they have re-occurrence of cholera outbreak.

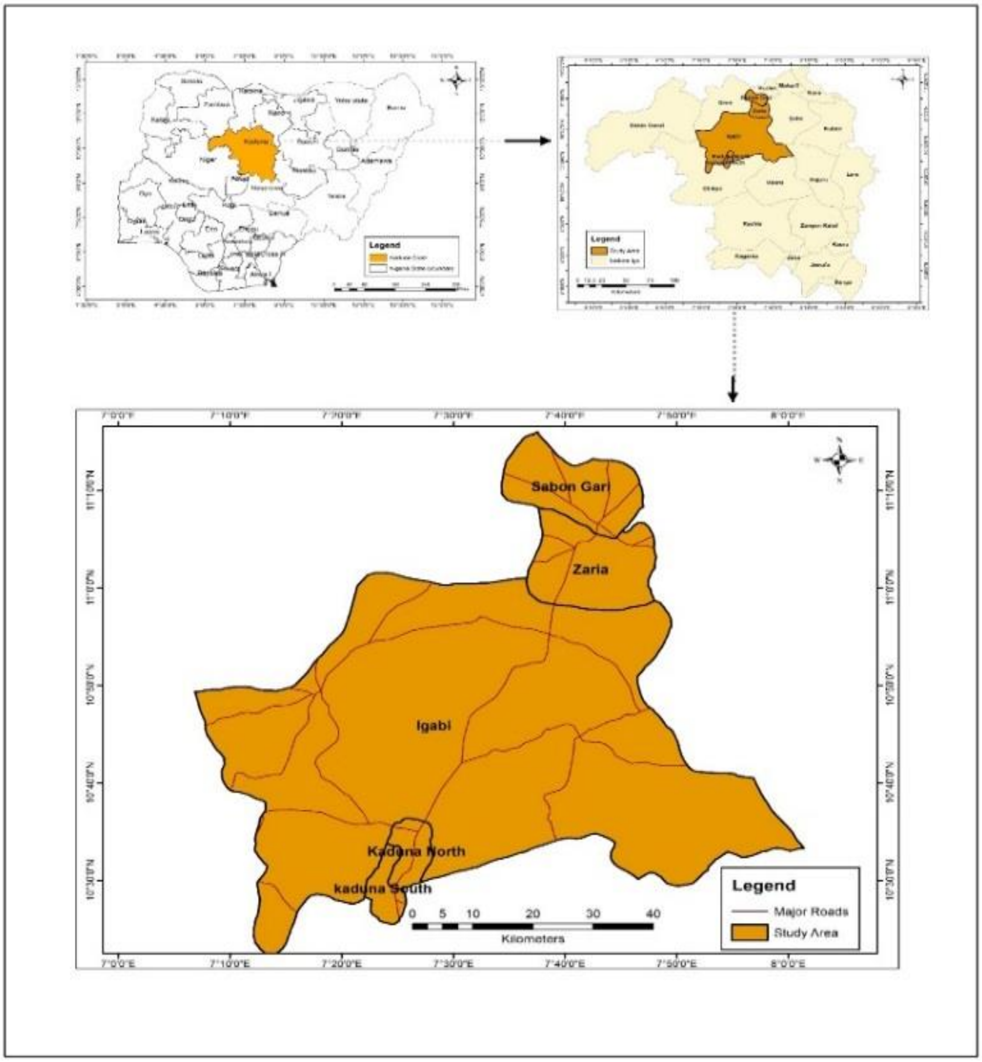

Figure 1: Map of Kaduna State showing the five Local Government Areas.
Source: Administrative Map of Nigeria 2015.

Methodology

The population under study is Kaduna State while the five Local Government Areas with frequent incidence of cholera outbreak constitute the sample. The type of data used in this research are the polygon and point data. The polygon data are the administrative map of the study area (polygon), location of the cholra cases (point data) and inventory data for the cholera epidemic which was used in populating the location of the cholera patients settlements. The data was obtained through secondary source.the secondary data is the baseline data list of all cholera outbreaks in Kaduna State from 2010 to 2015. The cholera outbreaks inventories information obtained comprises information on the locations of the cholera cases in terms of wards and localities, and number of people affected. The data was obtained from Kaduna State Ministry of Health.

The Estimators of K (h)

The Naive Estimator

A naïve approach consists of counting the number of observable pairs of objects, lying within the window D, that are less than a distance h apart. The resulting estimator, $K_1^{\wedge}$ (h) is given by the equation.

$$\lambda^2 \hat{K}_1(h) = \frac{\sum^n \sum^n_{i \neq j} 1_{ij}}{A} \quad (1)$$

The resulting estimator $\hat{K}_1(h)$ is evidently negatively biased, since it fails to take proper account of neighbouring objects lying undetected outside D but in its vicinity. Now

$$E\{A\lambda^2 \hat{K}_1(h)\} = E\{\sum^n \sum^n_{i \neq j} 1_{ij}\} \quad (2)$$

Ohser et al (1985) show that for a Poisson process, the right-hand side of (2) is.

$$E\{\sum^n \sum^n_{i \neq j} 1_{ij}\} = \lambda^2 \int_0^h \gamma_D(r) dK(r) \quad (3)$$

Where

γ_D (r) = E{ (area of $D \cap D + y\}$ and y is uniformly distributed on the boundary of the circle center at the origin and radius r. The function γ_D (r) can be interpreted in the following way:

For a rectangular window *Ohser et al.*, (1985) deduced that for small enough r, γ_D (r) is approximately equal to $A - r(2a+2b)/\pi$. Therefore,

$$E\{\sum^n \sum^n_{i \neq j} 1_{ij}\} = \lambda^2 \int_0^h \gamma_D(r) dK(r)$$

$$\approx \lambda^2 \{A \int_0^h dK(r) - [(2a+2b)/\pi] \int_0^h r dK(r)\}$$

However for a Poisson process, $K(r) = \pi r^2$ and

$dK(r) = 2\pi r dr$

$$E\{\sum^n \sum^n_{i \neq j} 1_{ij}\} = \lambda^2 \int_0^h \gamma_D(r) dK(r)$$ K(r) = πr^2, and dK(r) = 2π rdr.

Whence

$$E\{\sum^n \sum^n_{i \neq j} 1_{ij}\} \approx \lambda^2 A \pi h^2 - 4\lambda^2 h^3 (a+b)/3$$

thus:

$$E\{\hat{K}_1(h)\} = \pi h^2 - 4h^3(a+b)/3ab,$$

for small enough h.

Border edge correction

(S.I. Doguwa, 1988)Consider only those objects within a variable inner window D_0, which shrinks as h increases. For the case $h = h'$, the inner window is a centrally located rectangle of dimensions $(a - 2h')$ by $(b - 2h')$. The effect is that the positions of any object up to a distance h' outside the inner window are known. The resulting estimator $\hat{K}_2(h)$ is given by the equation (4):

$$\lambda^2 \hat{K}_2(h) = \frac{\sum_i^{n_0} \sum_j^n 1_{ij}}{A_0} \quad (4)$$

Here A_0 is the area of D_0 and n_0 is the number of objects in D_0. If λ^2 is unknown, it can be estimated by: $\frac{n_0(n-1)}{AA_0}$.

Evidently, $\hat{K}_2(h)$ is unbiased for all values of h that are less than $a/2$ and providing that the inner window is not empty of objects. To see this, we obtain the expected value of equation (4) conditional on the number n_0 of objects in D_0 as,

$E[\lambda^2 \hat{K}_2(h)] = [\sum_i^{n_0} \sum_j^n E[1_{ij}]$ for a Poisson process

$$= \sum_i^{n_0} \sum_j^n \{ \int_{D \cap \partial b(x_i, r)} dV\} dr / A$$ where

$r = d(x_i, x_j)$

$$= n_0(n-1) \int_0^h 2\pi r dr / A$$

$$= n_0(n-1)\pi h^2 / A$$

Where V is a one dimensional Lebsesgue measure on $\partial b(X, r)$, the boundary of the circle centered at X and radius r. Now

$$E\{\hat{K}_2(h)/N(D_0)=n_0\}=n_0(n-1)\pi h^2/AA_0\lambda^2=K(h)$$

However, the rapidly decreasing size of D_0 inevitably leads to a rapid increase in the variance of this estimator.

Ripley's Estimator

Ripley (1976, 1977) suggested considering every ordered pair of objects (X_i, X_J) within the sampling window and assigning a scaling factor S_{ij} to each pairing. The scaling factor is defined by,

$(S_{ij})^{-1}$ = The proportion of the perimeter of the circle, centred on object X_i and passing through object X_j, which lies within the sampling window D

$$=\frac{V[D\cap\partial b(X_i,r)]}{2\pi r} \quad (5)$$

Note that S_{ij} is not necessarily equal to S_{ij}. We shall refer to object X_i as the central object and object X_j as the distant object.

Ripley's estimator $\hat{K}_3(h)$ is given by equation (6) as:

$$\lambda^2\hat{K}_3(h)=\frac{\sum^{n}\sum^{n}_{i\neq j}1_{ij}S_{ij}}{A} \quad (6)$$

usually the value of λ^2 will be unknown, in which case we suggest replacing it by the estimate, $n(n-1)/A^2$ which is unbiased for a Poisson process. For a Poisson process, $\hat{K}_3(h)$ is unbiased for values of h for which $2h<d$

This follows, since

$$E\{\lambda^2 A\hat{K}_3(h)/N(D)=n\}=E\{\sum^{n}\sum^{n}_{i\neq j}S_{ij}1_{ij}\}$$

$$=\sum^{n}\sum^{n}_{i\neq j}E\{S_{ij}1_{ij}\}$$

$$=\sum^{n}\sum^{n}_{i\neq j}\int_0^h\{\int_{D\cap\partial b(x_i,r)}S_{ij}\,dV\}dr/A$$

$$=\sum^{n}\sum^{n}_{i\neq j}\int_0^h S_{ij}V[D\cap\partial b(X_i,r)]dr/A$$

But $S_{ij}V[D\cap\partial b(X_i,r)]=2\pi r$, for all i and j, provided that,

$$V[D\cap\partial b(X_i,r)]\neq 0 \quad (7)$$

However (4.10) is satisfied if and only if $2h<d$. Whence

$$E\{\lambda^2 A\hat{K}_3(h)/N(D)=n\}=n(n-1)/A\int_0^h 2\pi r dr$$

for $2h<d$

$$E\{\hat{K}_3(h)/N(D)=n\}=K(h)$$

Ripley's estimator is limited to values of h for which $2h<d$. The restriction occurs because the formulation of $\hat{K}_3(h)$, assumes that each of the objects in D can assume the role of a central object. However if $2h<d$, then there will be a 'null region' in the interior of D containing objects for which this central role has been removed, because the entire perimeter of the circle of radius h centered on one of these objects lies outside the sampling window.

Procedure for Data Analysis and Presentations of Results

The software used is Google earth image 2016. It was used to update digital map in ArcGIS 10.3 environment. The Microsoft-excel software was used to compile cholera data and ArcGIS 10.3 software was used as the engine for the data analysis and presentation of results.

The data was converted to Microsoft query format in excel. The query was done to extract the name of wards, name of localities and the cases of cholera with respect to the localities. This aids in locating the geographical locations of the localities and their coordinates on Google Earth Pro software. This was done in order to link both the spatial and non-spatial data because the data collected from the Kaduna State Ministry of health were not referenced to geographic locations. The data was then analyzed using the ArcCatalog window which is an ArcGIS software extension. The Spatial Analysis tool and K-Function was used for the spatial analysis of cholera epidemics. For each of the analysis conducted, a report was generated and the output of the results were presented in form of Figures, Maps and ArcMap documents.

The analysis of data consist of calculation the Euclidean distance between one point and the other point, using the Ripley's estimator as an estimator of spatial pattern of points.

Results and Discussion

Spatial Distribution

Figure 2 shows the location of the five selected local government areas that were highly affected by the cholera epidemic and the locations of the cholera cases in the areas. The five local Government areas are namely; Igabi, Kaduna North, Kaduna South, Sabon Gari and Zaria.

Figure 2 shows the total 187 locations with cholera incidence between the years 2010 to 2015. Five local government areas were highly affected with Igabi LGA having 53 locations affected by the cholera incidence, Kaduna North has 16 locations, while Kaduna South has 28 locations, Sabon Gari has 19 locations and with Zaria LGA having 71 locations. On the reported cases across the LGAs under study, 1363 cases were reported in Igabi LGA, 378 and 447 cases were reported in Kaduna North and South respectively, while 301 cases were reported in Sabon Gari LGA and 217 cases in Zaria LGA. The disease mapping provides a rapid visual summary of complex geographic information as supported by Goovaert and Jacquez (2004). The results show the advantages of advances in technology that allows disease and spatial distribution of disease mapping.

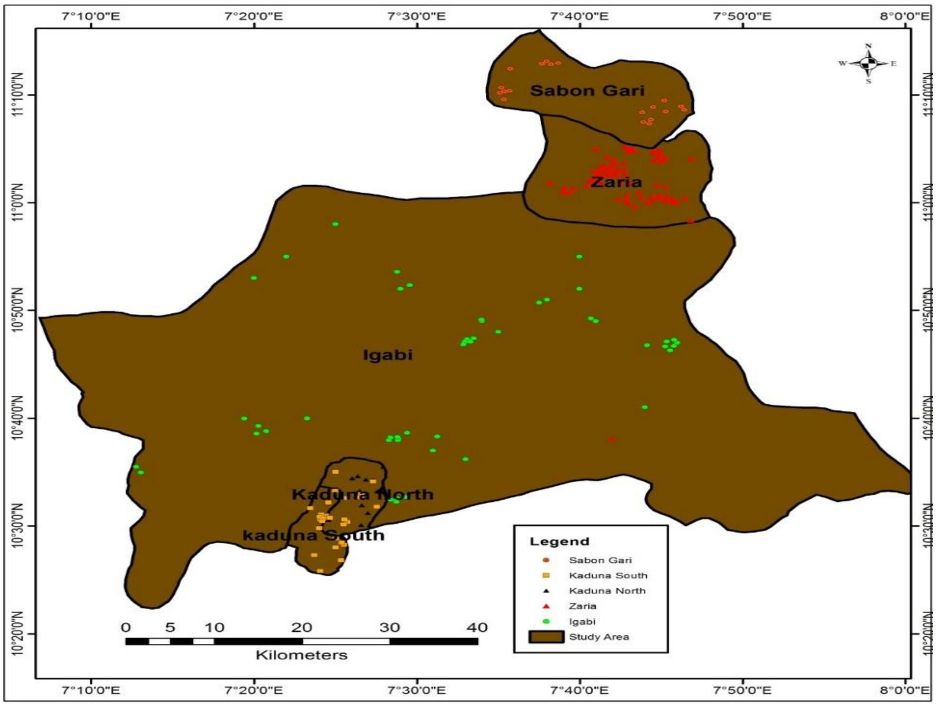

Figure 2: Location of the Cholera Epidemic in the Study Area

Spatial Patterns of Cholera Epidemic in the Study Area

The results of the analysis are presented in Figures 3 to 7. The red line in Figure 3 is the observed L-function and is above the Upper Confidence Envelop for values of h between 1000 and 3000 indicating clustering within the range. The result revealed that the diseases were clustered in Sabon-Gari LGA like the research conducted by Diego *et al.*, (2010) which show that spatial clustering of cholera cases were detected at different temporal and spatial scales. The result of Figure 3 was generated from the map in Figure 2 to show the charts of clustering and dispersed locations.

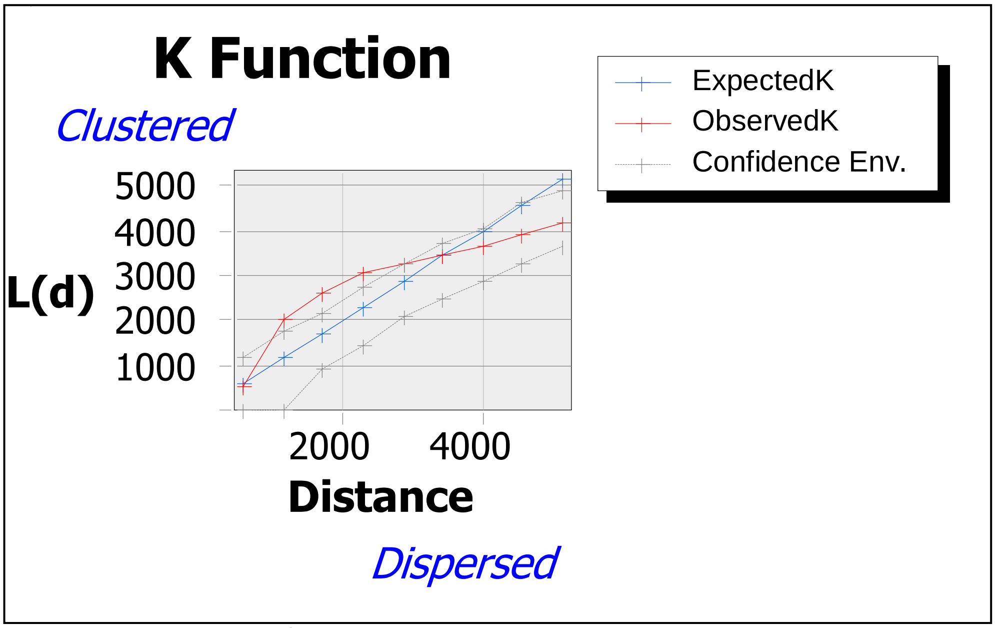

Figure 3: Spatial Patterns of Cholera Epidemic in Sabon Gari LGA

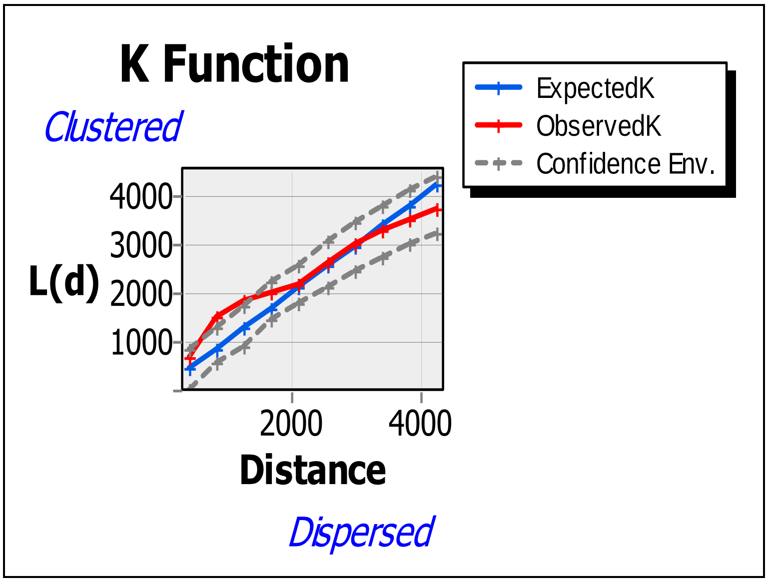

Figure 4: Spatial Patterns of Cholera in Kaduna South

Also from Figure 4, the red line revealed that the observed L(d) is above the Confidence level for values of h between 800 to 1100 indicating clustered pattern of spread of Cholera disease.

It was found from the result on Figure 5, that the spatial pattern of cholera disease in Kaduna North is random as shown from the red line that the observed L(d) is roughly within the Confidence Envelops. This finding also contradicted the research conducted by Diego et al., (2010) which showed that spatial clustering of cholera cases was detected at different temporal and spatial scales and cases relative to water sources also exhibit spatial clustering.

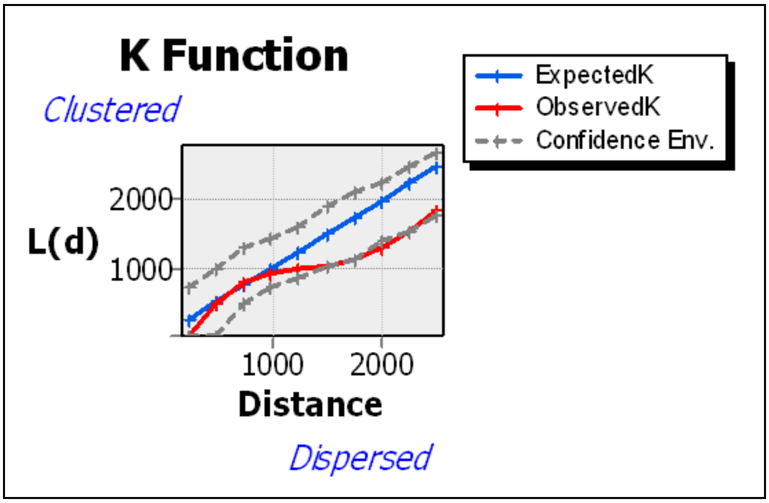

Figure 5: Spatial Patterns of Cholera in Kaduna North

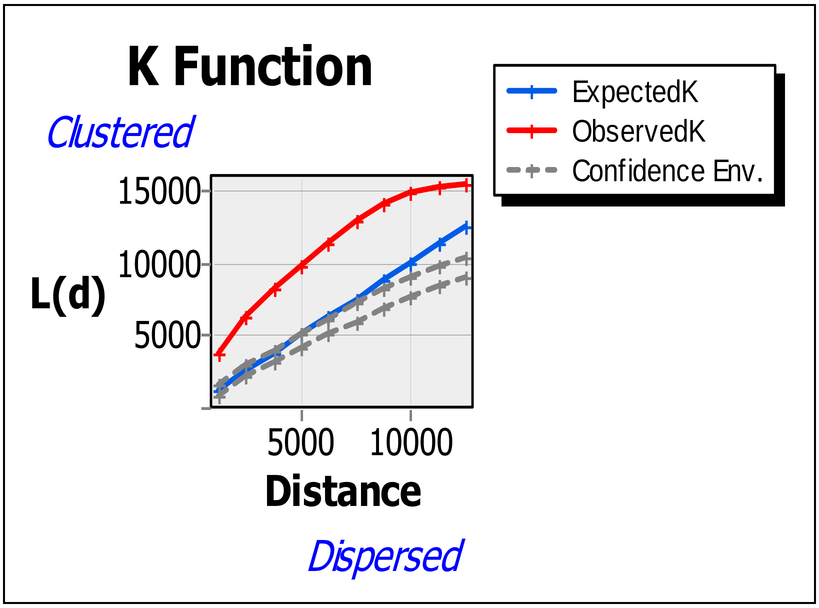

Figure 6: Spatial Patterns of Cholera in Zaria

The spatial pattern of cholera disease in Zaria is clustered. As indicated in Figure 6, the red line is constantly above the Upper Confidence Envelop as in the research finding of Ruiz-Moreno et al (2007) which observed that clustering of cholera in Bangladesh occur at different spatial scales. This result confirmed the outbreak reported in Zaria in the Kaduna state with 192 cases recorded in two weeks as at 2015 United nations children's fund (UNICEF, 2015). However, according to WHO (2013) the cholera outbreaks are attributed to the fact that Cholera is most likely to be found and spread in places with inadequate water treatment, poor sanitation, and inadequate hygiene.

Moreover, the observed red line in Figure 7 is above the Upper Confidence Envelop for values of h between 0 and 7000 indicating clustering pattern of cholera spatial distribution in Igabi LGA. The situation in Igabi LGA was as a result of socioeconomic and demographic factors because most of the people living in that area are farmers and fishermen and it has been reported (Ali et al 2002a, 2002b; Borroto and Martinez-Piedra 2000; Sasaki et al 2008) that socioeconomic and demographic factors significantly enhance the vulnerability of a population to infection and contribute to epidemic spread of cholera.

Degree of Spatial Clustering of Points and Disease Risks

The result for the degree of spatial cluster of Cholera locations and disease risks are presented in Figures 8 to 11. The point density was used to calculate a magnitude per unit area from point features that fall within a neighborhood around each cell in the study area. In evaluating the degree of spatial cluster, only the points that fall within the neighborhood were considered in calculating the density.

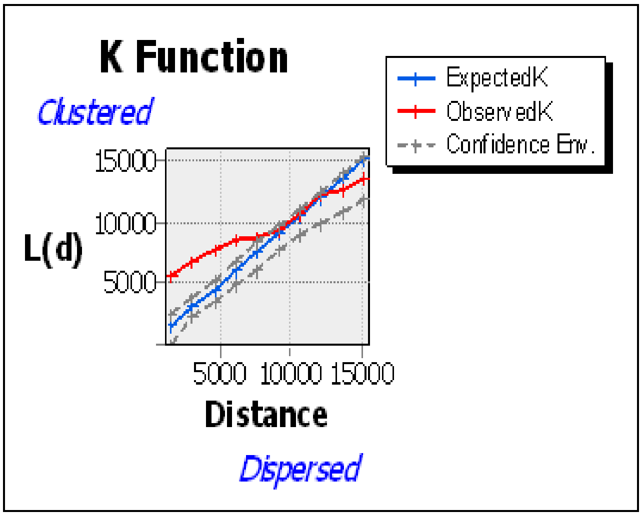

Figure 7: Spatial Patterns of Cholera in Igabi LGA

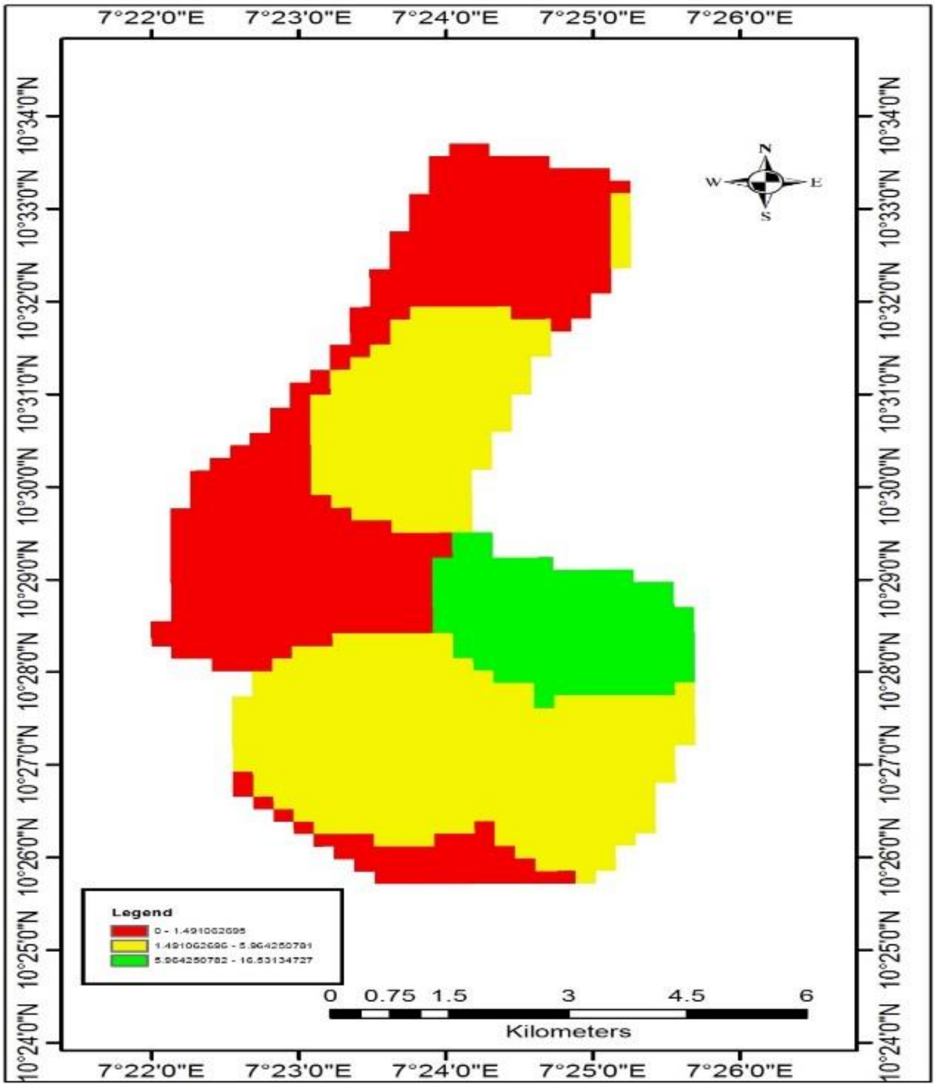

Figure 8: Spatial Clusters of Cholera in Kaduna North

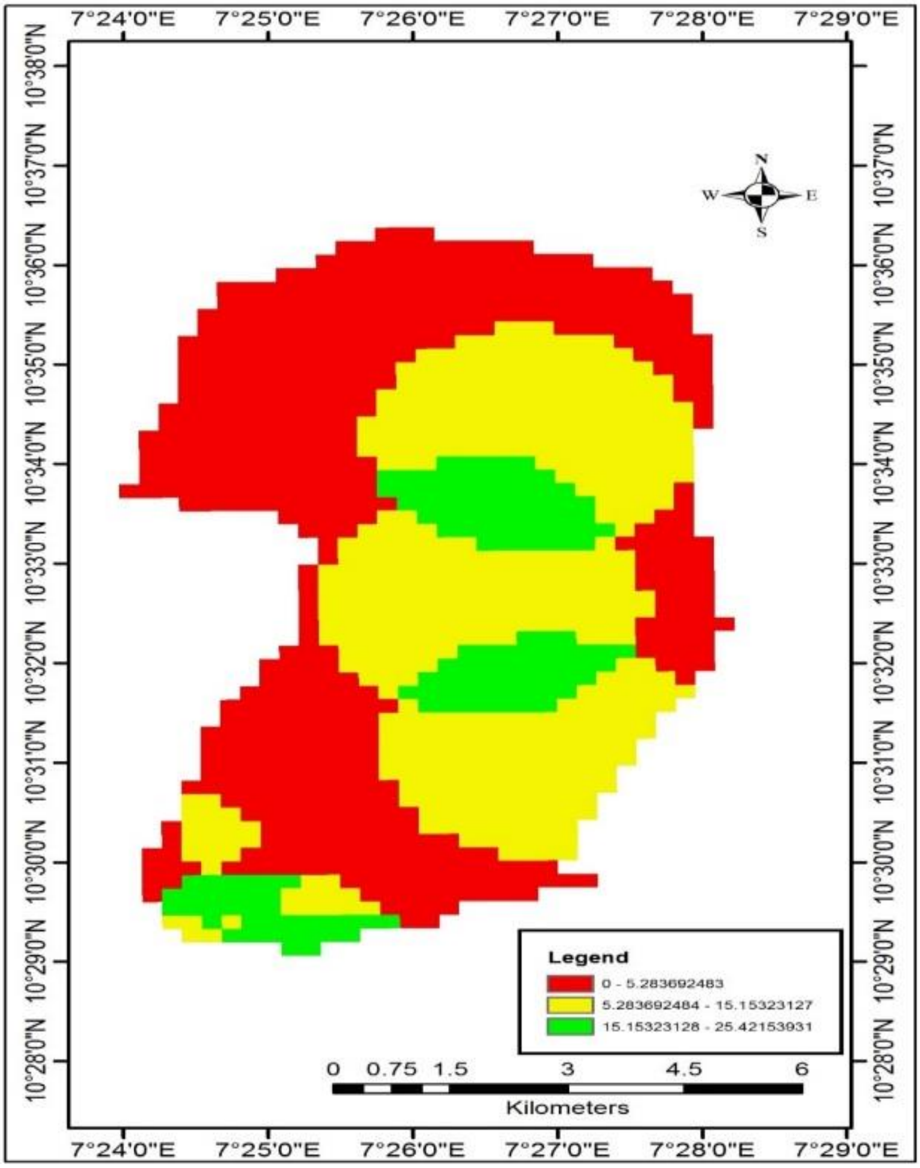

Figure 9: Spatial Clusters of Cholera in Kaduna South

From Figure 8, the result show that the yellow color constitute higher cluster which ranges from 5 to 15, red moderate cluster (0 to 5) and green (15 to 25) with lowest spatial cluster respectively. The spatial cluster in Kaduna North LGA ranges from high to low cluster. From Figure 9, the result shows that the yellow color constitute higher cluster which ranges from 1.4 to 5.9, red indicates moderate cluster (0.1 to 1.4) and green (5 to 16) indicates low spatial cluster. This shows that Spatial Cluster in Kaduna South LGA ranges from high to low cluster

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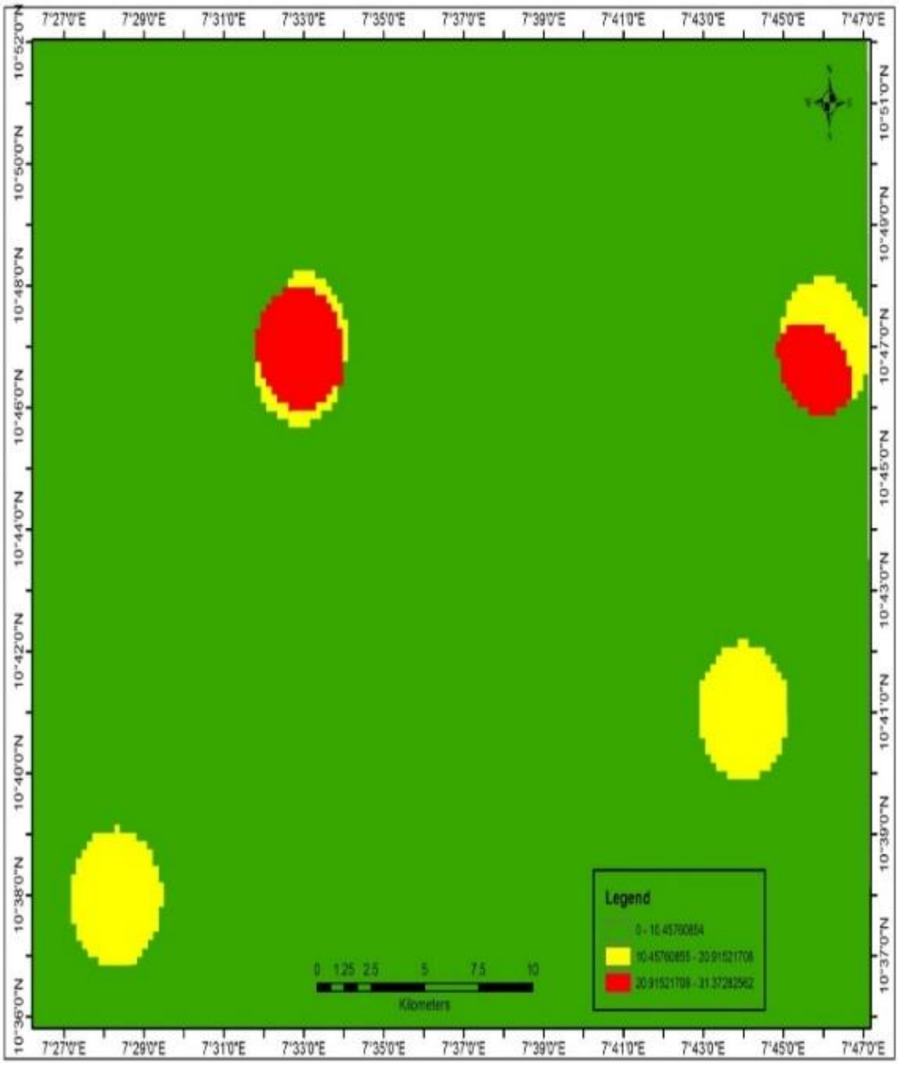

Figure 10: Spatial Clusters of Cholera in Igabi

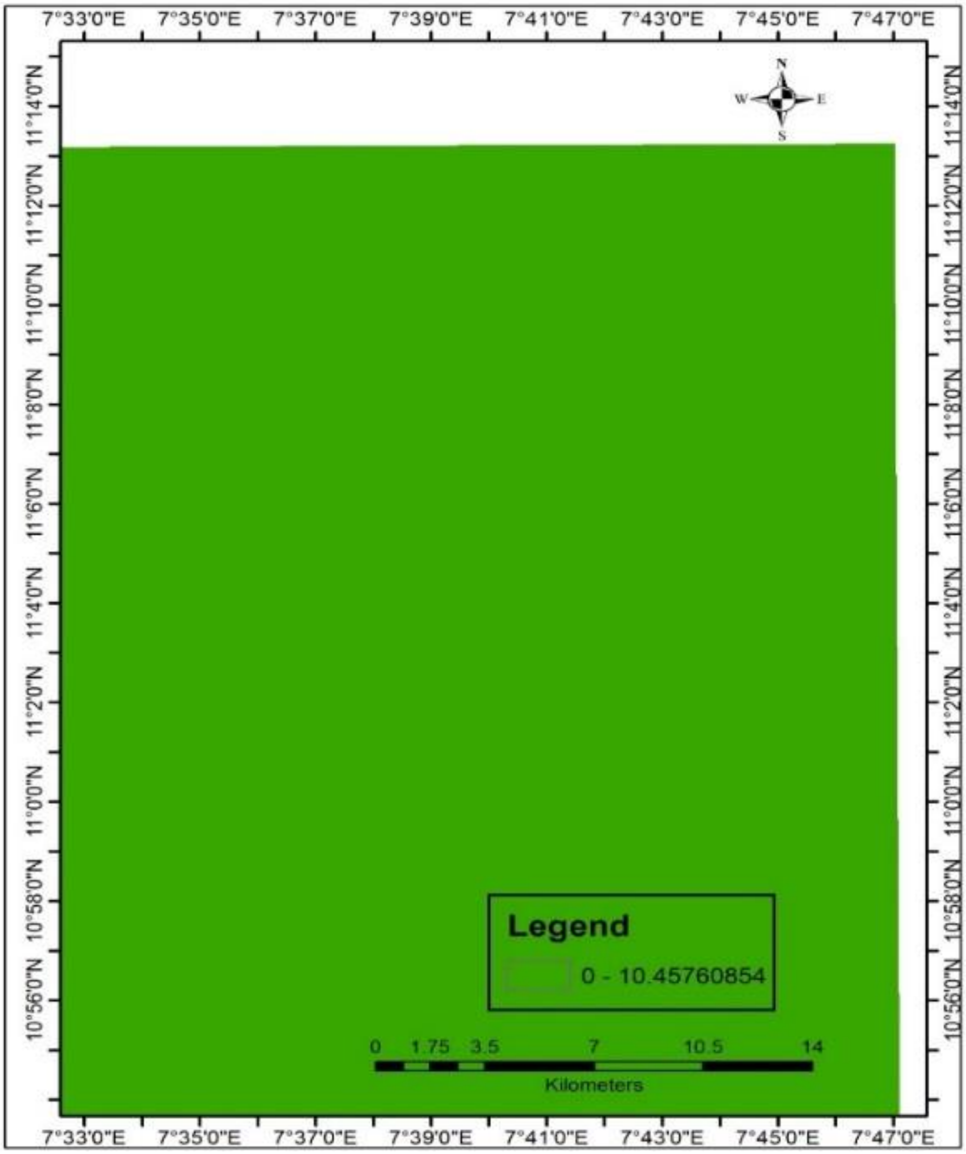

Figure 11: Spatial Clusters of Cholera in Sabongari and Zaria

From Figure 10, the result show that the green color constitute higher cluster which ranges from 0 to 10, followed by yellow (10 to 20) and red indicates moderate cluster (20 to 31) with low spatial cluster. The result shows that spatial clusters in Igabi LGA has low cluster. From Figure 11, the result shows that the green color constitute higher cluster which ranges from 0 to 10 with low spatial cluster. Sabon-gari and Zaria LGAs has low cluster.

It was generally found that the degree of cholera spatial cluster is Highest in Igabi, followed by Kaduna North, and Kaduna South and low in Sabon Gari and Zaria LGAs.

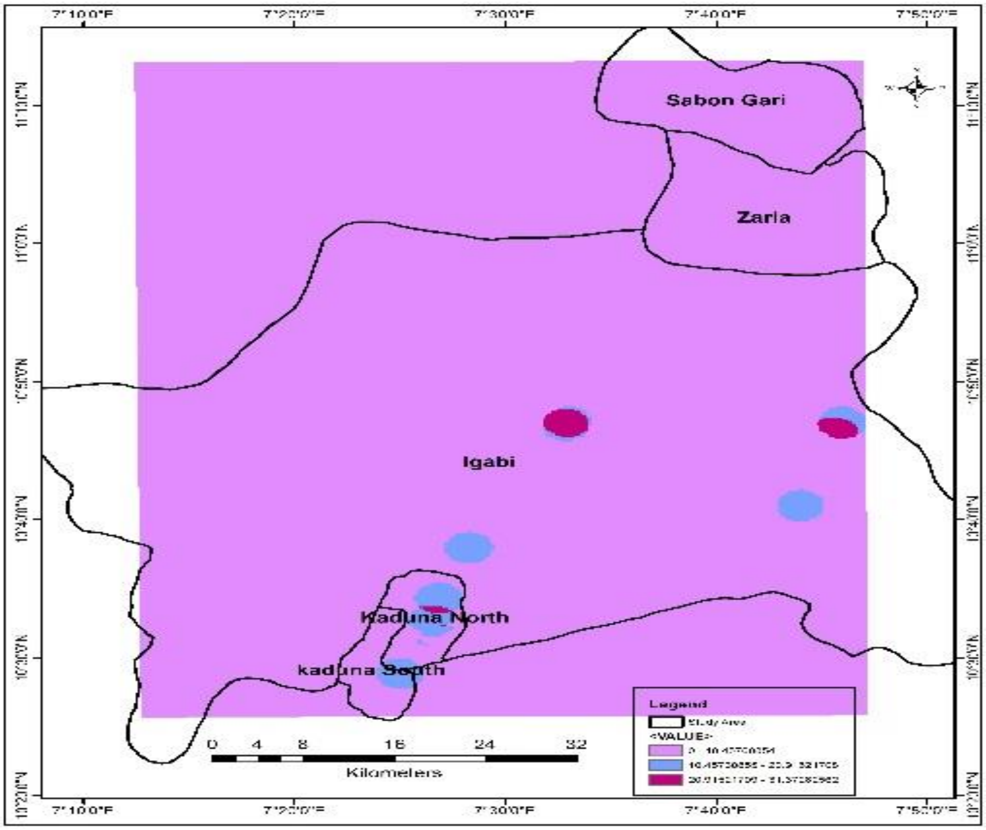

Figure 12: Spatial Clusters of Cholera Epidemic in the whole of the study area

Cholera Disease Risk

In order to evaluate the spatial pattern of cholera diseases risk, there is the needs to calculate a magnitude per unit area from point features using a kernel function to fit a smooth surface to each point. The larger values of the search radius parameter produce a smoother, more generalized density raster whereas the smaller values produce a raster that shows more detail. Cholera disease map for the study area is presented on Figure 13.

The five local governments in the study area are at risk of the Cholera disease outbreaks. However, the cholera disease risk was more concentrated in Igabi and Kaduna North LGAs. The high concentration in cholera epidemic in Kaduna North and Igabi LGAs could be as a result of the rivers in the two LGAs. The discharge of pollutants as a result of agricultural activities into the tributaries (rivers) in the study area is one of the major determinant factors that lead to the cholera outbreak.

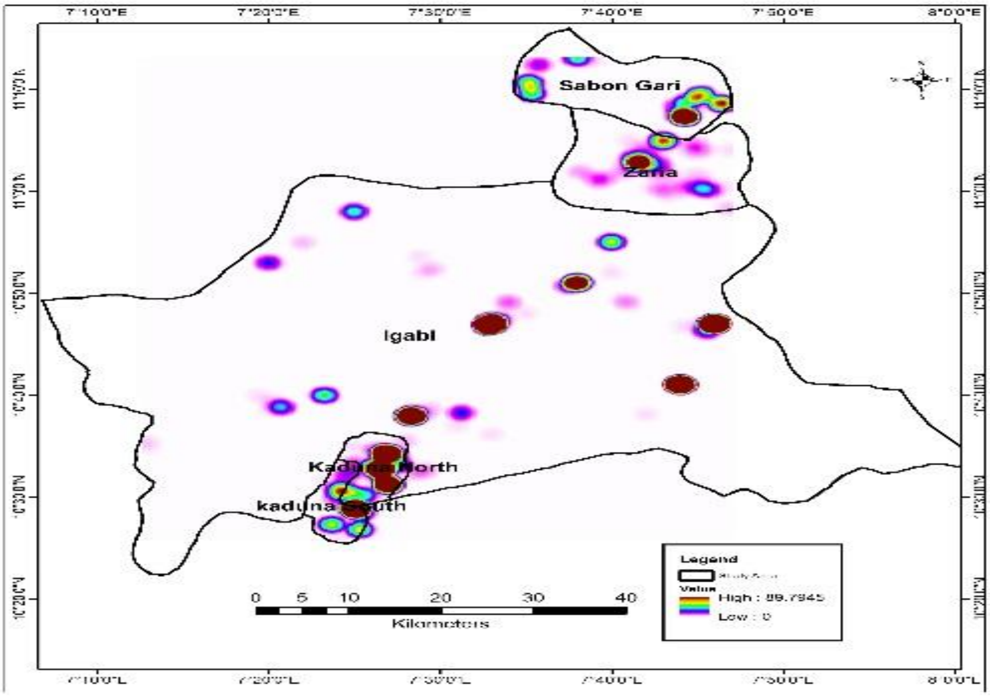

Figure 13: Cholera Disease Risk in the whole of the study area

Inventive Cholera Control Plan

Figures 8 to 11, has revealed that Igabi, Kaduna North and Kaduna South LGAs should be given priority for cholera control measures. The areas that are vulnerable to the disease risk are shown in Figures 12 to 16 and should be used as a decision making guide for cholera control plans in the study area especially. Finally, the GIS interface is an inventive cholera control decision making tool because the integration of GIS and epidemiological approaches are helpful tools to control the disease spatially and temporally as pointed out by Chang (2008). As such the outcome of this research serve as an innovative cholera control plan in five local government areas of Kaduna State as supported by Chin-Lai (2009). These intervention includes;

1. Case Management,
2. Surveillance of the outbreak including laboratory analysis and data management,
3. The WASH activities such as hygiene promotion, safe burial, household disinfection, water treatment etc
4. Community mobilization,
5. Possible oral- cholera vaccine (OCV) campaigns.

Conclusion

The study reveals that GIS is a useful tool to epidemiologists to visualize, manage, and analyze large volumes of data. It can help to better define populations exposures with perhaps better specificity. The results shows the advantages of advances in technology that allows not only disease mapping but also the application of spatial statistical methods such as cluster analysis. The study determined the presence and extent of clustering in the study area. The spatial pattern of cholera mirror the spatial pattern of the population at risk. The association between population density and environmental exposure was established.

Recommendation

It is recommended that surveillance should be intensified in Igabi and Kaduna North LGAs that has high incidence of cholera epidemic most especially during wet seasons. A further study can be carried out on the effects of socioeconomic and environmental factors on the pattern and risks of cholera.

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