SPATIAL DISTRIBUTION OF TUBERCULOSIS IN GOMBE STATE USING GEOGRAPHICAL INFORMATION SYSTEMS APPROACH

[1*]YILA CAIAPHAS MAKADI AND [2]BALKISU Y. AHMED

[1-3]Department of Geography, Gombe State University, Gombe, Nigeria

*Correspondence Author E-mail: ycaiaphas@gmail.com

ABSTRACT

This research was carried out to examine the spatial distribution of tuberculosis in Gombe State using GIS approach from 2010-2015. Used in this study were secondary data, obtained from the tuberculosis and leprosy control center in Gombe for a period, 2010-2015. Data and information for the research were collected from the eleven local government areas of the State. The Moran I index was used to examine the values of spatial autocorrelation of tuberculosis prevalence in the study area. Additionally, the IDW (Inverse Distance Weighing) method interpolation was employed in this study for identifying the spatial pattern of tuberculosis prevalence. The research revealed there were a number of reported cases of PTB (Pulmonary Tuberclosis) and EPTB (Extra Pulmonary Tuberclosis) over the years and in the eleven local government areas of the state for the period of study. The pattern showed decreasing and increasing cases between the years with few reported cases of PTB in 2010 in Dukku Local Government Area and escalating prevalence of over 15 percent in 2014. The hotspot regions of high PTB occurrence in 2010 were Dukku, Yamaltu/Deba, Nafada and Kaltungo, while in 2014 the regions of higher occurrence were Shongom, Kwami, Akko, Kaltungo and Nafada. The cold spot regions of low PTB occurrence included Dukku, Balanga, Billiri and Gombe Local government Areas. The study further revealed that the occurrence of tuberculosis among males and females varied and these variations were much higher between males and females in Nafada, Shongom, Kaltungo and Kwami Local Government Areas.

Keywords: Tuberculosis, Spatial distribution, Disease, GIS, Pattern

INTRODUCTION

Tuberculosis (TB) is a respiratory infectious disease caused by the bacillus, Mycobacterium tuberculosis, which has been a global public health concern for decades. In April 1993, the World Health Organization (WHO) declared TB a global emergency. According to the WHO, 22 countries, including Nigeria, were considered high burden countries (HBCs) due to their large number of reported prevalence. In 2013, the WHO reported that HBCs accounted for more than 80% of the global notified cases. The effort of the Federal Government of Nigeria in the fight against these diseases is being supported by the following development partners: Darnien Foundation Belgium (DFB), international Union Against Tuberculosis and Lungs Diseases (IUATLD), Canadian International.

Development (CID), United States Agency for International Development (USAID), Tuberculosis Control and Assistance Program (TBCAP), Centers for Disease Control and Prevention (CDC), and other Voluntary organization for effective implementation of the NTBLCP (National Tuberculosis and Leprosy Control Programme) (WHO, 2014). Since Tuberculosis infection is on the increase in Nigeria, (WHO, 2015) it is therefore necessary to study the distribution of this disease in Gombe state and to establish the prevalence rate of the disease. This will help the government and non-governmental agencies interest in the fight against this disease in their control intervention activities. Today it is far different Nigeria ranks fifth among the world's high burden countries with a number of tuberculosis (TB) cases of 450,000. The TB incidence is at 311/00.000 and the rate of new sputum smear positive disease is approximately 1371100,000. It is far worse in northern of Nigeria due to the crisis that has riddled this part of nation (Dickson, 2013).

The study revealed the TB burden in Nigeria was further compounded by the high prevalence of HIV/AIDs in the country, stating that 23 percent of 86 percent registered TB patient tested positive for HIV. It also revealed that the infection was more prevalence in males than in females with highest incidence in the age group of 45-54 years. For the first time in the history of the country, his survey provided a nationwide population – based estimate of the TB burden for Nigeria, unveiling a level of TB prevalence that is much higher than previously though. The TB prevalence survey was conducted by the National Tuberculosis Control Programme of the Federal Ministry of Health in close collaboration with the WHO and the US Center for Disease Control and Prevention (CDC) (WHO, 2016).

MATERIALS AND METHOD

Method of Data Collection

The major method of data collection was secondary data collected from Tuberculosis and Leprosy
Control Centre (TBL) Gombe, Gombe State.

Study Area

Gombe State is located between latitude 9^0 30' and 12^0 30'N and longitudes 8^0 45' and 11^0 45'E of Greenwich Meridian. The state has an area of 20,265mk2 and a population of around 2,353,000 people as of 2006 census. It lies within the North East region of Nigeria.

Methodology

The main data for this research was collected from a leprosy control Centre Gombe, Gombe State, from the year 2010-2015. Showing the prevalence of (PTB) and (EPTB) for 2010 and 2014 for each local government area, as well as the rate of prevalence among male and female in the year 2011, 2012, 2013 and 2015 for each local government of the State respectively (Figure 1).

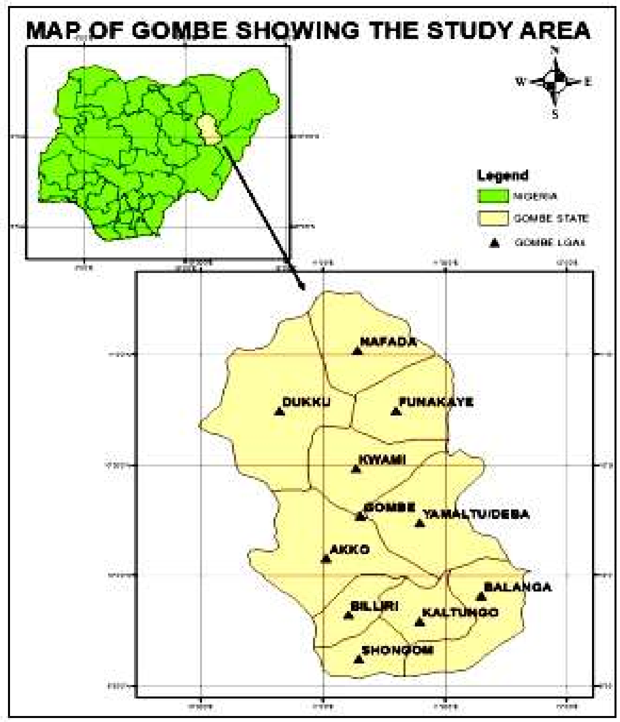

Figure 1: Study Area Showing Gombe State Local Government

Source: Authors Analysis GIS Lab Gombe State University (2017)

RESULTS AND DISCUSSION

Reported Tuberculosis Cases 2010-2015

The Figure 2 below shows the number of reported cases of PTB and EPTB across the years for the study area. The figure further shows the corresponding values or range across the eleven (11) Local Government of Gombe State as well as number of the reported cases at two periods (2010 and 2014). This raw data together with corresponding population data were used to obtained the tuberculosis prevalence. The pattern is showing decreasing and increasing cases between the years. There were few reported cases of PTB in 2010 in Dukku LGA which were adduced to medical treatment or campaign to raise awareness against the disease either by government or private corporations. But in 2014, the prevalence escalated by over 15% cases.

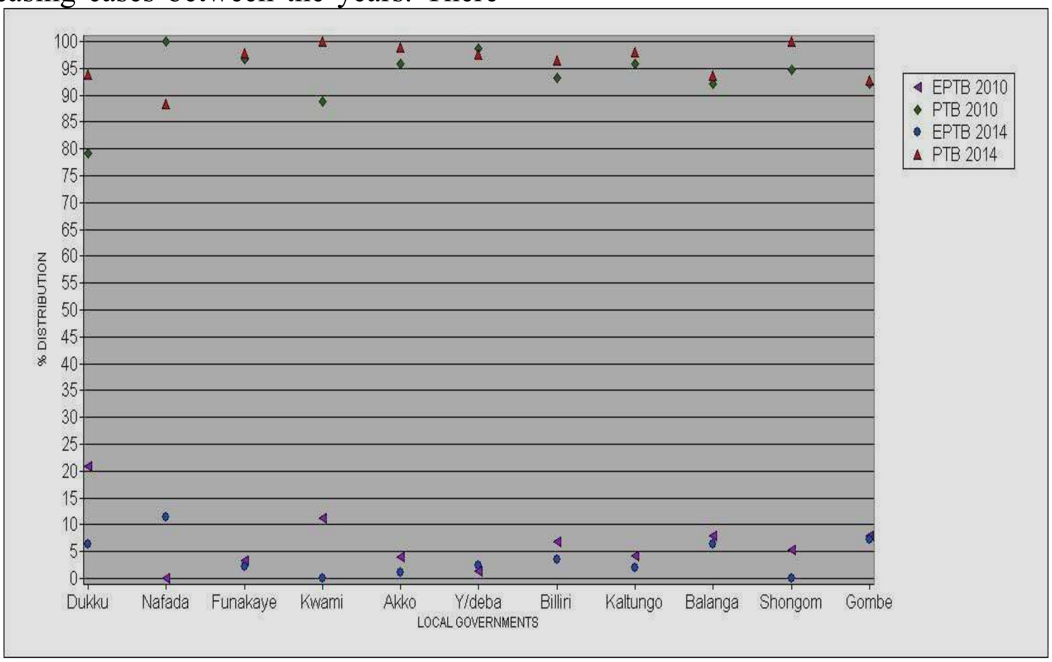

Figure 1: Scatterplot showing the Magnitude of PTB and EPTB prevalence between 2010 and 2014.
Source: Authors Analysis GIS and RS. Laboratory Gombe State University (2017)

Cluster Detection and Hotspot Mapping of PTB and EPTB between 2010 and 2014

Unlike the global measures, local measures IDW interpolation characterized individual units as to whether cluster or non-clustering pattern occurs. In most areas there are no significant clusters as shown by the Moran's I index below (Fig. 3 and 4). There are also very low spatial clusters. High clusters were located in three of the four major Local Government Areas of the state. In contrast to Anselin local Moran's I, Gestid-Ord G describes the clustering pattern as hot or cold spot locations (Table 2 to 4). It usually characterizes the TB prevalence into hotspots, cold spots or insignificant location at certain confidence interval. The Gestid-Ord G in this context indicated other hotspot locations around incidence points that were not regarded as clusters in the Moran's I index.

In Figure 3, most of the regions in the map have shown some level of clustering pattern of PTB at 96 -98% confidence interval especially Dukku, Yamaltu Deba, in 2010 and Kwami, Akko, Shongom in 2014. As explained above, Inverse Distance Weighting method of interpolation (IDW) was employed to determine the predicted values of other regions of the study. Hot and cold spot regions of PTB occurrence as shown in the figure ranges from dark red colour regions indicating hot spot zones to dark blue regions indicating cold spot regions. From this result the hot spot regions or areas of high PTB occurrence in 2010 are;

Dukku, Yamaltu Deba, Nafada, Kaltungo while in 2014, regions of higher occurrence are in Shongom, Kwami, Akko, Kaltungo and Nafada. The cold spot regions as indicated in the Figure 3 represent areas of low PTB occurrence and these include Dukku, Balanga, and Billiri and Gombe Local Government Areas.

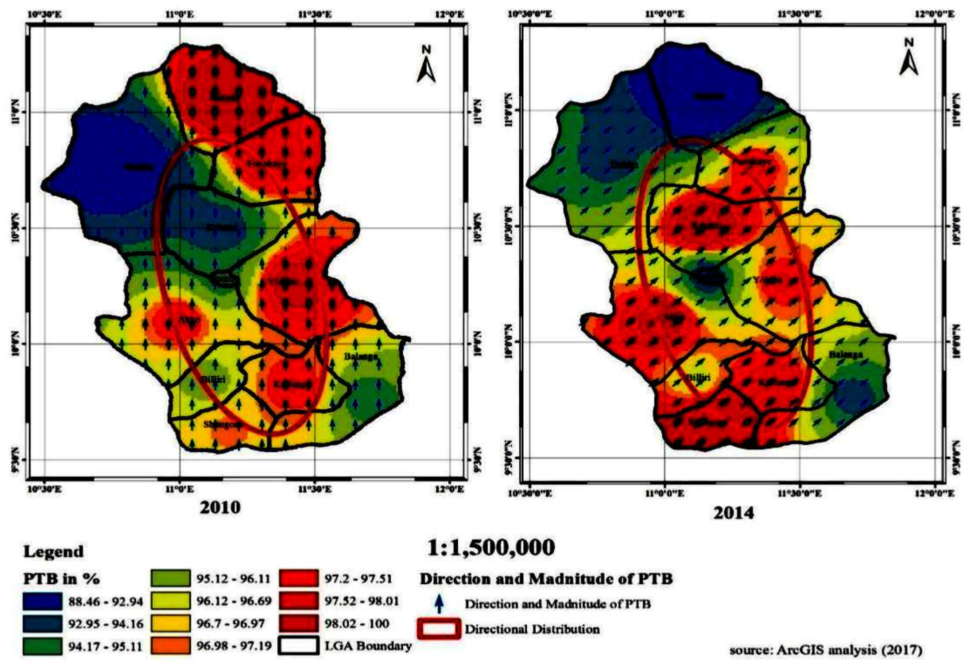

Figure 3: Spatial Pattern and Distribution of PTB in Gombe State between 2010 and 2014. Source: Authors Analysis GIS and RS. Laboratory Gombe State University (2017).

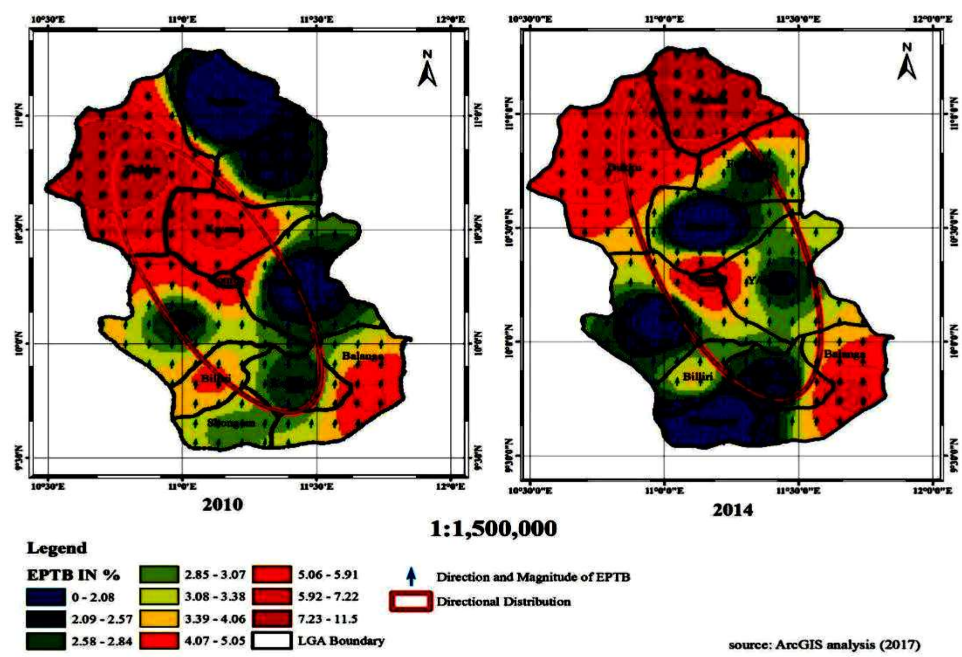

Figure 4: Spatial Pattern and Distribution of EPTB in Gombe State between 2010 and 2014 **Source:** Authors Analysis GIS and RS. Laboratory Gombe State University (2017).

The density of the TB prevalence from the dark-red colour to the very light colours away from it indicates the prevalence density as shown by the IDW) interpolation method. Thus, the model is variable in the estimate of these phenomena, it is the most accepted and reliable in terms of results because it considers the neighboring values and its distance from each cell containing recorded values.

Testing Global Measures for Spatial Autocorrelation of Tuberculosis Prevalence

Table 1 below shows results for global Moran's I test across the two periods (2010 and 2014). In all cases, the Moran's I index depicted negative values which indicated negative spatial autocorrelation of the TB phenomena being investigated. A further look at the p-value index of (0.604173 as the lowest recorded in all categories) also revealed that the neighboring features have dissimilar characteristics, as for the cluster to be considered statistically significant; the p-value for the feature must be small enough.

Considering z and p-values which are the measures of statistical significance in this context, the interpretation of these results may not be uniform as in the case of Moran's I. The year 2010 has recorded values of -0.5093333 and 0.610519 for the z and p-value respectively. This suggests that there is spatial low clustering of tuberculosis prevalence. The situation is quite different for the remaining period and is even unique for year 2014 where we have significant high z value (0.232791) as well as very high p-value (0.841354). This suggests somewhat clustering pattern of tuberculosis prevalence in the study area or rather the pattern TB across the local governments of Gombe State does not appear to be significantly different than random.

Table 1: Global Moran's I Summary

INDEX	2010		2014	
	PTB	EPTB	PTB	EPTB
Moran's Index	-0.197500	-0.199328	-0.055560	-0.048198
Expected Index	-0.100000	-0.100000	-0.100000	-0.100000
Variance	0.036644	0.036711	0.049294	0.049518
Z-score	-0.509333	-0.518410	0.200162	0.232791
P value	0.610519	0.604173	0.841354	0.815924

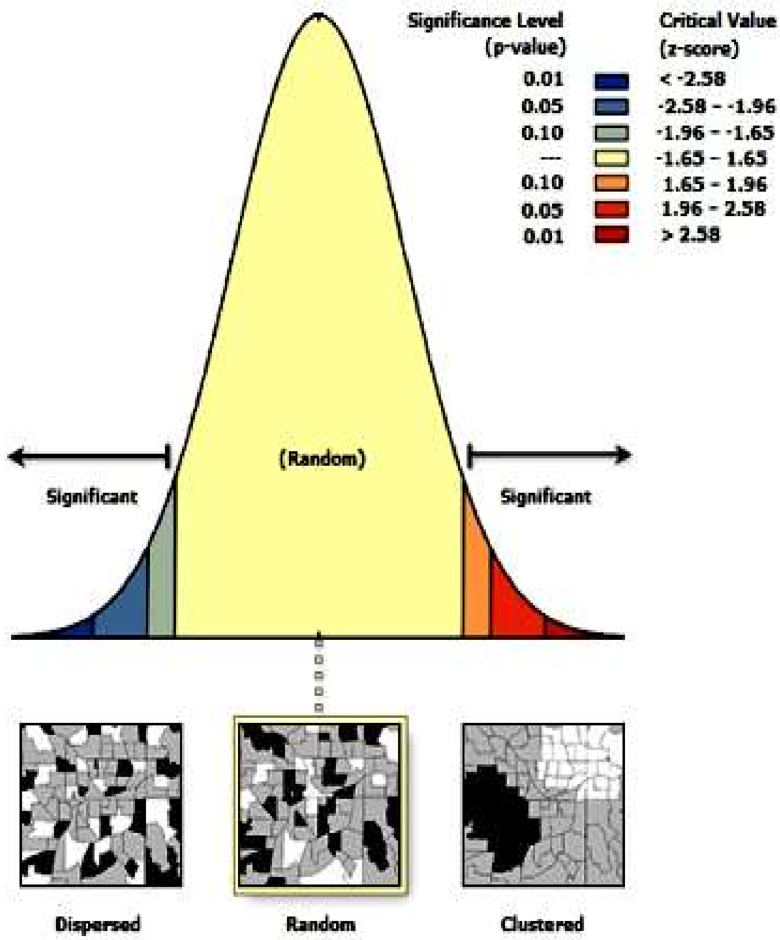

Figure 5: Moran's I test of spatial autocorrelation of tuberculosis prevalence given the z-score of 0.232792, the pattern does not appear to be significantly different than random.
Source: Authors Analysis GIS and RS. Laboratory Gombe State University (2017).

Table 2 to 4 portray the result of spatial autocorrelation between 2010 and 2014 TB cases. Interpolation values were extracted from field containing the distribution of PTB and EPTB between 2010 and 2014 there by creating the raster surfaces in (Figure4.2 and 4.3 above), it was also from each corresponding attribute field of PTB and EPTB to the estimated values for the observation data were generated using the Spatial Autocorrelation tool in ArcGIS. LGAs that were used for these estimates were overlayed on each of the corresponding raster cells. The Table (Table

3.) below indicates real data on TB prevalence for the year 2011 and their corresponding estimate values extracted from each of the interpolation method. Looking closely at each individual observation and corresponding values for each method, I is evident that some of the interpolation methods were not quite good for the prediction. There is however less than 1% chance that the high clustered could be the result of random chance.

Table 2. PTB 2010 observation data and corresponding values from interpolation models

LGAs	PTB 2010	LMi Index	LMi Z Score	LMi P Value	CO Type	N Neighbors
Akko	95.87	-0.0000115	-0.4725	0.2960		3
Balanga	92.11	-0.0000031	-0.3590	0.4040		1
Billiri	93.26	-0.0000008	-0.6752	0.3060		3
Dukku	79.17	-0.0000600	-1.5780	0.0020	LH	1
Funakaye	96.67	0.0000058	0.3444	0.4240		2
Gombe	92.18	-0.0000028	-0.2038	0.4940		3
Kaltungo	95.76	0.0000075	0.4254	0.4060		4
Kwami	88.88	-0.0000315	-0.6272	0.3300		4
Nafada	100.00	-0.0000413	-0.9828	0.1900		2
Shongom	94.73	0.0000027	0.2754	0.4680		2
Y/Deba	98.60	-0.0000170	-0.2340	0.3640		3

Source: Author analysis GIS and RS.

Table 3: EPTB 2010 observation data and corresponding values from interpolation model

LGAs	EPTB 2010	LMi Index	LMi Z Score	LMi P Value	COType	NNeighbors
Akko	4.0000	-0.0000121	-0.4092	0.3100		3
Balanga	7.8900	-0.0000032	-0.3954	0.3760		1
Billiri	6.7400	-0.0000009	-0.7207	0.2980		3
Dukku	20.8300	-0.0000596	-1.7281	0.0020	HL	1
Funakaye	3.3300	0.0000057	0.3655	0.4160		2
Gombe	7.8100	-0.0000030	-0.1947	0.4740		3
Kaltungo	4.2400	0.0000073	0.4791	0.3820		4
Kwami	11.1100	-0.0000318	-0.5090	0.3640		4
Nafada	0.0000	-0.0000412	-0.9606	0.1920		2
Shongom	5.2600	0.0000026	0.3116	0.4780		2
Y/Deba	1.3400	-0.0000173	-0.2796	0.3360		3

Table 4: EPTB 2010 observation data and corresponding values from interpolation model

LGAs	EPTB 2014	LMi Index	LMi ZScore	LMi P Value	CO Type	N Neighbors
Akko	1.2000	-0.0000060	-0.0598	0.4420		3
Balanga	6.4000	-0.0000125	-0.4488	0.3140		1
Billiri	3.5000	0.0000091	1.6266	0.0360	LL	3
Dukku	6.3000	0.0000296	2.2890	0.1000		1
Funakaye	2.3000	-0.0000127	-0.7207	0.2460		2
Gombe	7.1700	-0.0000833	-1.2935	0.0560		3
Kaltungo	2.0000	0.0000108	0.5492	0.3340		4
Kwami	0.0000	-0.0000006	0.2270	0.4480		4
Nafada	11.5000	0.0000034	0.5393	0.3780		2
Shongom	0.0000	0.0000218	0.5911	0.3540		2
Y/deba	2.3800	0.0000031	0.3164	0.4040		3

Source: Authors Analysis GIS and RS. Laboratory Gombe State University (2017)

Figure 6 below deficit the summary of distribution of TB prevalence among males and females across the local governments of the State between 2011 to 2015.The result shows that the occurrence of TB among males and females tends to be random among males and females in LGAs of Gombe, Y/Deba and Akko while higher variations between males and females are recorded in Nafada, Shongom, Kaltungo and Kwami LGAs where there were more females than in male occurrences.

On the other hand, LGAs that record high occurrence of TB in males include Balanga, Dukku, Funakaye and Billiri LGAs. This type of results is significant because it describe the role of gender in understanding the spatial distribution of diseases also it is relevant in decision making as to which approach of awareness on preventing TB could be employed in enlightening the target population in concern (males or females) in a particular community or local government areas.

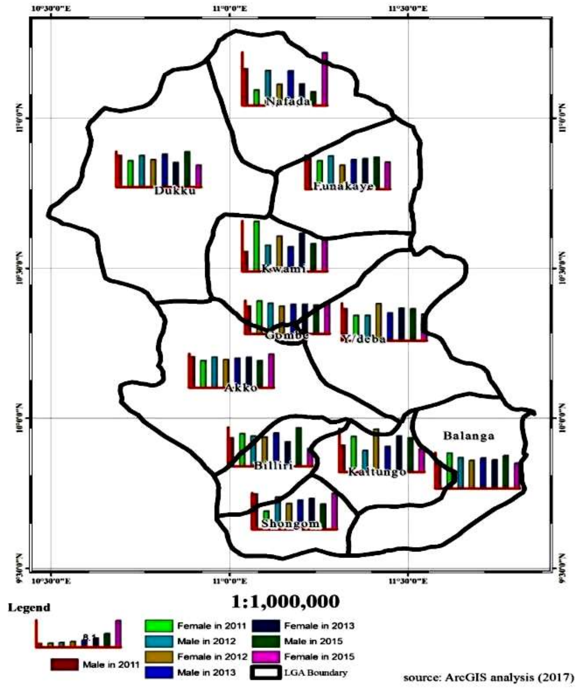

Figure 6: Map showing the prevalence of TB on Gender across LGAs.

Source: Authors Analysis GIS and RS. Laboratory Gombe State University (2017)

DISCUSSION

One of the main issues that emerge from this study is the reliability of global measures to test clustering pattern using disaggregated data. The use of global measures to understand the spatial pattern through cluster detection has been widely acknowledged in health research. In this study, the applicability of such measures (Moran's I and Gestid-Ord) was not quite successful using aggregated data as revealed by our result. Sometimes the conclusion based on the analysis of spatial autocorrelation index (high or low cluster) could be misleading depending upon the index in question, the viability of the dataset and modeling approach. Despite significant number of PTB and EPTB prevalence in some of the unit areas in the study area, our analysis for Moran's I did not detect any clustering pattern for aggregated data. Moreover, the global G statistics can be more advantageous than the Moran's I by allowing pattern to be expressed as either high or low clusters. The level of data aggregation has consequently affected the outcome of our data analysis in this context. It is obvious that the results of global measures could be misleading considering both the outcome of our analysis and the nature of our dataset on PTB and EPTB prevalence. However, spatial methods which used mathematical models to predict the unknown using the known points (interpolation) is one of the viable GIS techniques used to address data limitations. Such a technique has been tested in this study.

Although, all interpolation methods can be limited in way, IDW interpolation technique has been proved to be more advantageous since it assume substantially that correlations and similarities between points is proportional to distance between them. In this study result for IDW shows high-level agreement with the observation data considering the corresponding P values and z score obtained from clustering and outlier analysis as shown in table 2, 3 and 4. Judging from the outcome of global measures using the predicted data, it is a clear indication that there are significant Random clustering pattern of PTB and EPTB prevalence in all cases and for all the indices. This reflects prevalence that is closer to reality which significantly indicates the relevance of data prediction in analyzing and understanding spatial pattern. Similar situation is observed through the analysis of local measures of spatial autocorrelation which further supported these decisions.

Particular importance in this study, is the Local Moran's I which indicated high and low clusters and insignificant areas and the Gestid G* that analyses hotspot locations given out high and low hotspots as well as cold spot areas. This information which cut across every single administrative entities of the study site is very valuable for decision making process. Despite successful implementation of interpolation method for TB prevalence prediction, it was observed that the limitation of the dataset is still something to worry about. The lack of coordinate's locations for each case is one of the starting points. Sometimes ethical issues, confidentiality of the patient's information and health policies limit access to certain need to come with the data. However, in Nigeria, there is poor record data management system. In many cases, even the address of the patient may not be available for the recorded cases. Even where addresses were given, there is also no comprehensive geographic database (e.g. postal address file and their GPS points) with which to relate each individual cases. The United Kingdom's institutions with this responsibility has cited as a classical example of what can be considered in Nigeria.

This is not available for the TB prevalence in Gombe State. Despite viable techniques available in GIS to overcome data limitation, lack of socio-economic data may constrain our ability to apply various modeling approaches to certain group of the population. Analysis of socioeconomic components in disease mapping can be seen in many studies.

CONCLUSION

The IDW interpolation model for predicting the TB prevalence employed in this study for identifying spatial pattern of tuberculosis prevalence has high significant in disease mapping analysis especially in the circumstances of unavailable data for other regions in which clustering pattern can be hard to reliably detect. This study has shown that despite data limitation, GIS approaches are quite viable for understanding spatial pattern. Thus, the outcome of this study is quite imperative for enhancing policy and decision making in health service provision.

It is interesting for further studies to examine factors responsible for high density of PTB and EPTB prevalence in hotspot locations. If the environmental characteristics for cold spot location are not by chance, it is worthwhile to examine them so that similar condition can be considered in the hotpots locations. However, these hotspot areas (high risk) are concentrated in almost all of the eleven most urbanized areas of the state. It is possible that inadequate access to health facilities (mostly affected by the rural dwellers) may serve as an impediment for the discovery of people affected by TB and other related diseases in the state.

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