Mapping the Prevalence of Measles among Risk Population in Zamfara State, Nigeria

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Abstract: **Disease maps can be used to highlight populations at risk of a disease and its seasonal variability. Measles has been and is still being considered as one of the most infectious and perhaps the highest childhood mortality diseases world-wide. This paper examined the spatial risk of measles in Zamfara State, Nigeria with the objective highlighting areas of high risk and possible link with seasons and the available healthcare facilities. Measles prevalence and relative risk data of 2017 from the 14 LGAs of the state were used for the study. Relative risk rates were computed using 'at risk' population of ages 1-9 years as a proportion of the aggregated data. The maps were corroborated with seasons and distribution of healthcare facilities. While the raw data showed LGAs of highest risk located at the southernmost parts of the state, the reverse was the case with the relative risk rates. The later also highlighted relationships of relative risk rates with seasons and availability of healthcare facilities. It was concluded that the type of map drawn and the nature of data used could portray different virtualizations of disease pattern, and that both seasonality and availability of healthcare facilities play a role in the prevalence of measles in Zamfara State. It is recommended that, although the findings shed some light on the possible causal factors, more detailed studies should be carried out on these factors with a view to uncovering them for any informed actions to reduce the risk of the disease and its possible transmission chain, more especially with the current spate of banditry and forced migrations in the state.**

Keywords: **Prevalence, Prevalence Rates, 'At risk' population; Disease mapping; Seasonality**

I. INTRODUCTION

Disease mapping is aimed at isolating and displaying the role of location as a risk factor; other abstract factors, such as social inequality, differing control programmes, physical barriers, can also help to explain particular patterns of disease, thus requiring more abstract mappings for their study. In other words, account needs to be taken of the distribution of the population at risk to a particular disease, or cause, before mapping its pattern (Barford and Dorling, 2014:3). However, small populations tend to give rise to the most extreme disease rates, even if the actual rates are similar across the area.

Mapping is usually for descriptive purposes; to identify patterns of geographical variation in diseases, to develop new ideas about the cause of disease and also contribute to verifying hypotheses concerning factors associated with the distribution of the disease (Brewer, 2006; Gatrell & Elliot, 2015; Pickle, 2002; Ricam and Salem, 2010). Displaying disparities and spatial patterns from maps leads inevitably to the elaboration of hypotheses about associated factors. One of the Chloropleth mappings is one of such methods where characteristics of the population, such as the standardized mortality ratios (SMRs) or relative risk rates (RRR) are shaded accordingly. The indicators (SMRs or RRR) can be used as expected-cases of the characteristics when computed. Because a large share of the population typically occupies a small share of the land, it places the characteristics of homogeneity of population at odds. The smaller the population size of a LGA, the more likely it will have an extreme rate, either high or low because of their inverse relationships. If the population of an area shaded is small, the rate of disease estimates shows a larger figure. A slight difference in the number of cases can therefore make a huge difference in the rates, a situation often regarded as the small number problem which can be minimized by using smoothing techniques. Thus, when the areas differ in population size, as is typically the case, the calculated rates of disease for those areas have different degrees of reliability. As such, chloropleth mapping is the commonest way of analyzing disease clustering. It is particularly useful for mapping disease as privacy and confidentiality concerns often dictate that such data are released as counts aggregated to some administrative unit. Additionally, census data such as population counts and age-sex structures are also collected at the same spatial scales, thereby enabling easy calculations of crude or population age-sex adjusted disease rates. Tiwari and Rushton (2005) have addressed the issuer of small numbers in disease mapping using the chloropleth method, but the discrete nature of the administrative boundaries is also not reflective of the spatially continuous nature of the disease risk being mapped.

Measles is a deadly contagious respiratory disease of children, usually under fives, transmitted through the air by direct person-to-person contacts with infected secretions. In tropical regions, especially the arid and semi-arid areas, most cases of measles occur during the dry season. As it is well known, infectious disease easily spread to other areas when favourable conditions are ripe. The possibility of spread of measles is therefore high in an environment that is mostly dry and hot during a greater part of the year. That notwithstanding, possibility exists that other non-spatial factors could play a role in the spread. This study therefore seeks to map the distribution of measles in Zamfara State, Nigeria, with a view to uncovering geographical variations in addition to the seasonality of the disease so as to develop new ideas about the causes of the disease. Specifically, the study will compare and explain patterns displayed by different data sets and methods in a bid to hypothesize aetiological factors and areas of high risk of the disease, as well as hint on the mechanisms of transmission.

II. STUDY AREA

Zamfara State lies between longitudes 4°55"E and 7° 20"E and Latitudes 10° 15"N and 13° 25"N to the south of Niger Republic, east of Sokoto State, west of Katsina State and north of Kaduna, Niger and Kebbi States (Figure 1). It is one of Nigeria's states created out of Sokoto State on 1st October 1996 and had a population of 3,278,873 people as at 2006 (NPopC, 2006) a projected population of 4,560,808 in 2017, consisting of 14 LGAs, namely, Anka, Bakura, Birnin Magaji/Kiyawa, Bukkuyum, Bungudu, Gusau, Gummi, Kaura Namoda, Maradun, Maru, Shinkafi, Talata Mafara, Tsafe and Zurmi.

The climate of Zamfara is warn tropical continental, with temperatures rising up to 38 °C (100.4 °F) and above between March to May. Rainy season starts in late May to September while the cold season known as Harmattan lasts from December to February. The Harmattan comes with cold dry dusty winds which reduces visibility drastically. In terms of vegetation, the northern part of the state is grassland Savannah while in the southern part is the Savannah woodland. Most of the State also lies within the Basement Complex rock formation that has many rock outcrops featuring as the inselbergs in Kotorkoshi, residual hills in and rock rubbles in LGAs. The State is therefore blessed with a lot of solid minerals, especially gold, although the largest occupation is agriculture. However, this geological formation has limited potentials for aquifers that retain water during the dry season.

A more recent feature of Zamfara State is the issue of armed banditry and kidnappings, thereby generating forced migrations across the state and even beyond. This may have serious consequences on disease transmission.

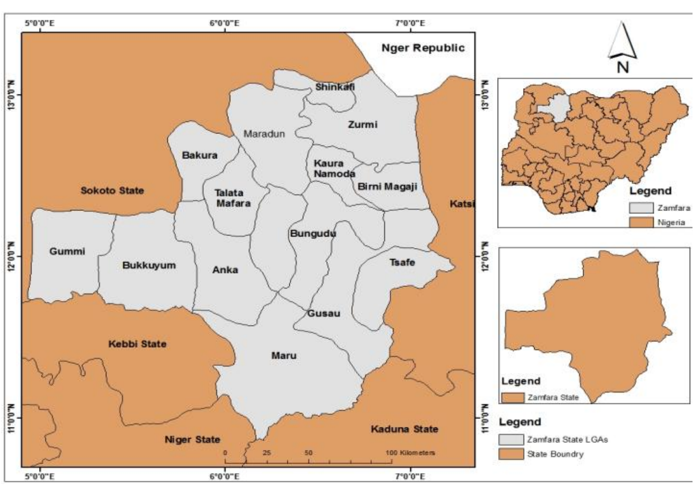

Figure 1: The Study Area

III. CONCEPTUAL FRAMEWORK

The study of human diseases has for long been through mapping as a tool to understanding the nature and pattern of the incidence or prevalence of the disease (Koch, 2005; Rao, 2003). In this study, we try to obtain reliable estimates of measles risk based on counts of observed cases and the 'at risk' population within LGAs in Zamfara State, Nigeria. Our goal is to statistically determine the precise local estimates of measles risk for each LGA by relating the observed cases with the 'at risk' population. Generally speaking, LGAs on the edges of the study domain often have fewer neighbours and hence less information to draw from than interior LGAs, thus resulting in "edge effects' of reduced performance. This also means that adjacency-based neighbourhoods can correspond to very different ranges of spatial similarity around geographically large LGAs. The framework utilized here is a hierarchical model of disease mapping adopted from Banerjee **(**2016). It provides a convenient conceptual framework wherein one induces positive spatial correlation across the estimated local measles rates through a *conditionally auto-regressive random* (CAR) effects distribution on specific areas. It offers a flexible and robust tool of estimating small area rates. This study made use of the Markov random fields (MRF) models that view the conditional distribution of a disease from a region (or an LGA), in relation to other regions (or LGAs), as depending only on the observations in its immediate neighbour (LGA) of which it shares a common boundary. For instance, if Yi is the observed number of measles cases of an LGA i,i =1,...,n, and Ei is the expected number of cases in this same LGA, the relationship will be:

$$Y_i \overset{ind}{\sim} \text{Poisson}\,(E_i e^{\mu i}),\ i = 1,...,n, \qquad 1.$$

where $\mu i = x_i^T \beta + \varphi_i$ represents the log-relative risk expressed in terms of departures of the observed from expected counts, each x_i is a vector of explanatory variables or covariates associated with the LGA i having parameter coefficient β, and $\varphi_i s$ are spatially correlated random effects. We place a form of Gaussian MRF model, commonly referred to as the conditionally autoregressive (CAR) prior, on the random effects $\varphi = (\varphi_i,...,\varphi_n)^T$, i.e.,

$$\varphi \sim N_n(0,[\tau(D-\alpha W)]-^1), \qquad 2.$$

$$f(x) = a_0 +$$

where N_n stands for the n-dimensional normal distribution, where D is a diagonal matrix with elements m_i that represent the number of neighbour LGA i, while W represents the adjacency matrix of the map where the parameters are τ^{-1} for the spatial dispersion and α for the spatial autocorrelation. The conditional distribution of φ_i is thus computed as:

$$\Phi iI\ \Phi j, j\ \neq\ i, \sim N\ \left(\frac{\alpha}{m\mathrm{i}} \sum_{i-j} \phi\, j, \frac{i}{\tau mi}\right),\ \ i,j = 1,,,,,n, \quad 3$$

where i ~ j represent LGA j being a neighbour to LGA i. This model reduces to the well-known intrinsic conditionally autoregressive (ICAR) model if α = 1which induces local smoothing by borrowing strength from the neighbours. The smoothing parameter α, controls the strength of spatial dependence among the LGAs.

IV. MATERIALS AND METHODS

Measles prevalence data for the year 2017 in each of the 14 LGAs of Zamfara State, furnished by the State Ministry of Health, were used, while the population data of children aged 0-9 years, considered as 'at risk', was obtained from the National Population Commission (NPopC,2006) and projected to 2017 for each of the LGAs. Data on available healthcare facilities and health personnel as at 2017 in the state were also obtained from the State Ministry of Health. The relative risk prevalence rates of measles were computed by dividing 'at risk' population by the overall LGA prevalence data and then calculating the relative risk using the standardized mortality ratio (SMR) method (Ijlal, Aziz and Kasim, 2017:133). Such rates were also separated into dry (November – April) and wet (May – October) seasons with a view to discerning seasonal variations. The SMR Method compares the observed prevalence with the expected prevalence calculated as: $O_i = Q_i/E,$

where O_i is the observed number of deaths cases of the disease in the area and E_i is the expected number of cases. The expected number of cases (E_i) was computed for each of the LGAs from the observed values (O_i), and using O_i and E_i as obtained based on the available data, the most common indices were calculated to estimate the relative risk

*O*i for LGA *i*, which is the SMR model defined as follows:

$r_i = O_i = Q_i/E,$

The relative risk indices (r_i) were used in plotting the chloropleth maps for both the annual and seasonal rates. Similarly, bar graphs were drawn using the monthly prevalence data so as to show monthly variations.

V. RESULTS AND DISCUSSION

Relative risk rates presented in Table 1 were used in drawing a chloropleth map (Figure 2a). Figure 1a shows the pattern of measles using raw prevalence data for the LGAs while Figure 2b shows the pattern using the relative risk rates. From Figure 1a, it is obvious that the most risky LGAs of measles are Shinkafi, Zurmi, Maradun and Bakura, with Maradun having the highest risk of the disease. These LGAs are followed by Bukkuyum, Anka and Talata Mafara. The least risk of measles is posed at Birnin Magaji, Bungudu, Gusau, Kaura Namoda and Maru LGAs. Gummi and Tsafe seem to be on the average. This pattern may seem normal if the locations of these LGAs are considered, being in the far north which is the arid part of the state, and believing that measles incidence is usually promoted by high temperatures and aridity. We should however bear in mind that other abstract factors such as population size, lifestyle, socio-cultural settings, differing control programmes and settlement forms and patterns may also play a role. Most especially in the case of measles, it is not every member of the population that gets infected: children under the age of ten are the susceptible population which form only a proportion of the LGA population. For this reason, the relative risk data were used to draw another chloropleth map to show this pattern,

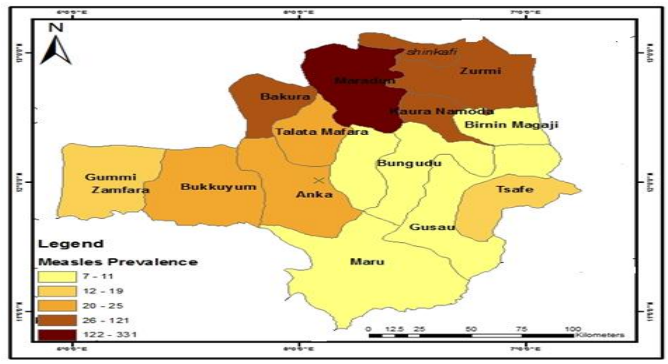

Figure 2a: Raw Measles Prevalence (2017)

Source: Data from Zamfara State Ministry of Health

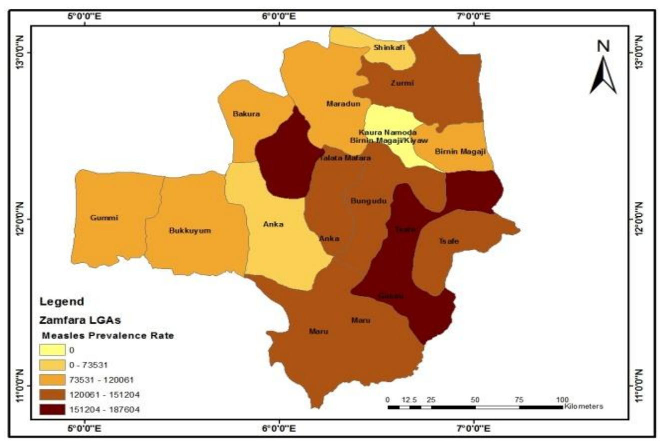

Figure 2b: Measles Prevalence (2017) Using 'at Risk' Population

Source: Data from Zamfara State Ministry of Health

Table 1: Computation of Standardized Mortality Rate (SMR) or Relative Risk Rate (RRR) of Measles

LGA	Measles Prevalence (2017)	Projected 'At Risk' Population (2017)	(O*i*)	(E*i*)	SMR or RRR r*i*
Anka	**72**	73531	1,021	0.345750085	1,021
Bakura	**20**	98876	4,944	1.674229597	4,942
Birnin Magaji	**269**	96234	358	0.121232645	358
Bukkuyum	**105**	120061	1,143	0.387064003	1,143

Bungudu	**422**	129928	308	0.104300711	308
Gusau	**377**	187604	498	0.168642059	498
Gummi	**119**	106995	899	0.304436167	899
Kaura Namoda	**26**	145774	5,607	1.898747037	5,605
Maradun	**07**	107458	15,351	5.198442262	15,346
Maru	**318**	151204	476	0.161192008	476
Shinkafi	**15**	70455	4,697	1.590585845	4,695
Talata Mafara	**152**	167115	1,099	0.372163901	1,099
Tsafe	**192**	141286	736	0.249238063	736
Zurmi	**36**	151191	4,200	1.422282425	4,199

Sources: Zamfara State Ministry of Health and National Population Commission (2006)

One of the aims of drawing disease maps is to identify spatial clusters so as to generate hypotheses regarding common underlying environmental, demographical, or cultural factors that explain the pattern of disease distribution. However, in identifying spatial clusters so as to generate hypotheses when drawing of producing disease maps, there are two kinds of processes that explain the pattern of disease distribution, i.e. the first and second order. The first order processes involve points being located independently but may result in clusters because of varying point density. The second order processes involve interaction between points and tend to cluster when interactions are attractive in nature, and disperse when they are competitive or repulsive. Thus, when crude incidence or prevalence rates are used for the analyses, conclusions are always spurious particularly when population sizes of areal regions (such as LGAs) are small, giving rise to large variability in the estimated rates (Banerjee, 2016: 48).

With the relative risk rates, Figure 2b shows that Zurmi LGA is still one of the LGAs with the highest risk of the disease. Others are Talata Mafara and Gusau LGAs, These are followed by LGAs mostly with the lowest risk using the raw data in Figure 2a (Maru, Bungudu, Gusau and Birnin Magaji LGAs). Bukkuyum LGA still maintains its position of average risk, while Gummi, Anka, Maradun and Birnin Magaji have the same average status as Bukkuyum. What is obvious here is that there is a shift in the relative risk more to the southern LGAs that appear to be more urbanized. It has been observed that when disease data is aggregated with that of areas of sparse population (leading to scale change), there could be a spatial variation in aetiological factors, such as between rural and urban areas, giving rise to unstable estimates and mis-information about “true risk”. Similarly, if data is collected and analysed based on aggregation, it is acceptable to the scale/shape of the unit – which are we know, are defined by administrative fiat and so these problems are unavoidable. Tufte (1983:200 has observed that “our visual expression of the data is entangled with the circumstances of geographic boundaries, shapes and areas” as in the case of Maru LGA. Large areas that draw the eye, such as Bungudu LGA, tend to have low population, so that the most prominent parts of the map have rates that are disproportionately extreme. In terms of compactness, then square and rectangular LGAs of Gummi and Bukkuyum, lend themselves to mapping and pattern identification more readily than the irregular LGAs of , Maru, Gusau and Bungudu. In view of this, one of the questions to be asked about distribution pattern of points where measles is prevalent is whether they display a random pattern in the sense that all locations are equally likely to contain a point where the disease is located, or whether more locations are likely than others, and particularly whether the presence of the disease makes other locations/areas either less or more in its immediate neighbourhood.

When looking at population size as a confounder, Shinkafi LGA with 37,979 people is more likely to have an extreme rate than Gusau LGA with 101,706 people. Figure 1 shows that nearly all of the LGAs in the highest and lowest quartiles for measles are in the rural parts of the state. This is the reality of the situation in the sense that cognizance was not taken not only of the spatial spread, but also of the actual people at risk. But the fact that the highest risk LGAs are in the southern part shows that many factors are responsible for the spread of the disease, not only climate or weather. The factors could include population size acting as a confounder, settlement patterns, nature of settlements or buildings, preventive measures against transmission, lifestyle and physical barriers such as hills and mountains as found in Tsafe and Maru LGAs.

In terms of minimum land area and population thresholds, the problem was not that the sparsely populated hilly LGAs (such as Maru and Tsafe), but that information about the densely populated LGAs (such as Gusau) was impossible to discern. Chromly (2003:12) has observed that more often than not, we tend to ignore other possible sources of disease agents, especially with the rising threat from biological weapons and the inherent risks of genetics research programmes, of whose locations, routes and modes of agents’ transmission are also little known. Another inherent danger is the spate of banditry and kidnappings that has generated series of forced migrations within and outside the state, a situation which could further spread the disease. The role of relocation in geographic disease diffusion has been succinctly discussed by Meade & Emch (2010).

To further illustrate whether climate or seasons have any effect on the pattern of measles in Zamfara, the relative risk rates were plotted for the dry and wet seasons. Wet season is expected to start in April and end in September while the dry season sets in between October and March. These patterns are shown in Figures 2a and 2b, which indicate that seasonality does not play a significant role in the prevalence of measles in Gummi, Bukkuyum, Maru and Talata Mafara LGAs. Zurmi, Shinkafi and Kaura Namoda LGAs in the far north however still show high relative risks, perhaps due to high temperatures and dryness. Conversely, Maradun LGA, which had the lowest relative risk during the wet season, has the highest risk during the dry season, together with Kaura Namoda LGA. Although seasonality plays a role among some LGAs during the dry season, spatial variations do exist to warrant attribution of the prevalence on other abstract factors. The maps have helped not only to visualize the pattern of prevalence, but also served as a means of hypothesising other causal factors.

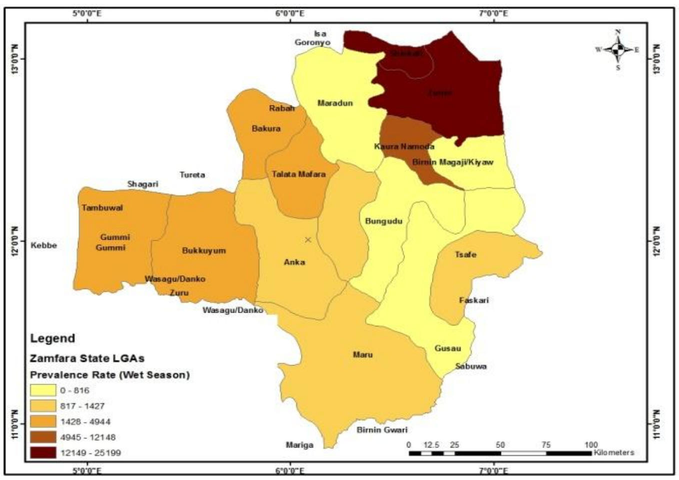

Figure 3a: Measles Prevalence (2017) - Wet Season (Apr – Sep.)

Source: Data from Zamfara State Ministry of Health

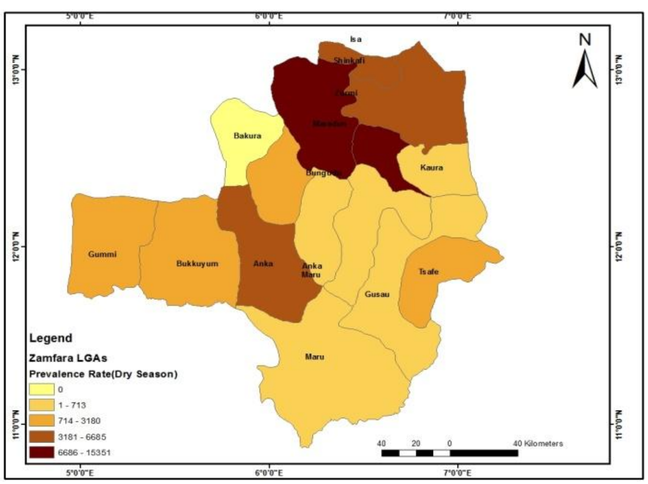

Figure 3b: Measles Prevalence (2017) - Dry Season (Oct. – Mar)

Source: Data from Zamfara State Ministry of Health

To further investigate the role of weather on measles prevalence, a bar chart was drawn for the monthly relative risk rates (Figure 3) This shows that March and April have the highest relative risk rates, followed by February and May from when it begins to decline. March and April are the months of highest recorded temperatures; immediately after the cold harmatan season and before the onset of the rains. The lowest risk is in January almost at the peak of the harmatan and some high rates in October, also at the onset of the harmatan. Perhaps, this goes to show that there is some relationship in the incidence of measles with hot climate but dryness does not necessarily promote the incidence of the disease except with high temperatures. The bar graph is supportive of the seasonal patterns depicted by the choloropleth maps. The cholropleth maps are however not without weaknesses. Hence, point patterns of disease should be experimented within spatial analysis.

According to Ruston (2003:44), several authors have observed the inferior status of choropleth maps as smoothed maps of disease with the areas serving as filters since changes in disease rates are always gradational. Similarly, chloropleth maps are likely to show variability among areas of small populations at risk, particularly with smoothed maps of LGAs along border areas where the filter area is curtailed by the border (Ruston, 2003: 48).

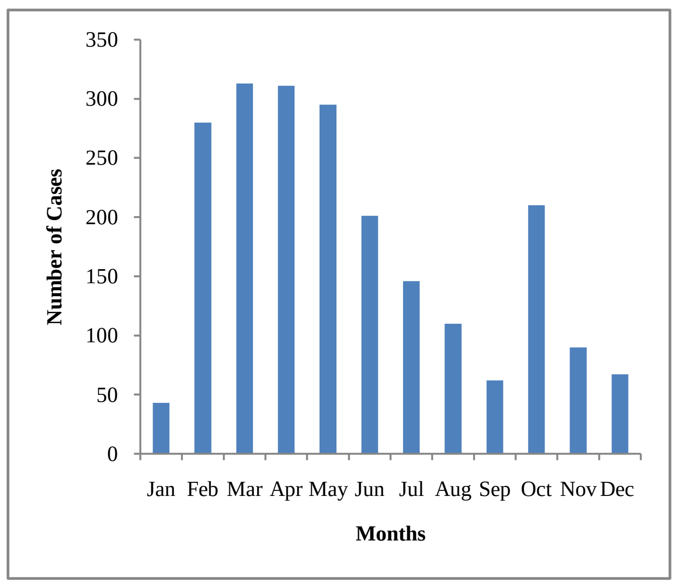

Figure 4: Monthly Prevalence of Measles in Zamfara State (2017)

Source: Data from Zamfara State Ministry of Health

To further find explanation on the nexus between healthcare provision and the prevalence of measles in Zamfara State, data are provided on the categories and numbers of healthcare facilities, physicians, nurses and other auxiliary staff available in all the LGAs of the state. These are presented in Table 2. LGAs with the highest number of facilities and personnel, and perhaps the required facilities that could counteract the incidence of measles are Gusau, Bungudu, Kaura Namoda and Tsafe. These are also the ones with the lowest relative risk rates, except perhaps Kaura Namoda LGA, which could be explained in terms of its location in the northern part of the state. Even where the number of healthcare facilities is large, the fewer number of personnel (physicians, nurses and midwives) seem to play a role in the prevalence. Buildings alone cannot deliver care without the services of personnel. This must have impacted on the incidence and spread of measles in the LGAs. Thus,

Table 2 Correlation between Number of health personals and the prevalence of measles

		Measles Prevalence	Personal
Measles Prevalence	Pearson Correlation	1	-.004
	Sig. (2-tailed)		.988
	N	14	14
Health Personal	Pearson Correlation	-.004	1
	Sig. (2-tailed)	.988	
	N	14	14

The Pearson's Correlation Coefficient used reveals a significant inverse correlation between the availability of health personals and prevalence of measles in the study area p=0.004; where provision adequate of health personals could reduce the measles prevalence by about 97.6% (r=0.988) Table 2). Chromley (2003: 7) has observed that the geographical differences in the availability and utilization of health services determine the accuracy in capturing spatial pattern of the prevalence and morbidity of a disease in a population. So, even where data are available, their accuracy matters, depending on the type and quality of staff and the available diagnostic facilities.

It will suffice to state that although the relative risk rates were computed to smooth out the prevalence so as to reduce the possible impact of population size as a confounder, issues of modifiable area unit problems (MUAP) are still persistent since not all the LGAs are of the same sizes and spatial configurations. The issue of rural and urban disparity is also there. It is therefore imperative that analyses and interpretations of the maps should always take these shortcomings into cognisance.

Table 2: Functional Health Facilities and Personnel in Zamfara State (2017)

LGA	GH	PHC	Doctors	Midwives	Nurses	Others
Anka	2	40	2	18	12	285
Bakura	1	24	3	5	10	208
B/Magaji	1	42	2	4	10	206
Bukkuyum	1	37	0	5	8	205
Bungudu	1	64	4	19	25	528
Gummi	1	39	2	11	28	161
Gusau	4	52	41	39	86	852
K/Namoda	2	61	7	22	54	310
Maradun	1	46	1	4	13	186
Maru	2	48	2	5	24	302
Shinkafi	1	39	1	5	14	212
T/Mafara	2	42	3	13	19	242
Tsafe	1	52	5	24	19	302
Zurmi	2	54	3	5	31	132

Source: Zamfara State Ministry of Health, 2017

VI. CONCLUSION AND RECOMMENDATION

The Chlorpleth maps of measles in Zamfara State have provided visualization of the spatial patterns of the disease, but interpretation is never conclusive. The study has simply provided highlights on LGAs of highest risk to the disease which may deserve immediate attention and possible monitoring. It has also highlighted on the possible factors responsible for hypothesising these causes with only first order hypotheses. More detailed studies need to be carried out so as to examine the role other variables like immunization with a view to addressing them where point-pattern analysis is employed. The study has also shown possible effects of data aggregation of which once done, any lost information cannot be recovered. This may invariably affect the general outcome of the pattern, particularly when trying to assess causative factors.

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