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Space-Time Mapping of Malaria Local Endemicity in Nigeria using Two Decades Incidence Rate Data

***Nkeki, F.N. and Omoroghomwan, A.E.**

UNIBEN Research and Training Team on Malaria (URTTM), Centre of Excellence in Reproductive Health Innovation (CERHI), University of Benin, PMB 1154, Benin City, Nigeria.
*nkekifndidi@gmail.com

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ABSTRACT

The few obtainable literatures focusing on the mapping of malaria endemicity are highly descriptive in approach. No studies have attempted to objectively identify the local strata of the endemicity or long-term hotspot and coldspot of malaria in high burden areas. Hence, this study analyses the spatial and temporal pattern of falciparum malaria endemicity using 20 years of incidence data on a second-level administrative boundary of Nigeria. Getis-Ord Gi hotspot detection statistic designed to identify significant hotspot and coldspot was used to identify the spatial dynamics of hotspot and coldspot. To detect malaria-endemic areas and derived the significant endemic temporal cluster maps, emerging hotspot analysis and local outlier analysis were carried out using an initially generated space-time cube. The result shows that there is local heterogeneity in the clustering patterns of the malaria incidence rate. Also, a local endemicity map was produced and this shows that high endemic malaria strata seem to cluster around the Nigeria-Benin Republic border and Nigeria-Cameroon border. This suggests that cross border transmission may be taking place over these years. The adopted approach in this study is a robust and appropriate way of modelling space-time data. In epidemiology, the major challenge in intervention deployment, smart resource allocation, surveillance, monitoring and evaluation is the ability to locate spatial clusters of disease infection. The implication of these results is that they provide the springboard for the design of various malaria control and elimination strategies and this will serve as a vital tool for informed decision-making during interventions and surveillance.*

1. INTRODUCTION

Africa is the most famous malaria-endemic region because of its *falciparum malaria* burden which has become pervasive in many countries of the region (Adetunji et al., 2022). Although, roughly 3.3 billion

people accounting for about half of the world's population in 106 countries are estimated to be affected by human malaria. The majority of these incidences occur in Africa countries. For example, of the over 215 million clinical cases of malaria recorded in 2010, African countries accounted for 81% of such cases. Also, 655,000 malaria mortality was recorded in 2010, and African countries accounted for 91% of the death cases (United State Embassy in Nigeria, 2011). Within the Africa region, there is also a pronounced level of uneven prevalence of the disease. Countries in sub-Saharan Africa carry a significant proportion of the global malaria burden. The 2017 World Health Organization (WHO) malaria report revealed that 15 countries in sub-Saharan Africa and India accounted for roughly 80% of the global malaria cases and among these, five countries carried almost half of the global cases (WHO, 2018). Concerning mortality, 13 sub-Saharan Africa countries account for 90% of the global figure (United State Embassy in Nigeria, 2011).

Contemporary studies have shown that since after the year 2000 the global burden of *falciparum malaria*, a parasite of the *plasmodium* genus, is on the decline (Bhatt et al., 2015). A significant decline has also been recorded in other endemic countries in sub-Saharan Africa. This decline may be credited to the various malaria interventions such as the distribution of insecticide-treated nets (ITN), use of vector control spray, rapid diagnostic tests, etc (Bhatt et al., 2015; Weiss et al., 2019). Despite the achieved significant global decline for nearly two decades, Nigeria's cases have remained high and insignificantly dropping even though various malaria interventions were implemented. Nigeria seems to be the most *falciparum malaria*-endemic country in the world because it carries about 25% of the global malaria burden (NPC, 2012; WHO, 2018; Adetunji et al., 2022; Ogbulafor et al., 2023).

However, *falciparum malaria* endemicity in Nigeria is not homogeneous as there may be a significant hotspot and coldspot of cases across space and time. Some areas may be consistently low over time, some may be consistently high and yet others may manifest fluctuating patterns. Earlier studies have revealed that malaria incident level is largely heterogeneous over space (Laguna et al., 2017; Grillet et al., 2010). Epidemiologists are interested in identifying both hotspot and coldspot areas of malaria incidence. Hotspot areas would provide insight and understanding of nature, the causative environmental factors, and other baseline information that may influence the spread of malaria. On the other hand, identifying coldspot areas may also provide needed information on the factors influencing such low cases. Overall, information on the spatio-temporal clustering pattern at the local level may be useful for identifying a high-risk area for prioritizing resource deployment, planning, monitoring, evaluation, surveillance, etc. for effective malaria elimination plan at the country-level and driving towards global eradication of the disease.

Literature review shows that only a handful of studies have been conducted on malaria incidence mapping, spatial and temporal modelling of the distribution of cases (Zacarias and Andersson, 2010; Bhatt et al., 2015; Shekhar et al., 2017; Weiss et al., 2019). A significant proportion of these studies focused on analyzing the factors that influence cases (Laguna et al., 2017; Alegana et al., 2013; Lucas et al., 2020; Adebayo et al., 2016; Weiss et al., 2015). There are far fewer than adequate studies on malaria endemicity mapping. The available literature on the global mapping of malaria endemicity shows that sub-Saharan Africa is a centre for *falciparum malaria* incidence, case mortality and clinical burden and these studies used descriptive approach in their analysis (Guerra et al, 2006; Dalrymple, 2015; WHO, 2018; Battle et al., 2019; Weiss et al., 2019). A substantial amount of other studies concentrated on predicting the incidence and risk of the disease in association with some covariates (Kleinschmidt, 2000; Weiss et al., 2015; Alegana et al., 2016; Adebayo et al., 2016; Cohen et al., 2017). Yet no studies have attempted to objectively identify the local hotspots and model the level of endemicity of malaria in high burden areas using long temporal span hotspot data. There is, however, a justifiable need to understand the spatio-temporal pattern of malaria incidence at a local scale. This is because malaria endemicity may strongly be determined by local factors that exist within such local ecology. Epidemiologists and public health practitioners have come to realize the importance of modelling the local heterogeneity of diseases as this would guide informed decisions and most importantly promote local elimination to the global eradication of malaria cases.

The major objective of this study is to analyse the local spatial and temporal pattern of *falciparum malaria* endemicity using 2 decades of incidence data on a second-level boundary administration geographic

information system (GIS) dataset. This was achieved by conducting a spatial statistical computation of hotspot and coldspot analysis for each temporal period so that areas with perpetual temporal hotspot would be identified. The rest of this paper is divided into Section 2- which describes the study area and data; 3- which looks at the methodology of the study; Section 4-which present the analysis and results; Section 5- which discusses the findings and then the conclusion.

2. METHODOLOGY

2.1. Study Area and Malaria Datasets

The study area is Nigeria that is located in West Africa and the sub-Saharan region where *falciparum malaria* has been known to be endemic for several decades. Nigeria is positioned geographically between latitude 4°9'N to 13°46'N and longitude 3°45'E to 16°54'E (Figure 1). Its area coverage is roughly 910,770 square kilometres with an estimated population of 206,139,589 at the mid-year of 2020 and projected to reach 401,315,000 (almost double) in 2050 (United Nations, Department of Economic and Social Affairs, Population Division, 2019). United Nations 2020 ranking placed the country at 7 most populous nation in the world containing 2.64 per cent of the world's total population. There are 36 states and a federal capital territory in Nigeria broken down into 774 local government areas (LGAs). The datasets and analysis are based on the 774 local administrative units or LGAs (Figure 1). Two major secondary datasets with spatial and temporal characteristics were obtained and utilized in this study. The first is temporal data on *falciparum malaria* incidence rate (annual mean) per 1000 persons at a sub-national administrative unit. This dataset was downloaded from the malaria atlas project (MAP) site and its temporal period spans from 2000 to 2019 accounting for two decades. The datasets in spreadsheet format (.csv) are respectively tied to the name of the LGAs for all temporal periods. This will facilitate the integration between the spreadsheet data and spatial data. Through country-wide surveillance and compilation, the clinical cases were reported as incidence per 1000 of the population in a year. These cases were confirmed either by the microscopic or rapid diagnostic test (RDT) method. The data was aggregated into LGA spatial boundaries (polygons). The second is the spatial boundary dataset in polygon shapefile format which was download from the GADM site (www.gadm.org). The dataset was provided at the level-2 administrative unit for the 774 LGAs of 37 states of Nigeria.

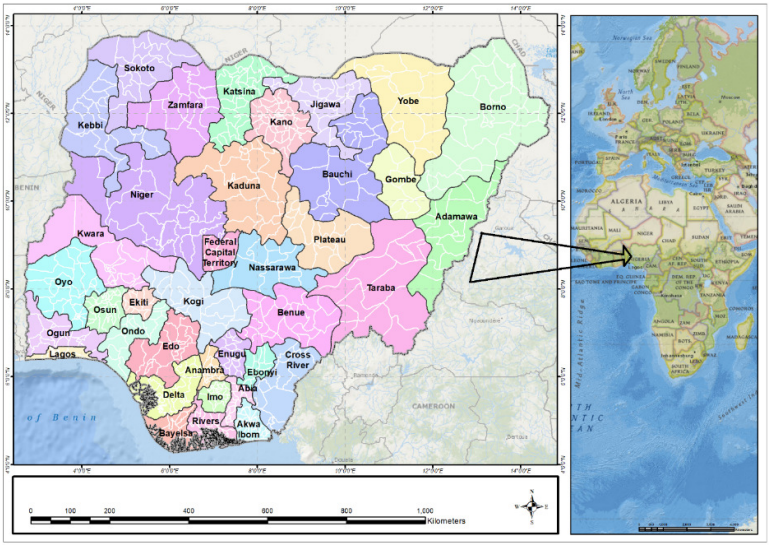


Figure 1: Study location-Nigeria State and LGA administrative boundaries (State and LGA boundaries are shown in black and white respectively)

2.2. Hotspot Detection of Falciparum Malaria Incidence

The spatio-temporal analysis was carried out with Getis-Ord Gi* hotspot detection statistic designed to identify statistically significant clusters of high values (hotspot) and low values (coldspot) (Getis and Ord, 1992). In the process, a series of maps were produced that enabled the visualization of the results of the different time steps. There is a 20-time step in the analysis which makes up 20 temporal periods on a year-to-year basis. This analysis would provide insight into the temporal dynamics and spatial patterning of *falciparum malaria* incidence rate in the study area. The Getis-Ord Gi* hotspot analysis has the capability of identifying and also quantifying local patterns of spatial dependence or autocorrection at multiple scales thereby detecting significant clusters of high values and clusters of low values in a dataset (Ord & Getis, 1995; Getis & Ord, 1992). In this case, Getis-Ord Gi* hotspot analysis in its original formulation was used to test the occurrence of malaria incidence clustering pattern at the LGA level. The local Gi* hotspot analysis formulation by Rogerson (2001) is presented as:

$$G_i^* = \frac{\sum_j w_{ij}(d)x_j - W_i^*\bar{x}}{s\left\{(nS_{1i}^* - W_i^{*2})/(n-1)\right\}^{1/2}} \quad (1)$$

In this formulation (Equation. 1), G_i^* is a local association of malaria incidence, s represents the malaria cases standard deviation (x values), $w_{ij}(d)$ is a weight matrix element which defines the LGA boundary relationship between i and j which is measured by the distance (d) between them and n is the number of malaria cases.

$$W_i^* = \sum_j w_{ij}(d) \quad (2)$$

$$S_{1i}^* = \sum_j w_{ij2} \quad (3)$$

The formulation for the weight matrix is presented in Equations 2 and 3. The weight of the spatial matrix will be equal to 1 if the LGA j has a contiguous distance relationship with LGA i and equal to 0 if otherwise.

In determining the appropriate parameter for the spatial weight matrix, the fixed distance band method of conceptualizing the spatial relationships between the LGAs boundary was applied. The fixed distance band method was selected because it is most appropriate for polygon datasets with largely uneven size as in the case of the LGA administrative boundaries of the study region (see Figure 1). In the fixed distance band method, each LGA feature is analysed within the context of neighbouring LGA features. Neighbouring LGAs that fall inside the specified critical distance or distance band receive a weight of 1 and exert influence on the computations for the target feature. Neighbouring features outside the critical distance receive a weight of 0 and do not influence the target feature's computations.

To select an appropriate distance band ensuring that every LGA has at least 5 neighbours, the incremental spatial autocorrelation statistics (Global Moran's *I*) was computed using the 2 decades of malaria incidence rate data in the 774 LGAs. In this way, the data is allowed to point to the best distance band by providing a Z-score for the entire study area. The incremental spatial autocorrelation revealed 10 bands and 1 significant peak. The incremental spatial autocorrelation statistics result reveals that the best distance band for the malaria incidence dataset is 139,677.38 meters with a significant Z-score peak of 68.5 (Figure 2). Hence, the selected distance band for the hotspot analysis is 139,677.38 meters.

2.3. Space-time Analysis of Falciparum Malaria Incidence

To identify *falciparum malaria* local endemic areas and derived the statistically significant endemic cluster maps through time, emerging hotspot analysis and local outlier analysis were computed. Emerging hotspot and local outlier analyses are both spatial statistical tools found in the space-time pattern mining geoprocessing toolbox of ArcGIS pro.

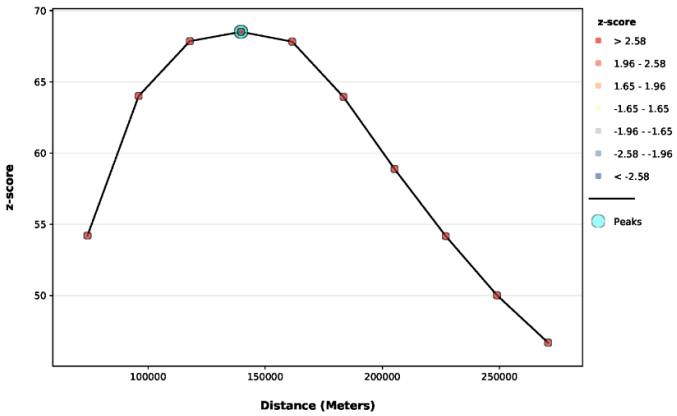


Figure 2: Incremental spatial autocorrelation for distance band selection

The emerging hotspot analysis is an extension of the Getis-Ord Gi* hotspot technique which incorporates the time factor into the initial formulation. It is expected that this technique would detect trends in the clustering of malaria incidence values in a space-time 3D cube that is created using *xyz* dimensions of the malaria datasets where the *x* and *y* represent the geographic location of the LGA polygon and the *z* represent the temporal or time step of the dataset. On the other hand, local outlier analysis is an implementation of the Local Moran's *I* statistic (Anselin, 1995). The local Moran's *I* in its original formulation have been used severally in health geography to model disease incidences and patterning, specifically to detect outliers and clusters (Goovaerts and Jacquez, 2005; Sugumaran *et al*., 2009; Imdad, et al., 2021). In this study, local outlier analysis (local Moran's *I*) was computed to identify statistically significant cluster outliers within the space-time context and such cluster was classified as malaria-endemic areas. The local outlier analysis like the emerging hotspot analysis depends on the space-time 3D cube of malaria incidence rate for its computation.

The space-time 3D cube is a vital component of the spatio-temporal analysis for malaria incidence rate because it would aggregate the set of LGA polygon into bins at the centre and then the malaria incidence data are further aggregated into the respective space-time bins. Each of the created bins in the space-time cube must have a location identification number, time step data and the incidence or event data. The bins that are associated with the same geographic location shares the same location identification number and jointly present time-series data. Likewise, bins with the same time step interval share the same time step identification number and jointly form a time slice. The malaria incidence values recorded on a particular bin reflects the incidence rate that occurred at the associated geographic location within the connected time step interval.

To compute the emerging hotspot and local outlier analyses, the space-time 3D cube was entered into each of the analyses as the baseline data. In the emerging hotspot analysis, the expected output after a successful computation is z-score, p-value, and hotspot bin classification. The resultant hotspot and coldspot trends are further analyzed using the Mann-Kendall trend test statistic and present a trend z-score and the corresponding p-value for each geographic location and the hotspot z-score and p-value for each bin.

3. RESULTS AND DISCUSSION

3.1. Falciparum Malaria Incidence Hotspot and Coldspot

Using the Getis-Ord hotspot analysis clusters of significant malaria incidence hotspot and coldspot were empirically identified and mapped. The full malaria dataset for the 774 LGAs with 20 temporal periods (2000-2019) was used for the analysis. Hotspot analysis produced 20 maps showing malaria cluster dynamics and patterns (Figure 3). Statistically significant hotspot and coldspot are LGAs that returned a *p-value* equal to or greater than 0.05 (95%) level of confidence. The hotspot that returned a 95% confidence level is described as being a hotspot 95% of the time. The same interpretation is applied to the coldspot category.

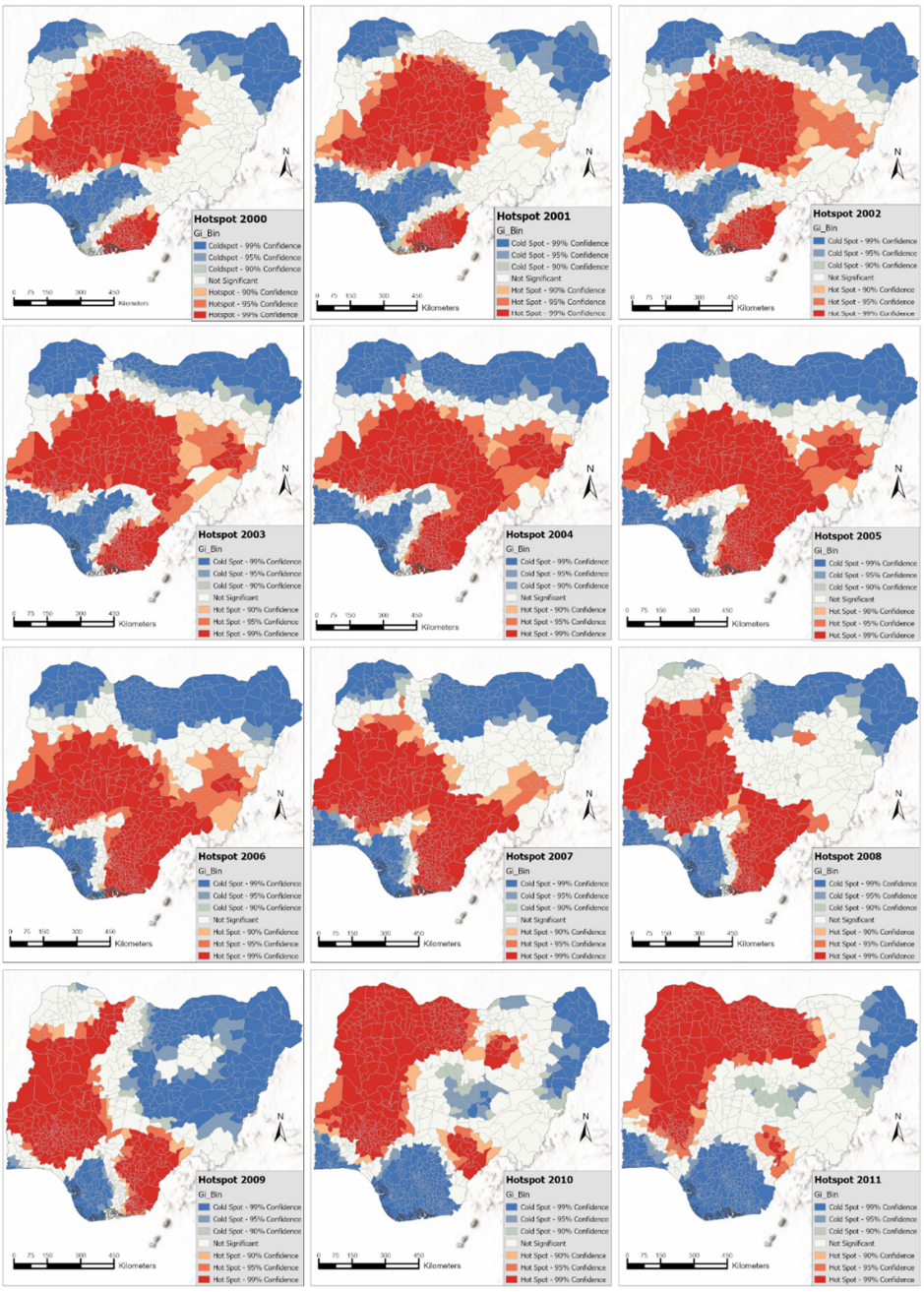
The result reveals that there are local heterogeneity and fluctuation in the clustering patterns of malaria incidence rate in Nigeria. A noteworthy observation from a deep visual inspection of the maps in Figure 3 shows that there may be a 3-year total change in the pattern and directional movement of hotspots and coldspots in the region. It shows that a new clustering pattern of hotspot and coldspot emerges within a 3-year temporal stage.

For example, the hotspot for the first 3-year temporal stage (2000-2002) seems to be consistent in pattern with slight yearly consecutive changes which involves the gradual growth of the hotspot and coldspot clusters. In this temporal stage, the *falciparum malaria* incidence hotspots cluster is largely concentrated in the north-central and western part of the country. This is followed by an isolated smaller cluster in the lower south-eastern part of the country. At the end of the first temporal stage, malaria hotspots had fully spread across the north-central region of the country and the lower south-east cluster shows a gradual growth towards the eastern part of the north-central cluster. On the other hand, the malaria coldspot cluster shows sectionalisation into 3 clusters (2 clusters at the upper north-east and north-west edges of the region and a cluster at the south-west part of the country) and a gradual aggregation of the upper north clusters.

The second temporal stage (2003-2005) marks the complete aggregation of clusters. The north-central hotspot completely merged with the lower south-east cluster. This stage presented a large cluster of malaria hotspots by LGA which spread across the north-central region and covers the greater part of the south-east region of the country. The same pattern is observed from the coldspot cluster. The upper north coldspot clusters completely merged forming a linear pattern on the upper northern edge. While the north coldspot cluster was growing, the south-west coldspot cluster was attenuating. The general pattern in this stage is a reduction in malaria incidence rate in the upper north and growth of hotspot clusters down south into the initial malaria coldspot.

In the third temporal stage (2006-2008), hotspots in the north-east and south-east began to shrink and started towards the north-west. In the same way, the initial north-west coldspot cluster began to diminish. The north-west hotspot clustering pattern in the fourth temporal stage (2009-2011) becomes intense as it extends toward the north-east along the northern edge of the country. In these LGAs, coldspot clusters were within 3 years converted to a hotspot. This indicates that there was an outbreak of *falciparum malaria* in the north-west LGAs at this temporal stage. Also, the south-east hotspot clusters continue to shrink while the coldspot clusters in the south-south and south-west continue to increase. The fifth temporal stage (2012-2014) show a general decline in hotspots and coldspot areas. The hotspot was concentrated in the north-west and the hotspot cluster began to resurface in the north-east and spread towards the south-east region of the country. Coldspot declined in the north and increased proportionately in the south specifically in the south-west LGAs.

The sixth temporal stage (2015-2017) shows a drastic reduction of the hotspot in the north-central cluster by outright conversion to coldspot, indicating a substantive attack (using perhaps an effective intervention method) on the initial malaria outbreak that emerged in the fourth temporal stage. This was confirmed by the work Ozodiegwu et al. (2023) which highlighted how the ITN intervention contributed to reduction of cases at this period. At this time, the hotspot clusters in the north-east region have extended further southward and several initial coldspot LGAs in the south-east were converted to a hotspot. In the same manner, south-west coldspot cluster became a hotspot. This means that in this temporal stage, malaria outbreaks occurred simultaneously in the north-west, south-west, north-east and south-east regions forming a strip along the Nigeria-Benin and Nigeria-Cameroon borders. This same pattern continued into the seventh temporal stage (2018-2019). The south-south coldspot cluster began to grow thin as the hotspot clusters from the south-west and south-east started to engulf the initial coldspot cluster. This observed boundary fluctuation and incidence dynamics have been reported by Grillet et al. (2010). Also, the temporal dynamic most likely is caused by series of intervention in various regions and the attitudes inherent in utilization (Makinde et al., 2021; Ozodiegwu, et al., 2023).



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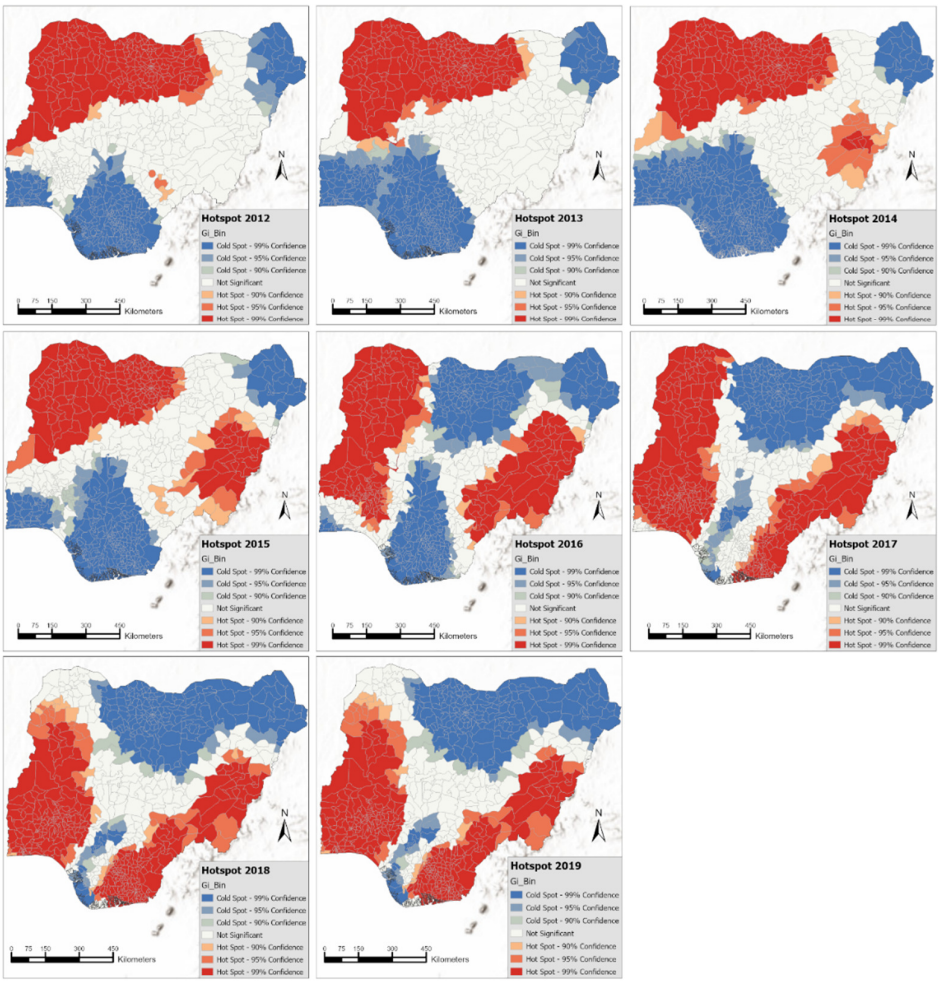

Figure 3: Local hotspot and coldspot of falciparum malaria incidence rate across Nigeria LGAs from 2000-2019

3.2. Falciparum Malaria Endemicity

The results of the spatio-temporal analysis for malaria local endemicity are shown in Figure 4, 5 and 6. Figure 4 reveals that from 2000 to 2019 malaria incidence rate had generally been on the decline. The rate of decline is quite slow and such observed decline started in 2008 perhaps due to the various intervention that became available such as the use of ITN and indoor spray. Figure 5 is the result of the emerging hotspots computed from the space-time cube to determine significant changes over time.

Several hotspots and coldspots patterns were revealed, for example, intensifying hotspot, consecutive hotspot, persistent hotspot, oscillating hotspot and historical hotspot occurred in the LGAs located in the western margin of the country along the Nigeria-Benin republic border. The intensifying hotspot that occurred in Kaiama LGA in Kwara State, indicate that Kaiama LGA has been significantly hot at least 90% of the time over the last 20 years (i.e. malaria cases in this LGA is significantly increasing). Also, the consecutive hotspot that occurred in 14 LGAs is an indication that these LGAs significantly manifest malaria hotspot year after year over the last 2 decades. Persistent hotspot occurred in 8 LGAs and this pattern of hotspot indicates that about 90% of the time over the 20 years, hotspot occurred here persistently. Oscillating hotspot occurred in 13 LGAs and this means that in these LGAs, there is an interchanging pattern from hot

to coldspot and vice versa. There are 2 LGAs that manifested historical hotspot pattern and this pattern indicates that these LGAs initially were a significant hotspot, though it has lost this characteristic, there is a chance for such pattern to reemerge.

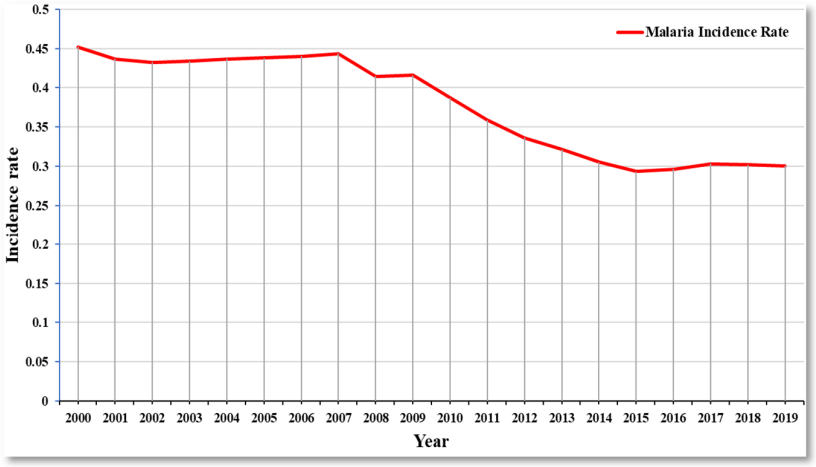

Figure 4: The temporal trend of malaria incidence rate (annual mean) from 2000-2019 in Nigeria

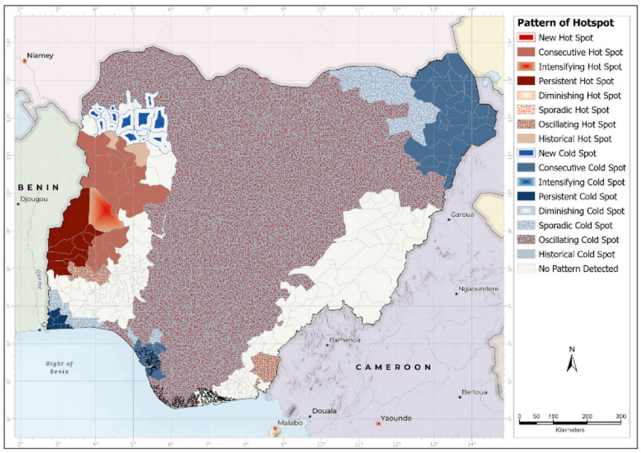

Figure 5: Emerging falciparum malaria hotspot and coldspot from 2000-2019

Four major coldspot patterns occurred in Figure 5. They occurred in clusters in the northeast edge, northwest and on the southwest edge of the country. These patterns are new coldspot, consecutive coldspot, persistent coldspot, and sporadic coldspot. To further understand and generate a malaria endemicity map from the spatio-temporal analysis, the need to compute significant clusters of hotspot and coldspot arises. Local outlier analysis was used to identify and combine the statistically significant clusters of hotspot and coldspot patterns that emerged from Figure 5 on the one hand, and the presence of local outliers on the other hand within the space-time context (Figure 6). Figure 6 shows that there are no significant high-low outlier and a low-high outlier in the result. The significant high-high cluster represents LGAs with a 20 years high incidence of malaria rate surrounded by LGAs with high cases also for 20 years period. This cluster seems to correspond with the intensifying hotspot, consecutive hotspot, persistent hotspot patterns that occurred in the western margin cluster in Figure 5. Another high-high cluster was revealed in the southeast margin of the country by the Nigeria-Cameroon border.

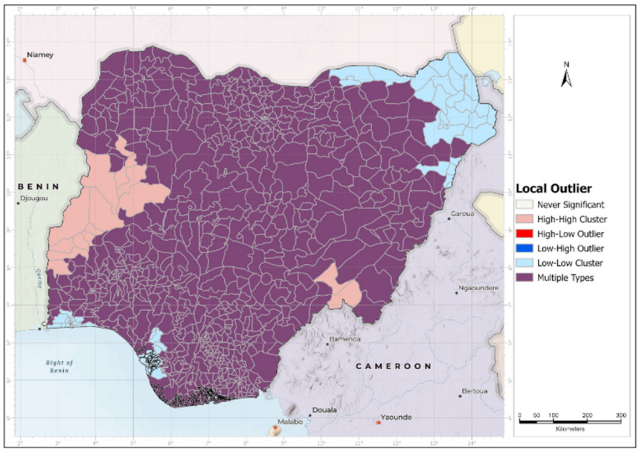

Figure 6: Local outlier analysis for detecting spatio-temporal clusters of malaria endemicity

The low-low cluster in Figure 6 also corresponds with coldspots in Figure 5. The low-low cluster indicates that for a temporal period of 2 decades LGAs with a low malaria incidence rate are surrounded by LGAs with a low incidence rate. The low-low clusters occurred in the northeast edge and southwest margin of the study area. The multiple types cluster is characterised by LGAs with oscillating clustering behaviour over time (not significantly homogenous to be called a hotspot or a coldspot). This cluster which falls in between the high and low clusters covers a larger proportion of the country. To further understand and simplify the cluster patterns, the high-high cluster was reclassified as a high endemic area. This is because the LGAs that makes up this cluster were significant malaria incidence hotspot for the 20 years under study. The low-low clusters were classified as a low endemic area since such LGAs manifest as significant coldspots through the 20 years. The multiple types of clusters were reclassified as medium endemic areas (Figure7) because they consist of LGAs with diverse cluster patterns that kept changing over time. The medium endemic cluster is as important as the others because it can metamorphose into high and into the low endemic area when changes in malaria incidence rate occur.

Figure 7 revealed two major clusters of high *falciparum malaria*-endemic area and 3 major clusters of coldspot. The identified significant 20 years high endemic areas are clustered along the greater part of the Nigeria-Benin Republic border, covering 13 LGAs in Kebbi State, Niger State, Kwara State and Oyo State. The second-high endemic cluster occurred along the Nigeria-Cameroon border covering 2 LGAs in Taraba State. The largest low endemic cluster occurred in the northeast region, along the Nigeria-Cameroon border and the Nigeria-Niger border. This cluster covered 25 LGAs in Borno State, Yobe State and Adamawa State. The second low endemic cluster occurred in the south-west region along the Atlantic coast. This cluster covers 20 LGAs in Lagos State and Ogun State. The third low endemic cluster occurred in the south-south region of the country, covering 8 LGAs in Delta State and Edo State.

The results of this empirical study revealed that there is a general decline in *falciparum malaria* in Nigeria. The temporal trend of malaria incidence rate per 1000 persons shows that the drop in the incidence started in 2007 up to 2015 from where it started to flatten out to 2019. Despite this decline, uncertainty characterises the thought of whether the country is driving towards the pre-elimination stage or how long it will take to get there. This is because Figure 7 shows that a significant amount of the LGAs (706) falls with the medium endemic cluster. This cluster type is a combination of cluster patterns oscillating from hot to cold and from cold to hot over the 20 years. Figure 3 presented a clear picture of this scenario where there is a 3-year consistent spatial and temporal change in the pattern of hotspot and coldspot clusters. This oscillatory behaviour may be caused by socio-spatial behavioural and or environmental dynamism inherent in these areas.

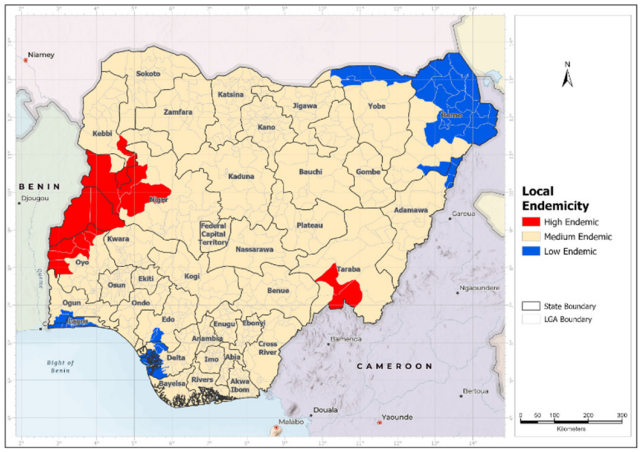

Figure 7: Local strata of falciparum malaria endemicity

Notwithstanding, other several interesting results are presented here, and they include the objective identification and classification of Nigeria into fine-grain (high resolution) *falciparum malaria* endemicity strata using a long temporal span incidence rate data. The objective or empirical analysis produced results much more robust compared with the existing studies on malaria endemicity mapping and modelling that is based on descriptive analysis which involved presenting and comparing results with choropleth maps (Weiss et al., 2019). The results were able to identify LGAs with a high malaria incidence rate. This is the first step to any malaria control measures or interventions. Figure 7 shows that high endemic malaria strata seem to cluster around the Nigeria-Benin Republic border and Nigeria-Cameroon border. This suggests that cross border transmission may be taking place over these years. Similar findings have been reported in Namibia (Alegana et al., 2013) and Kavango along the Angola-Botswana border (Noor et al., 2013).

The high endemic strata that occurred in the west margin covers 13 LGAs in 3 states (Oyo, Kwara and Niger). Among these 13 LGAs, 5 have a direct borderline with the Benin Republic and there are several border towns in these LGAs, such as Okerete-Ode (Saki West LGA in Oyo State); Chikanda (Baruten LGA in Kwara State) and Babana (Borgu LGA in Niger State). These areas are dotted with a plethora of unmanned border posts and the free trade treaty of the Economic Community of West African States (ECOWAS) makes these border posts predominantly porous. Further investigation and surveillance are required to ascertain whether a cross-border transmission is responsible for the high endemic layer that occurred in this cluster of LGAs. For example, genetic sequencing or genomic investigation needs to be employed to understand the transmission dynamics and the malaria parasite movement based on self-reported travel history data (Tessema et al., 2019). Also, genomic tracking would help to improve understanding of whether this cluster is a consequence of mobility or whether it is a product of some inherent behavioural practices of the people living in these areas or some environmental confounding factors.

The emerging high endemic cluster at the northeast Nigeria-Cameroon border occurred in 2 LGAs and may probably spread to other sounding LGAs. This high endemic cluster is classified as emerging because as shown in Figure 3 significant hotspot did not occur in the first temporal stage. Hotspot cluster started to emerge around this region in the second temporal stage and continued to the end of the third temporal stage. There was a period of hotspot degradation from the fourth to the fifth temporal stages. On the sixth to the last temporal stages, the hotspot re-emerged heavily and covered several surrounding LGAs. This cluster needs to be placed under surveillance and transmission interrupting intervention for these LGAs, if any, needs to be increased.

It is not unexpected that a low endemic cluster would occur in the northeast region of the country. Figure 3 shows that the LGAs that makes up this cluster in Borno State, Yobe State and Adamawa State were consistently malaria coldspot throughout the 20 years. This low endemicity may be attributed to environmental and climatic factors. For example, aridity and desertification that characterises this region are

an unfavourable condition for mosquito breeding since there would be less of ponds and other waterlog. Also, evidence from the malaria indicator survey shows that the north-east among other regions has the highest concentration of ITN intervention in the country (United State Embassy in Nigeria, 2011). These factors may have promoted the low endemic rate in this cluster. Low endemicity occurred in the south-west region (Lagos and Ogun States) and the south-south region (Edo and Delta States). These areas of low incidence rate would provoke the attention of health researchers, policymakers and planners to seek to investigate and understand the reason for this low incidence rate.

4. CONCLUSION

The approach adopted in this study is a robust and better accurate way of modelling space-time data. The results are empirically derived local and fine grain malaria incidence rate spatial and temporal maps revealing the nationwide dynamics in malaria hotspot and coldspot. Also, using a space-time cube method of data aggregation, 2 decades of malaria incidence rate datasets were used to objectively produce a local endemicity map which will serve as a vital tool for informed decision-making during interventions and surveillance. In epidemiology, the major challenge in intervention deployment, smart resource allocation, surveillance, monitoring and evaluation is the ability to locate spatial clusters of disease infection. The implication of these results is that they provide the springboard for the design of various malaria control and elimination strategies.

5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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