SPATIAL IDENTIFICATION OF HIGH-RISK OF HIV/AIDS IN KEFFI LGA USING SPATIAL AUTOCORRELATION AND KRIGING INTERPOLATION. Bulus Ezekiel Awhigbo, Monday Osagie Adenomon, Mary U. Adehi, Alhaji Ismaila Sulaiman.

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Abstract

Quite often, authorities and policies maker are confronted with the challenges to serve society with the little resources at her disposal. More so, the need to distribute the limited resources correctly to the needed persons and location remain nonnegotiable in the present dispensation. Indeed, it became very expedient to sort for means of allocating these minimum resources to the needy against all odds. The study seek to identify communities with severe cases of HIV virus across Karu Local Government Area of Nasarawa State and communities at high risk to this peril. The study used secondary data from the Keffi General hospital, which covered a period of ten (10) years, from 2013 to 2023. The study made used of Moran's I Statistics, Kriging Model and Semivariogram model, and employed the ArcGIS software to analyzed the data. The finding shows that the Moran's I statistics recorded a positive value of 0.154147, z-score of 5.062777 and p-value 0.0000 which is statistically significant and cluster. The Semivariogram showed that spatial autocorrelation flatten out at the range of 0.605 while the kriging model give the prediction of communities with high risk of HIV virus. This study conclude that resources should be allocated to the identified communities alongside with intervention program such as, campaign programs and medical awareness to stop further prevalence of this virus.

Keywords: Spatial Autocorrelation, Kriging, Moran's I, Semivariogram. HIV Virus

1. Introduction

The threat by HIV continues to prevail in the Nigeria society despite government effort with several intervention programs, the Nigeria prevalence rate is still at 1.4 percent, (NACA, 2025). Nasarawa state out of the statistics record in the public domain contributed 1.9 percent among the Nigeria states. Even with the declining of HIV infections records

by the state in 2023, the state still records 2934 incidences cases in 2024 across the thirteen Local Government Area by UB Executive Director on her world day HIV/AIDs speech of the year 2024. The need to identify the cluster of this ailment in the state become pertinent, so as to provide a valuable starting point for an informed and targeted intervention programs that will free our communities and state at large from this threatening diseases (Aturinde et al, 2019). The mapping of diseases by the Geographical Information System (GIS) software had tremendously assist in identifying incidence location for the policy makers (Nakama, 2020).

Additionally, Irene et al. (2016), speak on understanding the geographical distribution of a disease to be critical for policy and decision deployment by the government in managing resources to confront disease either with a view to totally eradicating it or at least control its spread, however, they revealed the spatial distribution of HIV/AIDs across the five zone of Oyo state with the Saki zone having 22 per cent and lowest in Oyo zone with 18.5 percent while Ogbomoso 21.5 percent, Ibarapa 19.0 percent and Ibadan 19.0 percent of respondents with the disease, according to the study, this result was attributed to the various factors which include cultural factors, promiscuity among several others. The government and the non-governmental organization relied on data to stage programs for HIV, therefore, the Nigeria HIV/AIDS Indicator and Impact Survey (NAIIS) data was used to targeted intervention strategy for mapping HIV prevalence, and was modeled using stacked generalization to analyze available covariates and a geostatistical model to incorporate the output from stacking as well as spatial autocorrelation in the modeled outcome. They showed the range of the prevalence between state at 0.3 to 0.4 percent, and LGA 0.2 to 8.5 percent. The Geospatial analysis across the HIV continuum of care, effectively highlight sub-state variation and identify areas that require further attention (Caitlin et al, 2022).

A precise location is an indispensable intervention strategy for achieving a set target, which is more cogent for health related goals like the minimization of the HIV pandemic, they micro scale estimates of four standard HIV/AIDS and sexual behaviour indicators of an area with a spatially enriched synthetic individual population which align with the added advantage of mapping fine grained spatial patterns to facilitate precise geographical targeting of relevant interventions (Abubakar et al, 2023). The need for HIV awareness status and transmission knowledge among adults in sub-sahara Africa is pertinent and urgent in the present dispensation of which geospatial analysis and machine learning techniques had revealed how this is lacking. Additionally, they examined that 4.9% prevalence rate of the infection were among adults which are not also aware, and the high risk area of the HIV infection were identified to be South-Africa (Endawkie et al, 2024). In another development, a study of spatial distribution of HIV in Nigeria using global Moran's I and local Moran's I to measure spatial autocorrelation, and they recorded twenty-seven states with 73 percent showed decline in the HIV, while ten states with 27 percent showed increase in HIV prevalence rate between 2008 and 2012. The global Moran's I showed a strong positive spatial autocorrelation in 2008 and 2012, and a significant hotspot too were identified (Olusoji et al, 2017).

Folorunso et al. (2019), examined risk factors of Potable Water that contribute to spread of HIV/AIDs in Ekiti state through the spatial analysis using primary data. They discovered that 44.5% of the respondent believed that availability of water can reduce the spread of HIV/AIDs, 84.5% of the respondents had an increased need of water after HIV infections, and 92.7% of the respondents agreed HIV positive people have increased need for better hygiene and sanitation, and they conclude that water, sanitation, hygiene and population are agents determining the spread of HIV/AIDS in the environment. The assessment of geographical heterogeneity of HIV among men having sex with men (MSM) and people who inject drugs (PWID) was studied to inform targeted HIV prevention and care strategies across seven state in Nigeria with severe cases and Nasarawa inclusive. The Global Moran I and Getis-Ord-Gi statistics revealed a clustered distribution of HIV infection among MSM and PWID with a less than 5% and less than 1% likelihood that this clustered pattern was due to chance, and significant clusters of HIV infection confined to the North Central (Nasarawa) and South South regions were identified among MSM and PWID (Amobi et al, 2021).

2. Sources of Data

The data used is a secondary data collected from Keffi General hospital alongside with their location coordinates, and the data was transformed to shape file format. The studied pursues to identified cluster area and prediction area that are prone to risk of HIV in Keffi Local Government Area of Nasarawa state with Morans I statistics and Kriging Model using ArcGis software.

3. Model Specification

The Kriging model was applied using the ArcGIS software to achieved the aim of the research work.

3.1 The Kriging Model

The general equation for the universal Kriging

$$z = \mu(x) + \varepsilon \tag{1}$$

Where, z is the dependent variable (variable of interest), $\mu(x)$ is typically a linear function of local explanatory variables (also known as location), and ε is a spatially dependent error term.

3.2 The Kriging Weights

$$\hat{z}(x_0) = \sum_{i=1}^n \lambda_i z(x_i) \tag{2}$$

 λ_i is the data weight, $z(x_i)$ is the data value, and $\hat{z}(x_0)$ is the estimate of unknow location. Also, in the case where the mean is not stationary, the residual is subtracted from the both sides which gives

$$\hat{z}(x_0) - m_z(x_0) = \sum_{i=1}^n \lambda_i (z(x_i) - m_z(x_i))$$
(3)

Given

$$y = z - m, y(x_0) = \sum_{i=1}^n \lambda_i z(x_i)$$
(4)

that is simplify residual.

3.3 The Moran's *I* Statistics

The Moran's I autocorrelation coefficient will be use to first measure the correlation between the neighboring observations within each state using this formula below

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij}\right) \sum_{i=0}^{n} (x_i - \bar{x})^2}, i \neq j$$
(5)

Where *n* is the number of Patients, ω_{ij} is the weight matrix of links between *i* and *j*, x_i and x_j variables in the *i* and *j* spatial units patients, and \bar{x} is the arithmetic mean of the variable for all units. The value of local Moran's *I* range from +1 indicating high- high or low-low clusters through a random pattern to -1 indicating high-low or low-high outliers according to (Wang et al., 2016).

For identification of statistically significant hotspot and cold spot of the clusters incidence, the local moran's *I* will be use

$$I_i = \frac{n^2}{\sum_i \sum_j ij} \frac{(x_i - \bar{x}) \sum_j \omega_{ij}(x_j - \bar{x})}{\sum_j (x_i - \bar{x})^2} \ i \neq j$$
(6)

3.4 The Semivariogram Model

Semi variogram: its the function of difference over distance, in other word its tells us about similarity and dissimilarity of points over time.

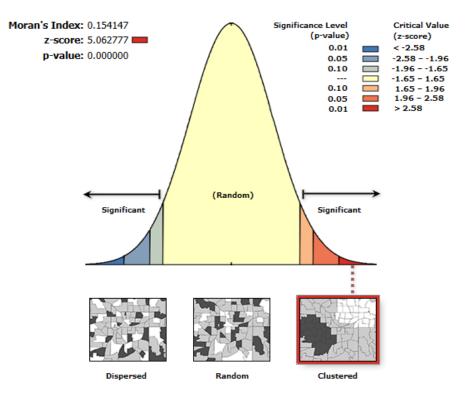
$$\gamma(\bar{h}) = \frac{1}{2N(\bar{h})} \sum (Z_i - Z_{i-\bar{h}})^2 \tag{7}$$

Where γ is the variogram, \overline{h} is the lag distance, Z_i is the tail, and $Z_{i-\overline{h}}$ is the head.

4. Ethical considerations

The studied data collection protocol for this work was given approval by the Nasarawa State Ministry of health through Health Research Ethics committee.

5. Result and Discussion



Keffi HIV Spatial Autocorrelation

Fig. 1. Spatial Autocorrelation

The fig.1 showed that there is spatial autocorrelation of HIV virus in Keffi LGA, and is statistically significant with P-value of 0.0000. The Morans I index value of 0.154147 is positive which indicate that patient with high records of similar number of visit to the health facility. This study affirmed to a Geographical Analysis of HIV/AIDS Infection in Nigeria, 1991–2001, that Spatial autocorrelation analyses indicated that HIV/AIDS rates were strongly autocorrelated (chinekwu 2012), additionally, Endwakie et al (2024) attested that spatial hotspots of high HIV prevalence rate are lack of awareness and transmission. Also, Caitlin et al (2022), highlight sub-state variation and identify areas that require further

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attention in order to achieve epidemic control of some intervention programs using geospatial analysis across the HIV continuum of care.

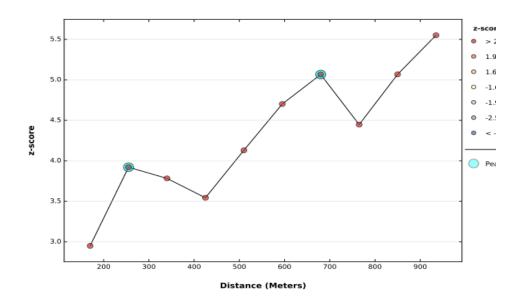


Fig. 2. Spatial Autocorrelation by Distance

The above graph showed the various clustering distance with a different of 85 meter at each interval and the z-score is statistically significant for each cluster. The peak with the lowest and higher clustering distance were indicated as the peak.

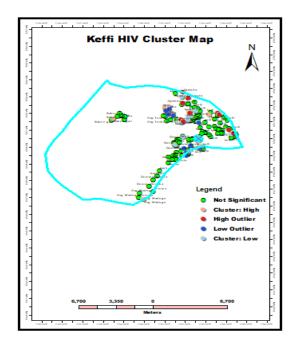


Fig. 3. Keffi LGA Cluster Map

The fig.3 showed the clustering levels of the HIV virus across the Keffi LGA, with the green colour showing that there is not clustering in those area, the light pink colour indicate that there is high cluster level of HIV virus in Tilla, Sabo Gari, Jigwada and Keffi communities, the red colour shows there is high cluster of HIV surrounded by individual with low infection, the blue colour also showed those with lower HIV infection virus surrounded by those with high level of HIV infection, and lastly, the sky blue indicate those communities with low cluster level of the HIV. This also, align with Irene et al (2016) on the HIV/AIDS in Oyo State State, analyzing Spatial Pattern of Prevalence and Policy Implication for Government that identified zones with highest percentage of the HIV virus

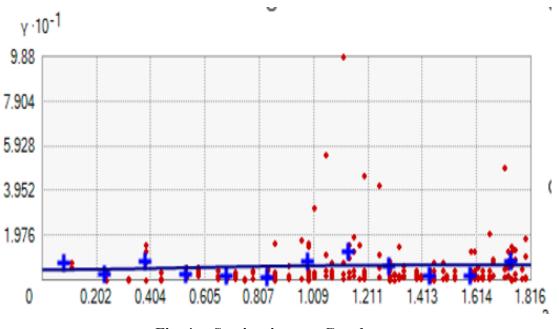


Fig. 4 Semivariogram Graph

The graph showed the spatial autocorrelation of the data as it flattens out at 0.605 at the x-axis. The graph also points the measurement variation with distance between all pairs of sampled locations within the range of dependencies.

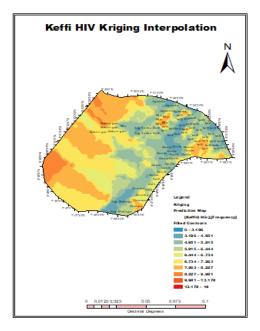


Fig. 5 Keffi Prediction Map of HIV

The map showed the prediction range levels of HIV virus of Keffi LGA at different communities, the prediction map also showing the area with low risk, starting from blue to red with the higher risk, and the result indicate that Gauta, Tilla, Dorowa and Keffi, have the high risk of HIV virus. This discovery indeed confirmed to how versatile are spatial statistics models, and established that they are now center stage in many applications domains (Noel et al, 2022).

6. Conclusion

This study was design to identified communities with high cases of HIV virus in Keffi Local Government Area of Nasarawa State, and also those communities at high risk to this threatening virus using the Morans'*I* statistics, Kriging Model and the Semivariogram Model. The study shows that there is clustering of this incidences in Tilla, Sabo Gari, Jigwada and Keffi communities, while severe cases from the study are Sabo Gari and the Keffi communities by the Morans'*I* statistics. The Kriging Models predicted Gauta, Tilla, Dorowa and Keffi communities to be at high risk to this life threatening diseases. Thus, this study recommends a prompt action by the relevant body to intensify intervention programs across the LGA with a special consideration on communities with high risk records to curtails further prevalence of this diseases. Furthermore, those communities identified with the severe cases, intervention and campaign station should be stage within their rich to reduce cost, because some of those communities are mostly in rural area which are also face with some barriers to health facilities, therefore, access to those health facilities are been deny (Elsa et al, 2023).

Additionally, this study attest to publication of PMCID (2018) that Malaria and HIV are two of the world's deadliest diseases that are widely spread, but their distribution overlaps greatly in sub-Saharan Africa, and consequently, malaria and HIV coinfection is common in the Keffi LGA. The HIV which shows high clustering in some of the communities in Keffi LGA also confirm with the work of Yin'Allah (2023) on prevalence of urinary schistosomiasis among primary school pupils in Keffi Local Government Area, Nasarawa State.

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