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Spatial Identification of high-risk level of HIV/AIDS in Karu LGA using spatial Autocorrelation and Kriging interpolation

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ABSTRACT

To appropriately serve humanity better, the need to distribute the limited resources correctly to the needed persons and location remain nonnegotiable in our present dispensation. Indeed, it became very expedient to sort for means of allocating these minimum resources to the needy against all odds. The study seeks to identify communities with severe cases of HIV virus across Karu Local Government Area of Nasarawa State and communities at high risk of HIV/AIDS. The study used secondary data from the Karu Medical center Mararaba, which covered a period of ten (10) years, from 2013 to 2023. The study used Moran's *I* Statistics, Kriging Model and Semivariogram model, and ArcGIS software was used to analyzed the data. The finding shows that the Moran's *I* statistics recorded a positive value of 0.026684, z-score of 5.880192 and p-value 0.0000 which is statistically significant. The spatial autocorrelation flattens out at 0.817 by the semivariogram and Kriging model predicts communities at high risk of HIV/AIDS. This study conclude that resources should be allocated to the identified communities and alongside intervention program such as campaign programs and medical outreach to stop further prevalence of this virus.

Keywords: Spatial Autocorrelation, Kriging model, Moran's I Statistics, Semivariogram, HIV/AIDS.

INTRODUCTION

Nasarawa state is been recognize as one of the state in the northern region with high prevalence rate of HIV/AIDS, though the record shows that there is decline in the number to 2,934 people in 2024, compared to the incidence cases of 4,222 and 6,614 in the year 2022 and 2023 (NASACA, 2024). Richard (2014), studied the prevalence rate of spatial variation of HIV/AIDS in Nigeria, he used exploratory spatial data analytics (ESDA) techniques, Global and Local Moran's I Statistics, and Getis and Ord Gi statistics to identify the pattern and communities with this threatening diseases, and the result shows that Nasarawa, Benue, Abuja, and Cross River recorded high prevalence rate in Nigeria.

The Global Moran's index, spatial scan statistics, and bivariate global and local Moran's indices were used to investigate the geographical clustering patterns of HIV and TB co-clustering in Uganda, where both diseases data were gotten for 2015, 2016, and 2017 from the Uganda ministry of health, and the result shows that they exhibit relatively different spatial clustering patterns across Uganda, while the TB/HIV prevalence shows consistent hotspot clusters around districts surrounding Lake Victoria as well as northern Uganda (Augustus *et al*, 2019).

A reviewed on Geographical distribution of diseases in the world was conducted, it was made a regional geographical overview of the distribution of diseases concerning natural and social factors. The reviewed considered the influence of the geographical environment on the prevalence of diseases, the impact of the social environment of the expansion of the

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disease, and also elaborated on globalization and the diseases. In conclusion, the reviewed contributed to publicity approach involving the autochthon of diseases in certain regions as their spread reckoning the present dispensation technological development and population dynamics across the globe (Blagoja *et al*, 2016).

Elsa *et al* (2023), investigate the spatial distribution and determinants of barriers to health care access among female youth in Ethiopia with a total weighted sample of 6143 female youths between the aged of 15 to 24. They used mix effect analysis to identify factors contributing to health access barriers and strength, also they used wealth inequalities concentration index and spatial analysis to search the spatial distribution and significant windows of barriers to healthcare access. The outcome of their work shows the barriers level to health facilities among youth between age 15 to 19 to be at 61.3%, while the barrier level among the youth with no formal education 13.18%, the barrier level among the youth with primary education is 2.95%, the barrier among the married ones is 1.21%, and that of poor household wealth is at 2.05%. Finally, they conclude that the barriers to healthcare were noticeably to be out of proportionate among the youth of the Ethiopia, hence, consistent study for intervention programs to address the challenges appropriately, its recommended.

A review articles was conducted on the use of basis-function models of spatial statistics with mostly nonstationary data cases. The reviewed aim at basis functions models that provide extreme flexibility and efficient computation on nonstationary data, additionally, they concentrate on the basis function models of spatial process on the Gaussian, Non Gaussian, Multivariate and spatio-temporal setting, and application in geophysics. Lastly, they stress on how skillfulness are these spatial models, which are now center stage in numerous analysis application. Their reviewed ended with examples and discussion on spatial statistics software for analysis which are now available and fit for spatial basis models (Noel *et al*, 2022).

Tsion *et al* (2024) examined Geospatial determinants and spatio temporal variation of early initiation of breastfeeding and exclusive breastfeeding in Ethiopia. Multiscale geographically weighted regression analysis was used with data from Ethiopian Demographic and health survey (EDHS). They used spatial autocorrelation to measure whether EIBF and EBF were dispersed, randomly or clustery distributed and Kriging interpolation techniques was used to predict the outcome variables in the unmeasured areas, also scan statistics was used to identify spatial clusters with high prevalence of cases. In the study, they find out that the trend analysis increase in the prevalence of EIBF from 51.8% in the year 2011 to 71.9% in 2019 and also that of EBF increases from 52.7% in 2011 to 58.9% in 2019. Also, there was spatial variation in EIBF and EBF across the country. Additionally, clusters of low prevalence of EIBF were observed consistently in the Tigray and Amhara regions, while there were significant clusters of EBF in Afar and Somali regions, and lastly the study showed that multiscale geographically weighted regression analysis was a significant predictors of spatial variations in EIBF.

Thi-Hien *et al* (2024), study the Identification of spatial clusters and spatial outliers of HIV/AIDS using local Moran’s I statistic to measure the number of HIV/AIDS cases in each cities of Vietnam, and then Spatial distribution of HIV/AIDS clusters and outliers was mapped. The result shows that High numbers of HIV/AIDS cases were mainly concentrated in the provinces of the north central region, and provinces in the south of

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Vietnam, while Low numbers of HIV/AIDS cases were detected in the northeastern provinces, central and southeastern provinces of Vietnam. Specifically, one high-high cluster and six low-low spatial clusters, and four low-high and high-low spatial outliers of HIV/AIDS cases were successfully detected. Whereas, the only high-high spatial cluster was discovered in Binh Duong province with 3598 HIV/AIDS cases.

Leo *et al* (2014), analyze spatial clustering and the spatiotemporal nature and trends of HIV/AIDS prevalence in Malawi from 1994 to 2010, they used Inverse distance to generate continuous surfaces of HIV prevalence for all the years, Spatial dependency and clustering of HIV prevalence was analyzed, and correlation and multiple regression analyses were used to identify factors associated with HIV prevalence for 2010 and their spatial variation/clustering mapped, compared to HIV clustering. The study outcome shows that there is wide spatial variation in HIV prevalence at the region and there is significant statistics of prevalence of spatial dependence across the nation. Locally, HIV was clustered among eleven southern district with multiple regression of 2010 HIV prevalence which produced a model with four significant explanatory factors with adjusted R^2 of 0.688 of mean distance to main roads, mean travel time to nearest transport, percentage that had taken an HIV test ever, and percentage attaining a senior primary education. Finally, Spatial clustering linked some factors to particular subsets of high HIV-prevalence districts.

MATERIALS AND METHODS

Sources of Data

The study uses the health data from the records unit of Karu General hospital alongside with their location coordinates, and the data were transformed to shape file format. This study seek to identify communities with cluster of HIV/AIDS and to also predict communities that are prone to risk of HIV/AIDS in Karu Local Government Area of Nasarawa state with Morans I statistics and Kriging Model using ArcGis software.

Model Specification

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.

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

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

Given

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

that is simplify residual.

The Moran's I Statistics

Moran's I is a tool that simultaneously measures spatial autocorrelation based on both feature locations and feature values. Having a set of features and an associated attribute, it measures whether the pattern expressed is clustered, dispersed, or random.

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The Moran's I autocorrelation coefficient was used to first measure the correlation between the neighboring observations within each LGA using this formula below

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

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

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

The Semivariogram Model

A semivariogram its a statistical curve or graph that shows the degree of similarity between two sets of observations. Additionally, its a probability graph with the x-axis that display the horizontal distance between pairs of observations, and the y-axis display some measure of similarity between those pairs, or its can be seen as the function of difference over distance, in other word its tells us about similarity and dissimilarity of points over time.

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

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

RESULTS AND DISCUSSION

The fig 1 show the distribution of HIV in the Karu Local Government of Nasarawa State. As noticed, the Moran's I index, z-score, variance, expected index and the probability value of the HIV virus in the LGA were 0.026684, 5.880192, 0.000024, -0.002375 and 0.000000 for the period of study from 2013 to 2023. The z-score which reflect the deviation of the points from the means show to be positive, which further indicate that there are points that are above the average points from the data distribution.

Karu HIV Spatial Autocorrelation

The figure 2 revealed that there is a Spatial Autocorrelation in the data set given the Moran's I index to be positive, and also indicate that there is clusters. Additionally, the variances quantify the dispersion of the data set, and expected index value tell us the probability of changes in the data set over the time period, which second to the assessment of geographical heterogeneity of HIV among men who have sex with men (MSM) and people who inject drugs (PWID), using HIV global spatial autocorrelation and hotspot analysis to highlight patterns of HIV infection and identify areas of significant clustering of HIV cases, whose shows that Global spatial

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autocorrelation Moran I statistics identified a clustered distribution of HIV infection among MSM and PWID of less than 5%, and less than 1% likelihood that this clustered pattern is as a result of chance. Consequently, a significant clusters of HIV infection with Getis-Ord-Gi statistics holds to the North Central and South South regions were seen to be among MSM and PWID Amobi *et al* (2021).

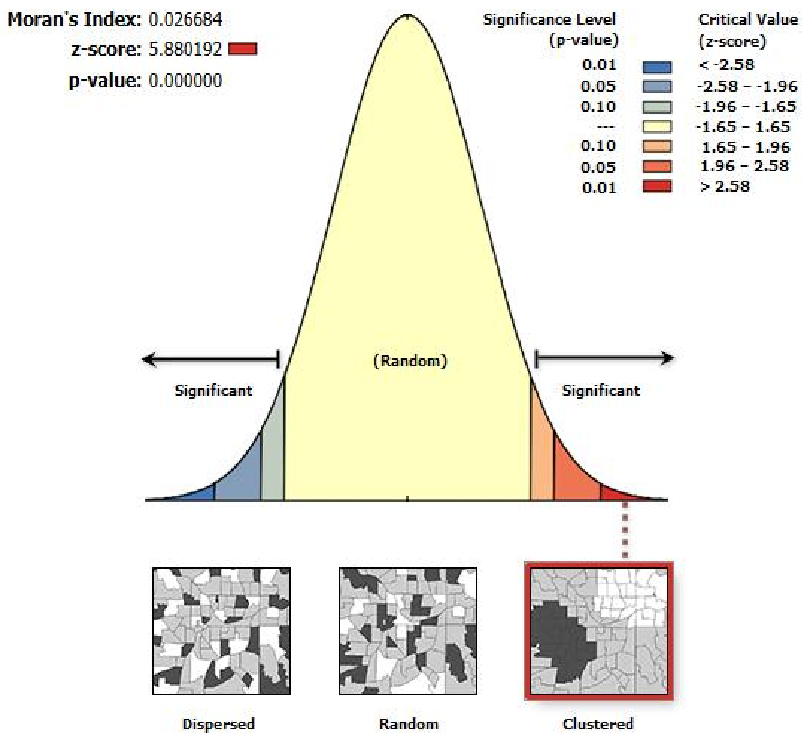

Figure 1: Spatial Autocorrelation.

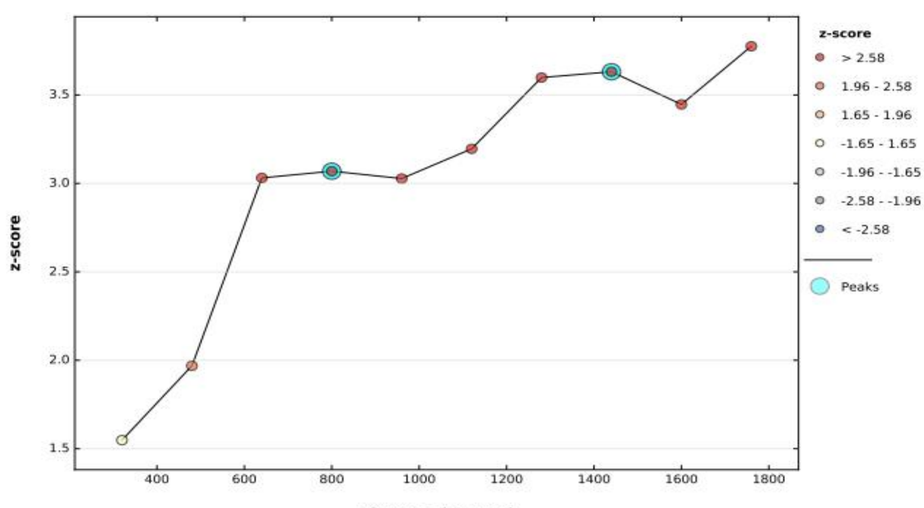

Figure 2: Spatial Autocorrelation by Distance.

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The above graph showed the various clustering distance with a difference of 160 at each interval and the z-score is statistically significant for each cluster. The peak with the lowest clustering distance was at 800.00 with Morans’*I* 0.079534, z-score 3.069134 value, variance 0.079534, expected index -0.002469 and its p-value 0.002465. While that of higher clustering was identified at maximum distance of 1440.00 with Morans’*I* 0.062603, z-score value 3.631456, variance 0.000321, expected index 0.002427, and p-value 0.000282.

The figure 3 shows the clustering levels across the Karu LGA of HIV, with the green color indicating that there is no clustering in those areas, the light pink colour indicate that there is high cluster level of HIV virus in Masaka, Koya, Kuchikau, Gwagwa, and Keffi Shanu communities of the Karu LGA, the red colour shows there is high cluster of HIV surrounded by individual with low severe infection cases, the blue colour also shows 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 diseases. This above finding align with the work of Leo *et al* (2014) on spatial clustering and the spatiotemporal nature and trends of HIV/AIDS prevalence in Malawi from 1994 to 2010, where their work revealed the spatial variation in HIV prevalence at the region and the significant statistics of prevalence of spatial dependence across the nation, and locally, HIV was clustered among eleven southern district.

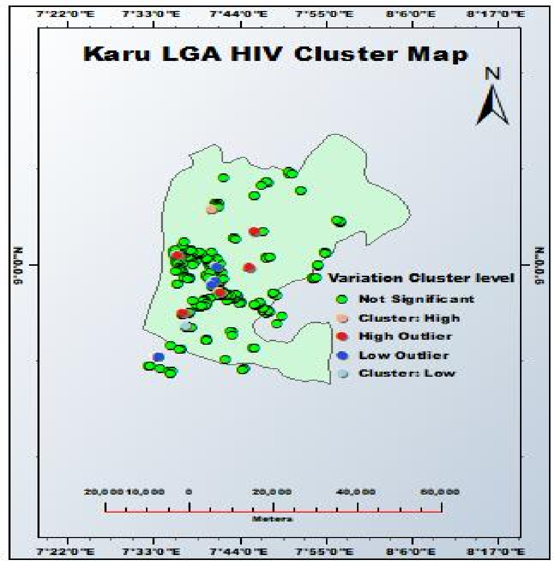

Figure 3: Karu HIV Cluster Map.

The graph (Figure 4) depicts the spatial autocorrelation of the data as it flattens out at 0.817 at the x-axis, and the binned helps us visualize the relationship between the variables. The plot further shows the measurement variation with distance between all pairs of sampled locations within the range.

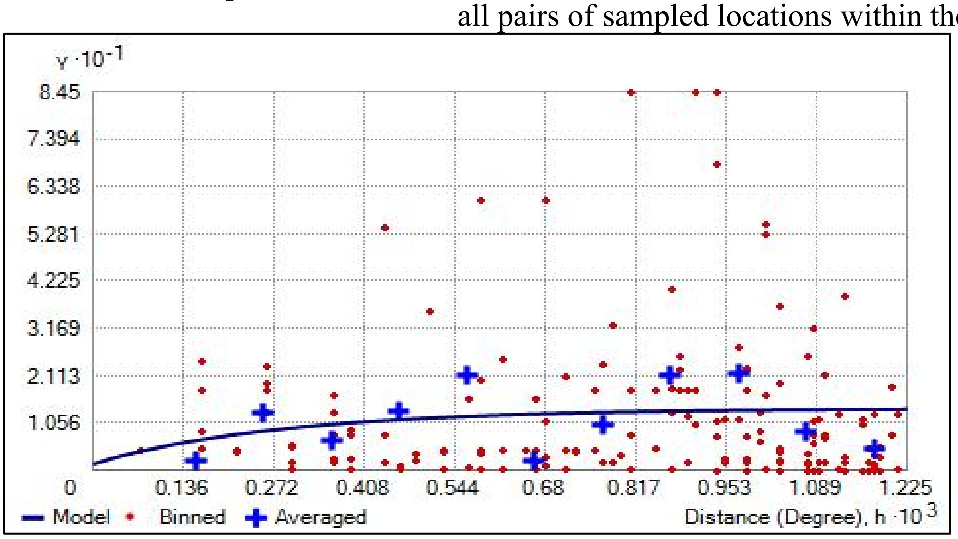

Figure 4: Semivariogram Graph.

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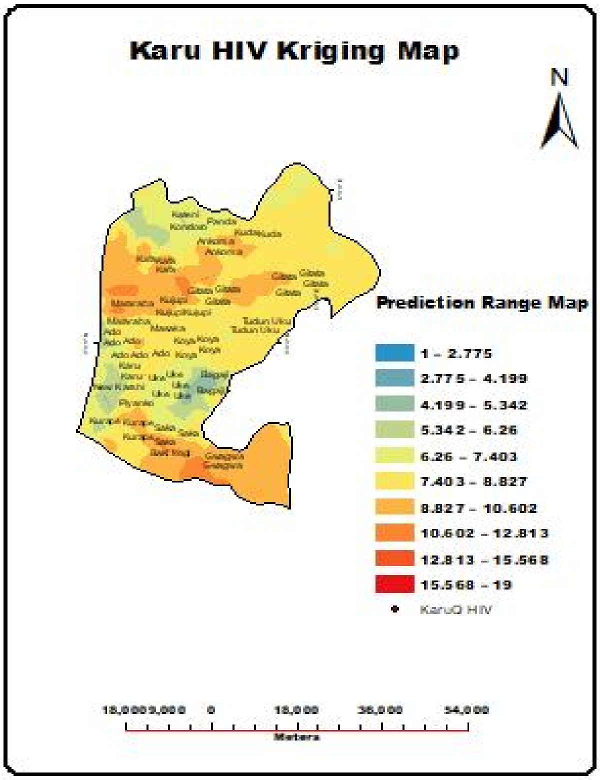

Figure 5: Karu LGA HIV Prediction Map.

The Figure 5 shows the prediction range levels of the HIV diseases of Karu LGA at various communities. The prediction map showed the area with low risk level, starting from blue to red with the higher risk levels across various communities, and the result indicate that Kugbaru, Kabusu, Kafa, Mararaba, Masaka, Ado, Kuchikau, Gwagwa, Bakin Kogi, Saka and Keffi Shanu recorded high risk of HIV virus. Hence, relevant authorities should put in place measures to curtail further escalation of this diseases. Thus far, the study aligns with the assertion of Noel *et al*, (2022), on how versatile are these spatial models, which are now center stage in numerous analysis application, where their reviewed articles further concluded with examples and discussion on spatial statistics software for analysis which take care of nonstationary data sets.

CONCLUSION

This study was design to identified communities with high cases of HIV virus in Karu Local Government Area of Nasarawa State, and also those communities at high risk of this virus using the Morans'*I* statistics, Kriging Model and the Semivariogram Model. The studied identified Masaka, Koya, Kuchikau, Gwagwa, and Keffi Shanu with clustered of HIV/AIDS by the Morans'*I* statistics, While the Kriging Models predicted Kugbaru, Kabusu, Kafa, Mararaba, Masaka, Ado, Kuchikau, Gwagwa, Bakin Kogi, Saka and Keffi Shanu 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 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, denying them access to this facilities (Elsa *et al*, 2023).

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