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Spatial Heterogeneity Association of HIV Incidence with Socio-economic Factors in Zimbabwe

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ABSTRACT

This study examined the spatial heterogeneity association of HIV incidence and socio-economic factors including poverty severity index, permanently employed females and males, unemployed females, percentage of poor households i.e., poverty prevalence, night lights index, literacy rate, household food security, and Gini index at district level in Zimbabwe. A mix of spatial analysis methods including Poisson model based on original log likelihood ratios (LLR), global Moran's I , local indicator of spatial association - LISA were employed to determine the HIV hotspots. Geographically Weighted Poisson Regression (GWPR) and semi-parametric GWPR (s-GWPR) were used to determine the spatial association between HIV incidence and socio-economic factors. HIV incidence (number of cases per 1000) ranged from 0.6 (Buzura district) to 13.30 (Mangwe district). Spatial clustering of HIV incidence was observed (Global Moran's $I = -0.150$; Z score 3.038; p -value 0.002). Significant clusters of HIV were observed at district level. HIV incidence and its association with socio-economic factors varied across the districts except percentage of females unemployed. Intervention programmes to reduce HIV incidence should address the identified socio-economic factors at district level.

1. Introduction

Approximately 36.7 million people are living with HIV and AIDS worldwide, with 1.8 million new infections and one million AIDS related deaths yearly^[1]. Globally, the highest burden of the HIV & AIDS pandemic is in East and Southern Africa where 800 000 new infections are recorded yearly, leading to 20.6 million people living with the disease, and 310 000 related deaths^[2]. This calls for

renewed obligation and improved tools and methods to reduce HIV infections especially in developing countries including sub-Saharan Africa^[3].

The relationship between HIV infections and socio-economic factors including poverty, education, food insecurity and employment is complex^[4]. There is a consensus among scholars that HIV can lead to deteriorated socio-economic conditions (poverty in particular) at individual and household level^[5]. In fact, poverty impedes

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access to preventive actions, healthcare and information thereby increasing the susceptibility of people to HIV infection^[6]. Contrary to this, poverty is considered to be one of the major drivers of HIV epidemics^[7]. Although HIV is not always concentrated among the poorest populations it is believed that socio-economic factors may act as a distal determinant of infection^[4]. Poverty may lead to adoption of high-risk sexual behaviour or practices including earlier sexual debut, earlier marriages, and transactional sex for income generation^[7]. Such practices increase the risk of acquiring HIV, especially among the young and poor women who mostly depend on men to earn a living^[4].

However, Gillespie et al.^[8] noted that the perception that poverty is the major contributing factor of HIV transmission is too simplistic because relative wealth has diverse effects on HIV risk. This view is supported by studies that showed that HIV infections can also be higher among wealthier people^[9-11] who indulge in risky sexual practices involving multiple partners. Gender is also an important driver for HIV transmission particularly in the case of poverty/wealth relationships^[7,8]. Poorer and less-educated women may be less knowledgeable about HIV risks and therefore less able to adopt the needed risk-reducing behaviour^[4]. Some studies have suggested that relative wealth initially can increase HIV risk, but may become a protective factor as epidemics mature^[12,8]. However, it is unclear whether this trend can occur in circumstances of rapid macro-economic changes^[7].

Since year 2000, Zimbabwe has been experiencing serious economic challenges that have disproportionately affected the socio-economic conditions of people across various districts^[13]. Despite recording remarkable progress in reducing HIV prevalence and incidence, wide variations still remain across districts of Zimbabwe and the HIV burden is still high among adolescent girls and young women than in men (15.3 percent vs. 10.2 percent)^[14]. This disparity in socio-economic challenges experienced across districts indicates the need to determine the spatial variation of HIV incidence and its association with socio-economic factors at district level thus warranting further research to understand the contributing socio-economic factors to these variations at district level.

Most of the recent studies in Africa, Zimbabwe included, have considered the modelling of spatial variation of HIV prevalence at fine resolution such as 5km X 5km pixel. The training data for these models is mostly derived from health facilities and testing centers which are then extrapolated to pixel level based on interpolation methods including kriging and co-kriging^[15-17]. Such studies would complement Pascoe et al.^[4] and Schur et al.^[7] who considered non spatial dimensions of this relationship in

Zimbabwe. Our study was therefore intended to address the gaps by examining the spatial heterogeneity association of HIV incidence and socio-economic factors in Zimbabwe. We complemented established models through an analysis of spatial variation of HIV incidence in relation to socio-economic factors at district level focusing on the spatial heterogeneity association of HIV incidence and socio-economic factors.

2. Materials and Methods

2.1 Study Area

This study was conducted in Zimbabwe, which is located in Southern Africa (Figure 1). Zimbabwe has an approximate population of 14 million with 60% of people living in rural areas^[18]. It has 10 provinces and 62 rural districts. Zimbabwe has a predominantly young population with about 61% of the population below the age of 24. Females constitute 52% of the total population^[19]. The economy of Zimbabwe is based on agriculture, which contributes approximately 13% of its gross domestic product (GDP)^[20]. Zimbabwe is in the low human development class ranking 156 out of 189 countries based on Human Development Index (HDI)^[21]. The country experienced a decline in the incidence rate from 0.74 in 2014 to 0.49 in 2017 and 0.38 in 2020^[22,23]. The HIV prevalence varies across the districts. For example, in 2017 Bulilima district had the highest adult prevalence (23%) while Gokwe North had the lowest (9%)^[22]. In 2015 the incidence of poverty was lower in urban compared to rural areas indicating that inequality levels varied between rural and urban settings in Zimbabwe^[18]. Income inequality estimated using the Gini coefficient also varies across districts as determined by the respective economic activities. These disparities, among others, may contribute to the spatial distribution or variation of HIV and AIDS incidence in Zimbabwe.

2.2 Datasets

Data used in this study include (i) estimated cases of HIV for 2017 obtained from the Ministry of Health and Child Care^[22]; and (ii) district socio-economic factors from the 2017 Poverty, Income, Consumption and Expenditure Survey (PICES) and Poverty reports, and Zimbabwe 2012 census data (<http://www.nada.zimstat.co.zw/>). These were the current and complete datasets available at the time of study. The socio-economic variables we used were poverty severity index, percentage of females employed permanently, percentage of females unemployed, percentage of male population employed permanently, night-lights index, and percentages of male and female lit-

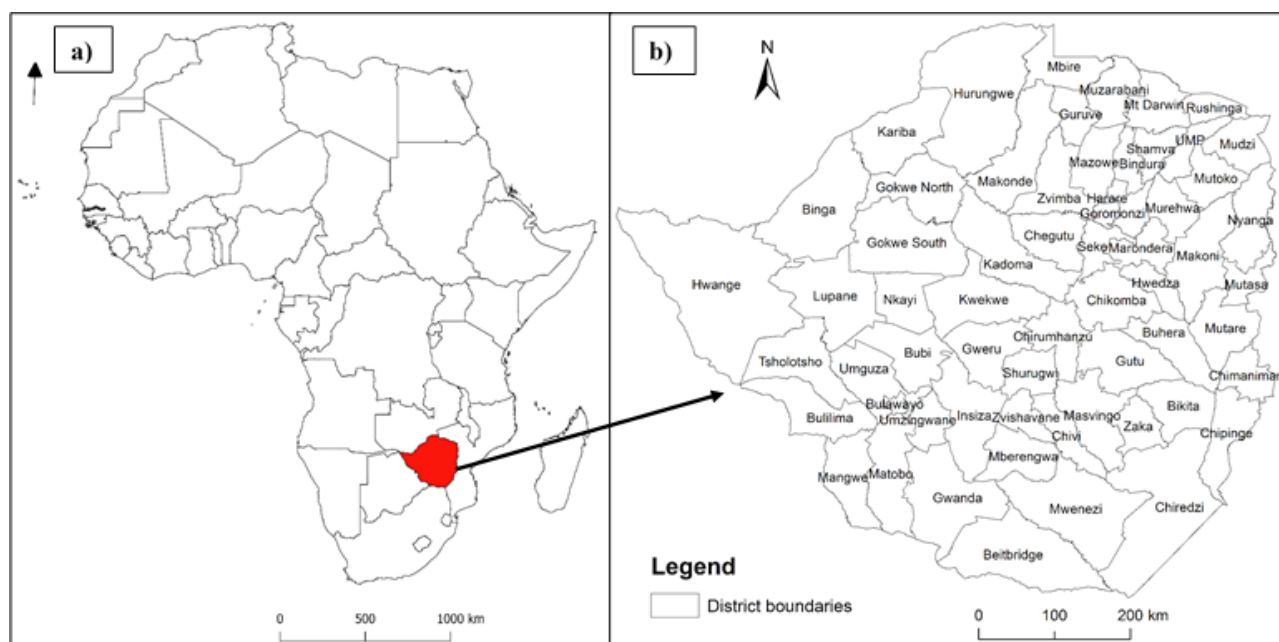


Figure 1. Study Area, a) location of Zimbabwe in Africa and, b) Zimbabwe district boundaries.

eracy, percentage of poor households in each district, the Gini index and the household food insecurity.

The selection of socio-economic factors was based on previous studies which proved their effects on the variation of HIV and AIDS [8,6]. For example, high poverty severity correlates very well with high incidences of HIV [5]. In a similar way, high percentages of male and female participation in the labour force reflect increases in economic productivity that enhance preventive actions, access to healthcare and information that reduce HIV infection [6]. Likewise, a higher literacy rate among the gender groups enhances the capability of the population groups to prevent the spread of HIV [4]. We also included the Night Lights Data (NLD), a satellite dataset (from NOAA National Centers for Environmental Information, <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>) which has been widely used as a proxy for local GDP and for measuring poverty. Light is essential for the consumption of any good or service at night hence the increase in light intensity may imply increases in economic activity or welfare [24]. Most of the economic activities in developing countries including Zimbabwe are informal and that makes data collection difficult resulting in poor quality of the data [24], thus NLD give the unbiased measure of spatial economic activity in Zimbabwe. Table 1 summarises the socio-economic factors used in this study.

2.3 Data Analysis

To understand the spatial distribution of HIV incidence, independent of the exploratory variables and in associa-

Table 1. Summary of socio-economic variables used at district level in Zimbabwe

Variable	Minimum	Mean	Maximum
Poverty Severity Index	1.8	16.710	36.60
Females employed Permanently (%)	1.1	8.077	30.10
Females unemployed (%)	0	4.460	41.08
Male employed permanently (%)	2.3	13.7	29.30
Poor Households (%)	4.9	16.934	100.00
Night Lights index (Max value)	0	19.049	63.00
Male literacy rate (%)	93	96.537	99.00
Female literacy rate (%)	86	94.183	98.17
Household food insecurity (%)	33.2	55.48	85.1
Gini index	31.5	46.0	36.79

tion with the socio-economic factors, we applied the Poisson model because data on HIV and AIDS cases is known to follow independent Poisson distributions [6]. The subsequent sections explain the three analyses we performed in this study.

2.3.1 Spatial Distribution/Clusters of HIV

Since HIV prevalence varies in space, flex scan statistical, Global Moran's I and LISA were employed to as-

certain geographical clusters of elevated HIV infections. Using ArcGIS10.4, four types of clusters are observed through LISA: (1) high-high, which means that high values are bordered by high values; (2) low-high, a low value was surrounded by high values; (3) high-low, a high value is bordered by low values; and (4) low-low, a low value was surrounded by low values. High-high and low-low denotes positive spatial autocorrelation and areas of contradictory values i.e., low-high and high-low indicates negative spatial autocorrelation [25].

We used the Poisson model based on original log likelihood ratios (LLR) with flexible scanning method and the maximum cluster size of 15 (default) and Monte Carlo replications to determine the spatial clusters of HIV incidence at district level in Tango’s flexibly shaped spatial scan statistic (FlexScan), FleXScan v3.1.2 [26]. Higher risk rates were related with higher LLRs. The methods for calculating the likelihood ratio (LR) and LLR are given in detail by Tango and Takahashi [27] and Takahashi and Shimadzu [28].

2.3.2 Spatial Regression Analysis

Geographically Weighted Poisson Regression (GWPR) analysis was performed in GWR4.09 to determine the spatial variation of the association between 2017 new cases of HIV and the related socio-economic factors at district level. Three forms of GWPR were considered in this study and their performance was compared based on Akaike information criterion that has a correction for small sample sizes (AICc) [29]. The first one is the global Poisson model, which assumes no spatial variation of the coefficients for the exploratory variables of the disease. The second one is GWPR, which assumes that all the exploratory variables in this case the socio-economic variable vary locally (Equation 1). The third one is semi-parametric GWPR, which assumes that some variables vary locally. Hence, they are termed local while those that do not vary are known as global variables (Equation 2).

$$y_i \sim \text{Poisson} \left[N_i \exp \left(\sum_k \beta_k(u_i, v_i) x_{k,i} \right) \right] \quad (\text{Equation 1})$$

$$y_i \sim \text{Poisson} \left[N_i \exp \left(\sum_k \beta_k(u_i, v_i) x_{k,i} + \sum_l \gamma_l z_{l,j} \right) \right] (\text{Equation 2})$$

Where y_i is the dependent variable, which has to be an integer greater than or equal to 0. N_i is offset variable (population at risk) at the i th location and in this case total population per district; x_k is the k th independent variable u_i is the x-y coordinate of the i th location; and coefficients β_k are varying conditionals on the location. z_l is the l th independent variable with a fixed coefficient

The fixed bi-square (Equation 3) was the geographical

kernel with the best performance based on AICc.

$$w_{ij} = \begin{cases} (1 - d_{ij}^2/\theta^2)^2 & 0 \leq d_{ij} \leq \theta \\ 0 & d_{ij} > \theta \end{cases} \quad (\text{Equation 3})$$

Where w_{ij} is the weight value of observation at location j for estimating the coefficient at location i ; i is the regression point index; j is the locational index; d_{ij} is the Euclidean distance between i and j ; θ is a fixed bandwidth size defined by a distance metric measure. The Golden search method was used for optimal bandwidth search. This automatically selected the optimum bandwidth size as defined by the performance assessment criteria and in this case the AICc.

Both GWPR and s-GWPR provided locally varying parameter estimates, for local variables and their *pseudo t* values [30]. *Pseudo t* values less than -1.96 or greater than $+1.96$ designates p -values < 0.05 indicating the significance of the locally varying parameters [30,31]. Comparison of the small sample size bias corrected AICc and the percent deviance explained were used to determine the model with the best performance [29,4]. Small values of the model signify a better performing model. If the difference between AICc is greater than 2, the model with lower AICc is chosen [32]. The model with the highest percent deviance explained is better performing. The local coefficients maps showed districts with significant estimates.

2.3.3 Multicollinearity

Multicollinearity was determined based on the variance inflation factor (VIF). The variables which had VIF greater than 5 [33] suggest severe multicollinearity. Hence female literacy rate was not considered in the analysis consistent with other similar studies [4,34,31].

3. Results

3.1 Spatial Variation of HIV in Zimbabwe

HIV incidence (number of cases per 1000) ranged from 0.6 (Buhera district) to 13.30 (Mangwe district). Spatial clustering of HIV incidence was observed (Global Moran’s $I = -0.150$; Z score 3.038; p -value 0.002). Significant clusters of HIV were observed at district level. Figure 2(a) shows the spatial variation of HIV incidence based on standard deviation and the location of clusters from Tango’s FlexScan while 2(b) shows HIV incidence hotspots or clusters based on LISA. As shown in Figure 2(a), HIV incidences are mostly concentrated in Bulilima, Mangwe, Umguza, Umzingwane, Bubi, Insiza, Zvishavane and Shurugwi district. Table 2 gives the details of the clusters from FlexScan. HIV is mostly clustered in Bubi, Bulilima, Insiza, Mangwe, Shurugwi, Umguza, Umzingwane and Zvishavane (Table 2). Other high-rank-

ing secondary clusters are found in Hurungwe, Buhera, Chikomba, Chirumhanzu, Hwedza and Seke. Districts from the western through to the central and northern part of the country had high level of deviation from the mean HIV incidence (Figure 2a). Two types of clusters were observed through LISA: (1) high-high, which means that a district with high value of HIV incidence was surrounded by district with high values; (2) low-high, a district with low value of HIV incidence was surrounded by districts with high values. The high-high cluster includes Bililima, Mangwe, Umguza, Bubi Umzingwane, Zvishavane and

Shurugwi district. All the high-high clusters fall within the most likely cluster identified through Poisson based original LLR with flexible scanning method in FlexScan. The low-high cluster is made up of Matobo district.

3.2 Regression Model Selection

Fixed bi-square was used as a geographical kernel and the best bandwidth size for all the models was 323.824 km based on golden search for optimum bandwidth. This means that HIV incidence or new cases in the district within 323.824 km were used in estimating the coeffi-

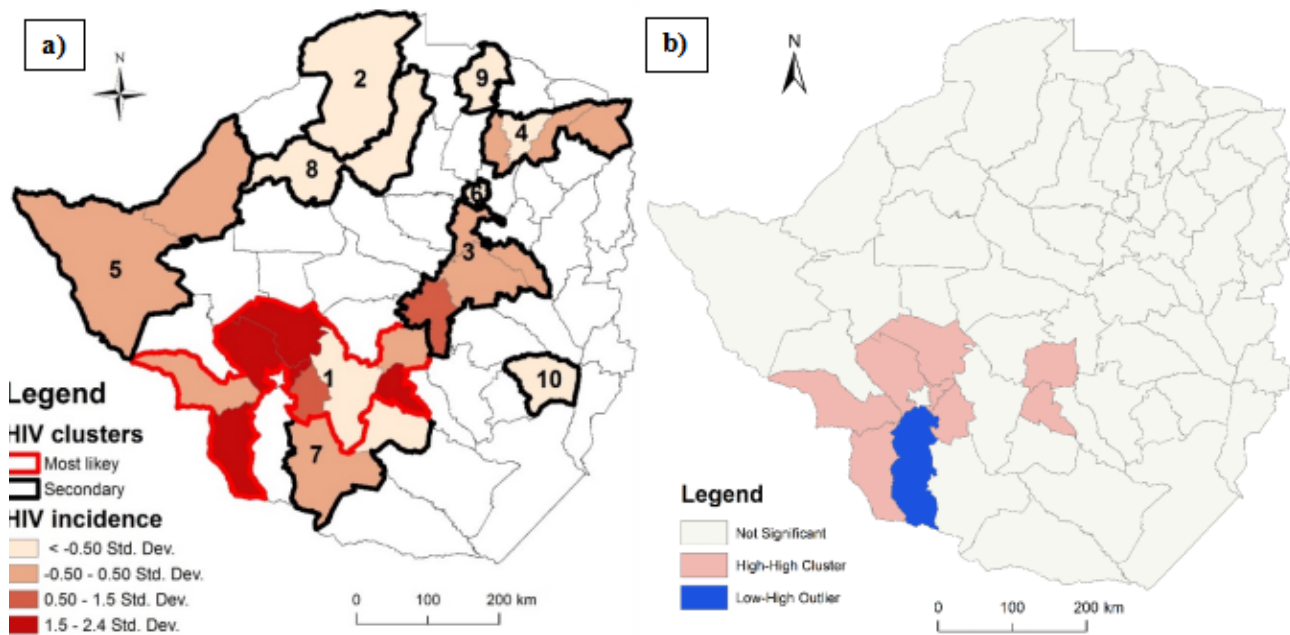


Figure 2. (a) Spatial variation of HIV incidence based on standard deviation and the location of clusters from Tango’s FlexScan (b) HIV incidence hotspots or clusters based on LISA

Table 2. Characteristics of the clusters identified through flex scan as shown in Figure 2a

Cluster ID	Characteristics			
	Districts included	Number of cases	Expected number of cases	Overall relative risk
Most likely				
1	Bubi, Bulilima, Insiza, Mangwe, Shurugwi, Umguza, Umzingwane, Zvishavane	6650	3020.49	2.202
Secondary				
2	Hurungwe	1300	166.156	7.824
3	Buhera, Chikomba, Chirumhanzu, Hwedza, Seke	2950	1726.84	1.708
4	Bindura, Mudzi, Shamva, UMP	3460	2219.38	1.559
5	Binga, Hwange	1700	1032.54	1.646
6	Harare	10000	8901.24	1.123
7	Gwanda, Mberengwa	1620	1329.25	1.219
8	Gokwe North, Makonde	2110	1780.25	1.185
9	Muzarabani	650	492.535	1.320
10	Bikita	750	593.416	1.264

coefficients at district of interest i.e., the regression point index. This bandwidth size had the lowest AICc (6163.638). The s-GWPR with percentage of females unemployed as a fixed or global variable and other variables as local (i.e., intercept, poverty severity index, females employed permanent, females unemployed, males employed permanent, poor households) outperformed other models considered in this study based on AICc. There were large differences between its AICc and Poisson global and GWPR i.e., 6402.392 and 27.335 respectively. It had the highest percent deviance explained of 0.602. These results show that most of the variables that explain the spatial variation of HIV incidence or new cases vary across the districts except a few such as females unemployed which do not vary by district. This indicates that models which incorporate local and global variables help to explain the variation of HIV incidence across the districts. More details on the variation of the contribution of these factors from the best model (i.e s-GWPR) are given in the next section.

3.3 Local Variation of Exploratory Variables in Determining the Heterogeneity of HIV Incidence

The s-GWPR model had one variable - Females unemployed (percentage) as global variable with a coefficient

value of 0.165, standard error (0.014) and z-value of 11.803. The maps in Figure 3 and Table 3 show the spatial variability of the exploratory determinants of the heterogeneity of HIV incidence at district level. All the variables considered had significant coefficients in the identified clusters except the male literacy rate, which was not significant in Shurugwi district. Negative values of DIFF of criterion indicates spatial variability while a positive value indicate no spatial variability (Table 4).

The percentage of permanently employed females showed a negative relationship with the HIV incidence in most of the districts. This means that the number of permanently employed females in Zimbabwe does not influence the incidence of HIV in most districts. The positive coefficients were very small with a maximum of 0.075 (Figure 3a). This includes districts such as Bulilima, Umguza, Bubi, Mangwe, Insiza and Umzingwane. The poverty severity index showed a negative association with HIV incidence in most of the districts except those in the southwestern region of the country (Bulilima, Gwanda, Matobo, Mangwe and Tsholotsho) including some parts of the identified cluster (Figure 3b). A few districts on the western part including Hwange, Lupane and Tsholotsho had the highest positive coefficients of the percentage of

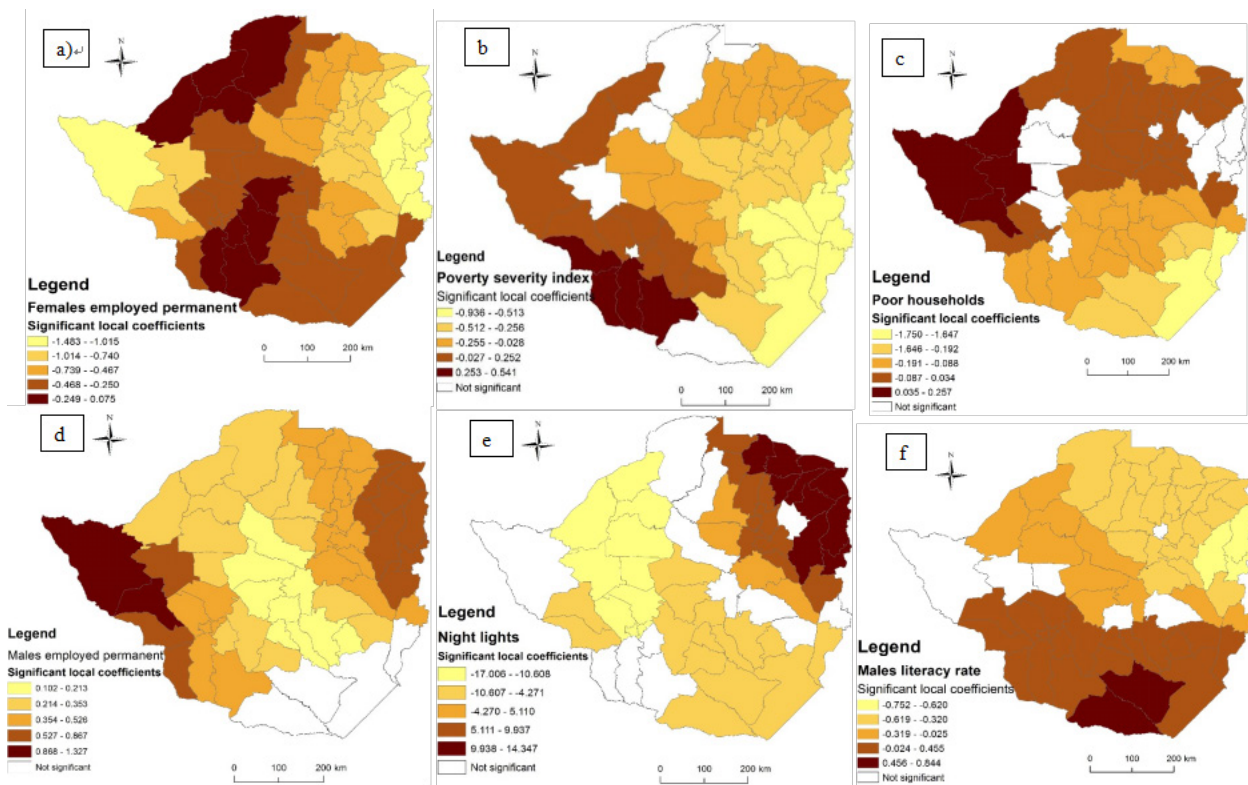


Figure 3. Spatial variation of the socio-economic factors considered in the current analysis of the spatial variation of HIV and AIDS incidence at district level in Zimbabwe a) Females employed permanently, b) Poverty severity index, c) Poor households d) Males employed permanently e) Night lights and f) Male literacy rate.

Table 3. Summary statistics of varying (local) coefficients in semi-parametric geographically weighted Poisson regression (s-GWPR) model for HIV and AIDS incidence in Zimbabwe

Parameter	Minimum	25 percentile	Median	75 percentile	Maximum	DIFF of criterion
Intercept	-6.335	-5.610	-5.560	-5.404	-4.867	-1335.443
Poverty severity index	-0.936	-0.329	-0.171	0.017	0.541	-916.352
Female employed permanent	-1.483	-0.882	-0.525	-0.277	0.075	-715.616
Male employed permanent	-0.062	0.235	0.412	0.525	1.327	-672.155
Poor households	-1.750	-0.112	-0.054	-0.029	0.257	-483.283
Night Lights (Max value)	-0.272	-0.102	-0.007	0.095	0.204	-162.327
Male literacy rate	-0.752	-0.465	-0.148	0.189	0.844	-600.431

^aNegative values of DIFF of criterion indicate spatial variability; ^bPositive values of DIFF of criterion indicate non-spatial variability

poor households (Figure 3c). The percentage of permanently employed males had a positive association with HIV incidence with the highest coefficients observed in the southwestern districts (Hwange, Lupane, Tsholotsho and Bulilima districts). Moderate coefficients were noted to the northeastern districts of the country (Figure 3d). Nightlights, used as a proxy for local economic development, had the highest positive coefficients to the northeastern part of the country. Only Mangwe district to the southwestern part had a high and positive coefficient. This maximum was noted in the most likely cluster as well (Figure 3e). The male literacy rate had higher coefficients in the southern districts of the country with the highest rates in Beitbridge and Mwenezi, (Figure 3f).

4. Discussion

This study has shown that HIV incidences vary across the districts in Zimbabwe with the major cluster located in the rural districts as previously noted by Gwitira et al.^[35]. The socio-economic variables considered in this study showed geographical variation of associations between HIV incidences and all the socio-economic factors except the percentage of females employed which was constant across the study area. These associations were significant in most of the districts with their contribution either positive or negative. Therefore, we concur with Alves et al.^[4] that the effects of some of exploratory variables of HIV incidences are not constant throughout a landscape, thereby opposing the assumptions in the global models. In this study we have shown the need for combining local and global variables to understand the spatial variation of HIV incidence since the s-GWPR outperformed other models.

Although it may be noted that AIDS may result in poverty, this disease may not be regarded as a disease of poverty. Our study has noted a relationship between gender and related economic inequalities and HIV incidence in Zimbabwe. We noted that the percentage of males permanently employed had high and positive coefficients in

most of the districts in the country. This also applied to the economic activities as indicated by night-lights. This is in agreement with Gillespie et al.^[36] who noted that higher incomes from males tend to be associated with higher HIV incidence while income inequality does show a strong association with HIV prevalence. This was also augmented by the night-light data, which is a useful tool to measure spatial economic activity over fine geographical areas in unmeasured economies such as Zimbabwe^[37,38].

The percentage of females employed permanently had a negative relationship with HIV incidence. This was shown by negative coefficients in most of the districts and slightly small size of positive coefficients in a few districts. This may indicate that when women are permanently employed, they have the capacity to take care of themselves. They stop relying on men; are able to negotiate and stand for safer sex; and can adopt different HIV prevention methods. The economic dependence of women on their male partners may make it difficult for them to insist on safer sex (e.g., condom use)^[8].

The percentage of poor households per district and poverty severity index showed mixed relationship with HIV incidences. We concur with the substantiation by Gillespie et al.^[36] that poverty is a major driver of HIV and may exacerbate poverty. Wealth can be both negatively and positively associated with HIV infection depending on the livelihoods of the affected population. Poverty places individuals particularly women at greater risk of exposure to HIV as they end up engaging in transactional sex^[39]. On a different note, Masvawure^[40] noted that exchanging sex is also regarded as a 'high-status, successful modern subject' i.e., from well up individuals. This has also been linked to increased risk of HIV^[41]. Similar to males employed permanently, male literacy rate showed a positive relationship with HIV and AIDS incidences in most of the districts in Zimbabwe. Instead of showing a protective sign, it seems male literacy is giving power to males to negotiate for whatever form of sex they want. This could increase the

HIV incidence. Xiong^[42] highlighted that although the general impact of poverty on HIV/AIDS remains unclear, there is some evidence that HIV-related outcomes are more detrimental among those who are already poor.

This study also showed that the detection of flexible noncircular clusters of the HIV is complementary to using the Kulldorff's circular spatial scan statistic. The Tango and Takahashi's flexible spatial scan statistic used in this study also agreed with LISA as applied in ArcGIS10.4, except that Insiza district was considered as part of the more likely significant cluster in the former and not in the latter. This could be explained by the differences in the sensitiveness of these methods. Our study findings can be used for tailor making programmes targeting socio-economic issues to address the HIV incidence and prevalence. For example, women empowerment programmes through education and employment creation as well as place specific programmes targeting HIV programmes. These programmes should consider all socio-economic groups in the communities including youths and women and taking into consideration the complex relationships between socio-economic factors and HIV. The conventional view that educated and wealthy men can make wise decisions including safer sex should be challenged.

In this study we considered only key socio-economic variables related to HIV in Zimbabwe. The inclusion of other variables related to the control measures or intervention strategies at district level could also be considered in future studies. Our study contributes to the diversity of GIS and spatial analysis themes and methodologies in understanding the HIV dynamics in Zimbabwe. The GWPR results may be useful for public health stakeholders involved in reviewing local and regional policy and services. As noted in the current study, there is no universal agreement in the literature nor strong statistical evidence that poverty increases exposure to HIV. In line with Xiong^[42] the mixed conclusions from literature indicates that HIV is a complex problem and it may not be appropriate to strictly define HIV as an infection driven by poverty^[42]. As also highlighted by our study was cross-sectional and hence prone to the criticism of the limitation to infer the temporality of the associations^[4].

5. Conclusions

HIV incidences and their association with socio-economic factors vary at local level. There is need to empower women as the percentage of permanently employed females showed a negative relationship with the HIV incidence in most of the districts. This could also be complemented by implementing programmes that may reduce the percentage of poor households across the districts. The

results of this study can be used by different stakeholders including MOHCC and NGOs in the development of HIV intervention strategies at district level as opposed to the blanket strategies that are developed at national level. These interventions should target the identified socio-economic factors at district level so as reduce the HIV incidence. Theoretically and methodologically, our study demonstrates the usefulness of a geographical approach to the study of disease and, relatedly, the importance of (a) acknowledging the positionality and situatedness of one's knowledge^[43-45], and (b) studying a given medical phenomenon across geographical scales, from the personal to the social^[46-48].

Data Availability

All data generated or analysed during this study are included in this manuscript.

Compliance with Ethical Standards

Funding: The authors did not receive support from any organization for the submitted work.

Conflict of interest: The authors have no conflicts of interest to declare that are relevant to the content of this article.

Informed consent: There was no involvement of human participants. All the data used in this study was obtained from publicly available reports.

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