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Assessing spatial patterns of HIV prevalence and interventions in semi-urban settings in South Africa: Implications for spatially targeted interventions

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Abstract

Equitable allocation of resources targeting the human immunodeficiency virus (HIV) at the local level requires focusing interventions in areas of the greatest need. Understanding the geographical variation in the HIV epidemic and uptake of selected HIV prevention and treatment programmes are necessary to identify such areas. Individual-level HIV data were obtained from a 2012 national HIV survey in South Africa. Spatial regression models on each outcome measure (HIV infection, sub-optimal condom use or non- anti-retroviral treatment (ART) adjusted for spatial random effects at the ward level were fitted using WINBUGS software. In addition, ward-level data

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Author contributions

Chimoyi L. provided the initial idea/design of the Bayesian analysis, participated in data acquisition, created the geographical maps, interpreted results, and drafted the first draft of the manuscript.

Matsena-Zingoni Z. Conducted the Bayesian analysis using WINBUGS and reviewed the paper

Charalambous S. and Marinda E. participated in the interpretation of the study findings.

Musenge E. and Manda S. provided substantial contributions to the Bayesian approach and interpretation.

All authors approved the submitted version and agreed to be responsible for any part of the manuscript.

Disclosure statement

All authors declare no conflict of interests except one co-author, Prof Manda who is an editor in this journal.

Ethics and consent

Ethical clearance was sought from the Wits Human Research Ethics committee (HREC; M181088). Additional permission was sought and approved from the National and Gauteng Department of Health (to access DHIS data) and the Ekurhuleni Metropolitan Municipality Research Committee. The current research was conducted using secondary datasets. Data accessed were grouped by ward and did not represent individual participants or clinics. Patient and participant consent was waived due to the use of retrospective data.

was utilized to estimate condom use coverage and ART initiation rates which were obtained from routinely collected data in 2012. Ordinary Kriging was used to produce smoothed maps of HIV infection, condom use coverage and ART initiation rates. HIV infection was associated with individuals undertaking tertiary education (posterior odds ratio (POR):19.53; 95% CI: 3.22–84.93). Sub-optimal condom use increased with age (POR:1.09;95%CI:1.06–1.11) and was associated with being married (POR: 4.14; 95% CI: 1.23–4.28). Non-ART use was associated with being married (POR: 6.79; 95%CI: 1.43–22.43). There were clusters with high HIV infection, sub-optimal condom use, and non-ART use in Ekurhuleni, an urban and semi-urban district in Gauteng province, South Africa. Findings show the need for expanding condom programmes and/or strengthening other HIV prevention programmes such as pre-exposure prophylaxis and encouraging sustained engagement in HIV care and treatment in the identified areas with the greatest need in Ekurhuleni Metropolitan Municipality.

Keywords

HIV prevention; HIV treatment; Spatial heterogeneity; Targeted interventions; Bayesian; South Africa

Introduction

Previously, the human immunodeficiency virus (HIV epidemic in sub-Saharan Africa (SSA) was generalised but more recently, research is showing the presence of concentrated epidemics (Cuadros et al., 2013, Ramjee et al., 2019, Zulu et al., 2014). At the country level, the presence of key populations at higher risk of HIV leads to such concentrated epidemics (Cuadros et al., 2017, Cuadros et al., 2018). In South Africa, HIV prevalence varies significantly at the sub-national and district levels (Tanser et al., 2014) due to complex economic and localised social, behavioural and cultural factors (Hallman, 2005). Similar to other countries in SSA, South Africa reports substantial numbers of HIV incidence from key populations at high risk including sex workers and their clients, people who inject drugs, men who have sex with men, and inmates in correctional institutions (Coburn et al., 2017, Cuadros et al., 2017, Tanser et al., 2014).

Significant resources are being invested in scaling up prevention and treatment programmes to address these concentrated epidemics (Grabowski et al., 2017). Condoms are highly effective in preventing sexual transmission of HIV as long as they are consistently and correctly used (Versteeg and Murray, 2008); they are most effective in high-risk individuals (Coburn et al., 2017). Anti-retroviral treatment programmes have been scaled up in South Africa to prevent transmission of HIV (Granich et al., 2009, Wilson, 2012). Previously, homogenous distribution of such interventions was resource intensive. To improve the efficiency of the limited resource allocation, funding agencies shifted towards optimizing the resources allocated in areas where they are most needed (Boyda et al., 2019, Cuadros et al., 2017, Cuadros et al., 2018, Tanser et al., 2014). The implementation of spatially targeted interventions requires identifying areas where the burden of HIV infection is concentrated and utilisation of preventive techniques is low (Boyda et al., 2019, Tanser et al., 2014). This strategy is challenging due to the scarcity of spatial data caused by the costly implementation of population-based surveys in resource-limited settings. However, this strategy identifies populations at higher risk of infection as well as areas of high and low risk (Aral et al., 2015). Having such data on HIV spatial distribution patterns at the local level could help prevent new HIV infections and scale up treatment and prevention by prioritizing the allocation of resources to high-burden areas and aligning service delivery modalities to the needs of the population (Schaefer et al., 2017).

In SSA, spatial analysis of health data is gaining traction and has established variations in HIV prevalence, service use and risk factors. Using population-based survey data from demographic health surveys (DHS) spatial clusters and geographical variation at the district-level revealed hotspots of HIV infection in Uganda and revealed non-condom use and non-circumcision as factors driving HIV infection (Chimoyi and Musenge, 2014). Spatial analysis at the district level identified high-risk populations and regions in Malawi where targeted interventions for HIV prevention and treatment programs are needed (Nutor et al., 2020). These authors also mapped the spatial distribution of HIV infection at the provincial level which revealed associations of high-risk sexual behaviour with HIV infection in high-burden provinces.

Focusing progress at the sub-national level addresses gaps at the national or provincial levels, which negatively affects resource allocation due to masked local heterogeneities (Cuadros et al., 2018). Development of spatial analysis at lower spatial units, such as the ward-level is likely to improve accuracy in health estimates (Manda et al., 2020). Spatial epidemiologists have used spatial smoothing and spatial interpolation such as Kriging to improve the estimation of health outcomes and disease burdens by incorporating geographic information systems (GIS) allowing the use of values at observed locations to estimate values at unobserved locations (Manda et al., 2020). Spatial cluster techniques at the local level identified patterns of HIV prevalence, high HIV testing and counselling and anti-retroviral treatment (ART) uptake, which improved resource allocation of HIV prevention and treatment interventions in two towns in Zimbabwe (Schaefer et al., 2017).

In the absence of costly population-based surveys, clinic-based routinely collected data on HIV services from different health facilities at the ward or sub-district level can be explored (Cuadros et al., 2018) and applied to monitor progress and provide scientific evidence to guide targeted resources allocation in areas with the greatest need (Boyda et al., 2019). A study in KwaZulu Natal, South Africa illustrated the use of readily available programme data to map the heterogeneity of the HIV epidemic in a hyperendemic setting. The authors demonstrated the feasibility of using these sources to identify areas for the implementation of spatially targeted interventions (Cuadros et al., 2018).

The current study combined data from a national survey and routinely collected HIV programme data to identify the heterogeneity of HIV infection, condom use and ART initiation in Ekurhuleni Metropolitan Municipality (EMM), Gauteng Province, South Africa. EMM, a hyperendemic HIV district, is considered a high priority district as it is characterised by a high population and a high HIV prevalence (National Department of Health, 2017). Resources to control HIV have been allocated to the district however, the HIV prevalence remains high at 14% (Magege et al., 2009, Simbayi et al., 2019). The objective of this study was to understand the underlying geographical patterns of HIV prevalence, condom use coverage and ART initiation rates in EMM using spatial techniques. Further, we sought to understand the drivers of the negative health outcomes (sub-optimal condom use and lack of ART use) in the study area using statistical techniques accounting for spatial random effects.

Material and methods

Study design and population

This study used national- and local-level data collected in 2012 from adults participating in a national survey and patients attending routine visits in primary health care clinics in EMM, South Africa.

Study area

EMM borders the city of Johannesburg, the city of Tshwane and the Sedibeng District Municipality. The population is over 3 million and its density is 1 718 people per km^2 according to the 2011 census. The HIV prevalence in 2012 was 12% and increased to 14% in 2017 (Human Sciences Research Council, 2018, Simbayi et al., 2019). EMM is sub-divided into three sub-districts (North, South and East) and 101 wards. There is a district hospital, seven community health centres and 87 primary health clinics. These facilities are staffed by clinical personnel and offer health care services, including HIV prevention and care, with no out-of-pocket payments required from patients. Also, various non-governmental organisations, through support and collaboration with the U.S. President's Emergency Plan for AIDS Relief (PEPFAR) and the U.S. Centers for Disease Control and Prevention(CDC) work in collaboration with the South Africa National Department of Health (NDoH) to increase services such as direct service delivery and health systems strengthening (Gaal et al., 2005).

Data sources

Retrospective data for this study were acquired from publicly available datasets. We used two datasets for this study namely: i) The 2012 South African National HIV Prevalence, Incidence and Behaviour Survey by the Human Research Sciences Council (HSRC). This was used to acquire data on HIV infection and socio-demographic information in the different sub-districts at a national level. ii) Data on the uptake of HIV interventions at the clinic level in EMM was abstracted from the District Health Information System (DHIS) hosted by the NDoH, which routinely collects individual-level data from all South African public health facilities at the local level.

From a database of 86 000 enumeration areas (EAs), 1 000 EAs from the 2001 population census stratified by province, locality type and race were randomly selected using probability proportional to size. These EAs were mapped in 2007 using aerial photography to develop the 2007–2011 HSRC primary sample for selecting households. The EAs formed the primary sampling units. Oversampling of smaller strata e.g., racial groups was done to meet the required minimum sample size. In each sampled EA, a total of 15 households were used as secondary sampling units. Within each household selected for the survey, all household members (including consenting and non-consenting household members) constituted the ultimate sampling unit. In Ekurhuleni, 57 EAs over 33 wards were sampled.

Variables

Three outcomes from the national survey were: (i) HIV infection, defined as reported HIV positive test; (ii) sub-optimal condom use, defined as reporting not consistently using condoms in the past month; and (iii) non-ART use, defined as reporting not using ART despite a positive HIV status. Data on the coverage of male condom use and ART initiation rates were provided by Gauteng DoH. The HIV interventions used were abstracted from DHIS (April – Dec 2012). Aggregated male condom coverage was calculated as the number of condoms distributed by the clinic and other non-medical sites per the number of males ≥15 years of age. The ART initiation rate was calculated by estimating the total number of HIV patients remaining on ART over the estimated number of PLHIV reporting to the clinic at the end of each month. An annual average by ward was calculated based on the HIV prevalence, defined as the proportion of individuals testing HIV-positive over the total population sampled per ward during the survey.

Other measures included socio-demographic (age, gender, and employment status) and high-risk behavioural variables such as number of lifetime sexual partners, age of coital debut and drug use.

Data analysis

The population profile was described using frequencies, percentages, median and interquartile ranges (IQR). A p-value <0.05 was considered significant. Model building was performed in Stata (https://www.stata.com/) through a stepwise binary logistic regression approach and the final model used for Bayesian analysis. The latter was carried out in WinBUGS, version 1.4 (MRC Biostatistics Unit, Cambridge, UK), which included fitting three models: standard, random-effects model and spatial effects logistic regression model that assessed the risk factors for HIV infection, sub-optimal condom use and non-ART and describe the heterogeneity of these outcomes in space. Bayesian methodology, using Markov Chain Monte Carlo (MCMC), estimated the parameters in the three models through 20 000 iterations with burn-in of 1,000 iterations. Parameter estimates of each outcome at the ward level from this analysis were used to create interpolated maps in ArcGIS v.10.7.1 (Environmental Systems Research Institute, 2019). Posterior odds ratios (POR) and their corresponding 95% credible intervals (CI) were reported. A significant effect is observed when the CI does not contain 1. A deviance information criterion (DIC) was used to assess model fit and the model with the lowest DIC value was taken to be the best model. In addition, a difference >5 implied no differences in the models (Spiegelhalter et al., 2002).

Statistical modelling

Each regression model was fitted using a Bernoulli distribution for binary outcomes. The outcome with respect to HIV infection, sub-optimal condom use and non-ART use (Y_{is}) took values $Y_i = 1$ when an event occurred or 0 otherwise with regard to an individual i residing in ward $s = 1, 2, \ldots, 33$. Therefore, Y_{is} follows a Bernoulli distribution with a probability of experiencing an outcome p_{is}, that is, $Y_{is} \sim Ber(p_{is})$. The probability density function of the outcome variables is $P(Y_{is}) = p_{is}^{Y_{is}}(1 - p_{is})^{1 - Y_{is}}$. Using the generalised linear model for a binary outcome, the probability can be modelled using logistic regression as:

$$logit(p_{is}) = P(Y_{is} = 1 \mid x_i) = \beta_0 + \mathrm{X}_i^T \beta_i + G_{is} \qquad \text{Eq 1.}$$

where $\boldsymbol{\beta}_0$ is the intercept terms; β_i the vector of regression coefficients of fixed effects; X_i the vector of subject-level covariates; and $\mathbf{G}_{is}$ the spatial random effects corresponding to the binary response of an individual i residing in ward s. Since we assumed that the outcome variables were spatially correlated and the independence assumption in the response variables questionable, we introduced a spatial structure. The spatial random-effects $(\mathbf{G}_{is})$ were decomposed into subject-specific uncorrelated (U_{is}) and spatially correlated random effects; hence, the following convolutional model was fitted:

$$logit(p_{is}) = \beta_0 + X_i^T \boldsymbol{\beta} + \mathrm{U}_{is} + H_{is} \qquad \text{Eq 2.}$$

We fitted a fully Bayesian inference approach whereby we assigned priors to all unknown random and fixed parameters and variance parameters (hyperparameters). Parameters of the fixed effects were assigned diffuse priors, $\beta \propto \text{ constant }$. The uncorrelated spatial effects U_{is} were assumed to be independent and identically distributed Gaussian priors, that is, $U_{is} \overset{iid}{\sim} N\left(0, \tau_u^2\right)$ where the unknown hyperparameters of the variance components, τ_u^2 was assigned highly dispersed gamma priors $\left(\tau_u \sim G\left(a_{\tau_u}, b_{\tau_u}\right)\right)$ with known parameter values $\mathrm{a}_u = \mathrm{b}_u = 0.01$. The structured spatial wards $(S = 33)$ modelled in this study were assumed to follow a conditional autoregressive (CAR) prior. In the full conditional distribution, each H_{is} is conditional on the sum of the weighted values of its neighbours $\left(w_{jk \in s} H_s\right)$ and has an unknown variance, which is:

$$H_j \mid H_k, j \neq k, \sim N\left(\sum_{j = 1}^{n} W_{jk} H_s, \tau_h\right) \qquad \text{Eq 3.}$$

where W is an $S \times S$ adjacency weighting matrix that defines the relationship of $S \times S$ areal units (wards). For two adjacency neighbour ward polygons, $j \sim k, j \neq k$ the W matrix entries take values 1 if the wards are neighbours or otherwise 0. In the CAR model, the neighbour relationship is symmetric but not reflective and a ward/polygon cannot be its neighbour. The hyperprior for the variance parameter was assumed to follow an inverse Gamma distribution, $\tau_h \sim G\left(a_{\tau_h}, b_{\tau_h}\right)$. Since this posterior function had no closed form, we used the Gibbs sampling (Hrycej, 1990) to estimate the posterior parameters or MCMC with Metropolis-Hastings algorithms (Chib and Greenberg, 1995).

The Bayesian models were fitted with 15 000 MCMC iterations, and the prior sensitivity was done by varying parameter values. Model convergency was assessed using trace plots and autocorrelations plots. We used DIC to identify the preferred model among the non-spatial l, unstructured spatial random effects only, structured spatial random effects only and convolutional models DIC define as seen in Eq 4:

$$DIC = D(\bar{\theta}) + 2p_D = \overline{D} + p_D \quad \text{Eq 4.}$$

where $D(\bar{\theta})$ is the deviance statistic evaluated at $\bar{\theta}$ (which is the posterior means of the parameter of interest); p_D the effective number of parameters in the model; and $\overline{D}$ the posterior mean of the deviance statistic. The lower the DIC, the better the model.

Kriging analysis

Kriging was done to calculate an average value for locations with no data using values from nearby weighted locations and used to predict hotspots of clusters of high HIV infections, sub-optimal condom use coverage and low ART initiation rates (Cressie, 2015). The value of the outcome (z) at a specific location (s_i) is modelled as the sum of the regional mean (m) and a spatially correlated random component ($e(s_i)$) as follows:

$$Z(s_i) = m + e(s_i) \quad \text{Eq 5.}$$

Aggregated data were available for 33 wards from the datasets collected. For the wards with no data (X_0), prediction is required to estimate the unknown mean. Each point (X_0) was predicted as the weighted average of the values at all sampled points and the weights assigned to each sampled point summed up to 1 making the prediction unbiased (Oliver and Webster, 1990) using the equation:

$$\mathrm{E}\left[\widehat{\mathrm{Z}}\left(\overrightarrow{\chi_0}\right) - \mathrm{Z}\left(\overrightarrow{\chi_0}\right)\right] = 0\Big] \quad \text{Eq 6.}$$

Two sets of maps were produced; firstly, interpolated maps describing the patterns of HIV prevalence, male condom use coverage and ART initiation rates across the district from the national survey, and secondly, smoothed maps showing the likelihood of HIV infection, suboptimal condom use and non-ART use using the routinely collected data from the regression analyses. The maps showed areas with increased proportions of poor outcomes (red colour) and those whose proportions were lower (green colour) (Figures 1–6).

Results

Characteristics of the study population

A total of 1 189 respondents participated in the 2012 HSRC Survey from 32 of 101 wards in the study area (Supplementary file 1). The respondents' mean age was 37.6 years, and there were significant differences across the sub-districts (p =0.003) (Supplementary file 1). More than half of respondents were females (51.2%; 95% CI: 49.3%−53.0%). In the South sub-district, more respondents were male (50.3%; 95% CI: 48.4%−52.3%).

Unemployment was high in the study area (45.9%; 95% CI: 43.1%−48.7%) and highest in the East sub-district (53.0%; 95% CI: 51.6%−54.4%) compared to the North sub-district (46.3%; 95% CI: 44.0%−48.7%) and the South sub-district (41.5%; 95% CI: 36.1%−47.0%). The mean age of coital debut was 18.3 years (SD: 18.1–18.6), and the mean number of lifetime sexual partners was 4.87 (SD: 4.6–5.1); differences across the sub-districts were observed. The overall proportion of those reporting consistent condom use was low across the district (26.4%; 95% CI: 24.2%−28.8%) and even lower for those living in the North sub-district (19.4%; 95% CI: 15.9%−23.7%). The proportion reporting drug use was lowest in the East (12.3%; 95% CI: 7.2%−20.2%) and highest in North (27.4%; 95% CI: 24.6%−30.3%) sub-district.

HIV prevalence and factors associated with HIV infection

The overall HIV prevalence was estimated at 16.6% (95% CI: 15.1%−18.1%). The highest HIV prevalence was reported in the East sub-district (18.9%; 95% CI: 16.5%−21.6%) (Supplementary file 1) and observed in wards within Clayville, Kempton Park areas (North), in Katlehong and Germiston (South) and in Kwa Thema, Etwatwa and Brakpan (East) (Figure 1). HIV infection in these areas was associated with being a student (POR:12.74: 95% CI:3.29–95.01) (Table 1). Upon adjusting for spatial random effects, the magnitude increased (POR: 19.53: 95% CI:3.22–84.93) (Table 1). A high proportion of HIV infection was seen in wards within Thokoza, Katlehong, Kempton Park, Edenvale, Tembisa and Brakpan areas (Figure 2). In these wards, inconsistent (66% (POR:0.34: 95% CI:0.18–0.63)) and consistent (52% (POR:0.48: 95%CI:0.24–0.87)) use of condoms was associated with lower HIV infection (Table 1).

Male condom use coverage and factors associated with sub-optimal condom use

In 2012, the average male condom use coverage as reported from routine clinics across the wards ranged between 1% and 21% (Figure 3). Sub-optimal male condom use coverage was observed in Tembisa and Kempton Park (North), in Springs, Brakpan and Kwa Thema (South) and in Dukathole, Boksburg, Alberton and Katlehong (East). The proportion of those who reported consistent condom use during the 2012 National survey was 26.4% (Supplementary file 1). The odds of sub-optimal condom use were associated with increased age (POR:1.09; 95% CI:1.06–1.12) and marriage (POR:3.19; 95% CI:1.23–4.12) before and after adjusting for spatial random effects (Table 2). Increased likelihood of sub-optimal condom use was seen in wards within Kempton Park, Springs, Etwatwa, Brakpan, Alberton, Thokoza, Katlehong and Edenvale areas (Figure 4). In these wards, males were less likely not to have unprotected sexual acts (POR:0.52: 95%CI:0.33–0.80).

ART initiation and factors associated with non-ART

In 2012, the average ART initiation rate as reported from routine clinics across the wards ranged between 1% and 75%. Lower ART initiation rates were observed in Tembisa (North), in Katlehong, Germiston and Boksburg (South) and in Springs, Brakpan and Kwa Thema (Figure 5). The proportion of those who reported not starting ART during the 2012 National survey was 71.3% (70.1%−72.5%) (Supplementary file 1). The odds of non-ART initiation increased in those married before (POR:6.12; 95% CI:1.37–20.28) and after (POR: 6.79; 95% CI:1.43–22.43) adjusting for spatial random effects (Table 3). Increased likelihood of non-ART use was seen in wards within Valorous, Springs, Etwatwa, Brakpan, Alberton, Thokoza, Katlehong and Harry Gwala areas (Figure 6).

Discussion

This study focuses on the heterogeneity of HIV prevalence and uptake of HIV interventions and has shown the feasibility of using routinely collected data from primary health care facilities to reveal areas for spatially targeted interventions. Findings from this data source corroborate the sub-optimal uptake of condoms and linkage to ART reported from the national population-based survey conducted in the same year in this setting.

This is the first study to analyse geographical variations in HIV prevalence, coverage of condoms, and uptake of at the ward level which is often overlooked by national population-based surveys. The variation was considerable, e.g., lower HIV prevalence was observed in certain wards, together with low ART initiation rates and condom use coverage, and in other areas HIV prevalence could be higher, also the reported HIV prevalence was higher in some areas with low uptake of HIV interventions. On the other hand, in other wards, as expected, the observed HIV prevalence was low when the uptake of interventions was high.

The importance of using spatial data to visualize gaps in service coverage has been a recurring theme across many studies highlighting the critical role of geography in informing access to HIV-related health services in low-income settings (Boyda et al., 2019). GIS and spatial analysis allow for a more efficient allocation of resources and appropriate targeting (Aral et al., 2015, Coburn et al., 2017). Condom and ART program implementation could benefit from dynamic, interactive, and iteratively updated maps with verified health facility coordinates and infrastructure data, and simple mapping may be a good entry point for more advanced geospatial techniques (Cuadros et al., 2018). Also, our study further investigated the reasons driving these unfavourable health outcomes in this setting.

Our findings identified drivers of HIV infection, sub-optimal condom use and non-ART use. We found that HIV infection was associated with being in school. Students, usually young people undergo various psychological and behavioural changes that put them at risk for HIV infection (Bekker and Hosek, 2015, Dellar et al., 2015). Findings further showed an increased likelihood after adjusting for spatial effects signifying the importance of including space for targeted interventions. The wards within the areas with increased odds of HIV infection are likely to have a considerable proportion of younger people (<35 years) and mostly female, and other key populations including men who have sex with other men, injection drug users and female sex workers living in informal dwellings, high levels of unemployment (>30%) and a small proportion of the population with tertiary education (<3%). Although we did not find an association with being female, other studies have shown the disproportionate high HIV burden in young women compared to men. Indeed, a recent systematic review showed that the HIV incidence rates in young women far outweigh male counterparts (Birdthistle et al., 2019). Expanding existing HIV treatment and prevention programmes in communities and educational facilities to include youth-centred interventions through innovative technologically driven platforms is recommended.

This study found that males were more likely to consistently use preventive techniques compared to females. The spatial effect was not observed implying that the likelihood was homogenous across the wards. Consistent with previous studies, females were less likely to use technical prevention (Muchiri et al., 2017). Reasons for this from similar studies indicate the need to show faithfulness to a male partner, the ability to negotiate condom use as well as the perceived inefficacy of condoms (Jama Shai et al., 2010). Married unemployed women are less likely to use this kind of technical prevention due to financial dependence on their male partners and the expectation to bear children (Ayiga, 2012, Jama Shai et al., 2010, Versteeg and Murray, 2008). High self-efficacy of condom use is often associated with those with secondary school education, and it is assumed that with this level of education, knowledge of HIV transmission and prevention is high (Ayiga, 2012, Jama Shai et al., 2010). Our findings contrasted with what has been found in other settings where sub-optimal condom use was observed in those with secondary school education. A study conducted in Kwa Zulu Natal, South Africa among university students reported low condom use and a lack of confidence in using condoms at sexual debut due to poor negotiation with a partner and were likely to form negative attitudes about condom use (Haffejee et al., 2018).

Notably, sub-optimal ART uptake was associated with being in school. This is confirmed by several studies globally which have shown barriers to retention in care include having to attend a clinic during school hours, fear of disclosure to others, social isolation, and conflict with clinical staff (Zanoni et al., 2019, Lall et al., 2015). As the HIV prevention model shifts to treatment-as-prevention strategies, identifying drivers that promote adherence to and retention in care to antiretroviral regimens among HIV-positive young people is necessary (Lall et al., 2015). At the ward level, drug use was a factor that may prevent optimal ART uptake and addressing these challenges may promote adherence in identified areas and subsequently improve HIV outcomes. However, this association was not observed in any of our models.

The limitations of this study include underestimation of HIV prevalence due to the inability to fully link the 2001 census enumeration areas data with what was provided by the HSRC as not all wards were sampled. As a result, underestimation, or overestimation of study outcomes from HSRC was likely. However, condom use and ART initiation estimates from the national survey data were almost similar to the estimates from the DHIS which validates these findings. Data from DHIS may have been incomplete as clinics may not have submitted all their clinical data timeously. Despite these limitations, the use of interpolation allowed the calculation of predicted values from areas not sampled using observations from nearby locations. Although outcomes were derived from two different data sources, we attempted to compare findings between outcomes from the population-based survey with those from the routinely collected data.

Conclusions

This study adds valuable information to the growing body of knowledge prevention of HIV in South Africa. It confirms what is already known about the heterogeneity of HIV prevalence in South Africa. The study utilized two data sources; a national survey and routinely collected data for a high priority district in 2012 with similar findings. Further, the study's novel contribution is conducting spatial modelling at a far higher spatial resolution than used before thereby visualizing patterns of poor HIV outputs and outcomes in the study area.

The use of maps to visualize HIV prevalence and interventions provides support how to apply limited resources to where they are most needed. Thus, our findings have important public health implications for program planners. Furthermore, modelling revealed the heterogeneity of outcomes at the ward level. From this study, it would be recommended to scale up condom uptake and reinforce ART programmes according to the need to prevent HIV transmission. Addressing the drivers for the sub-optimal condom use and ART initiation identified in this study is encouraged. This may mean strengthening partner counselling and expanding access to condoms in existing HIV prevention and treatment programmes. This study also demonstrates the feasibility of using readily available programme data for planning, without expensive research studies. This can be a model for similar studies in other settings, and potentially have a high impact on the HIV epidemic.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available as permission from the gatekeepers is required for access.

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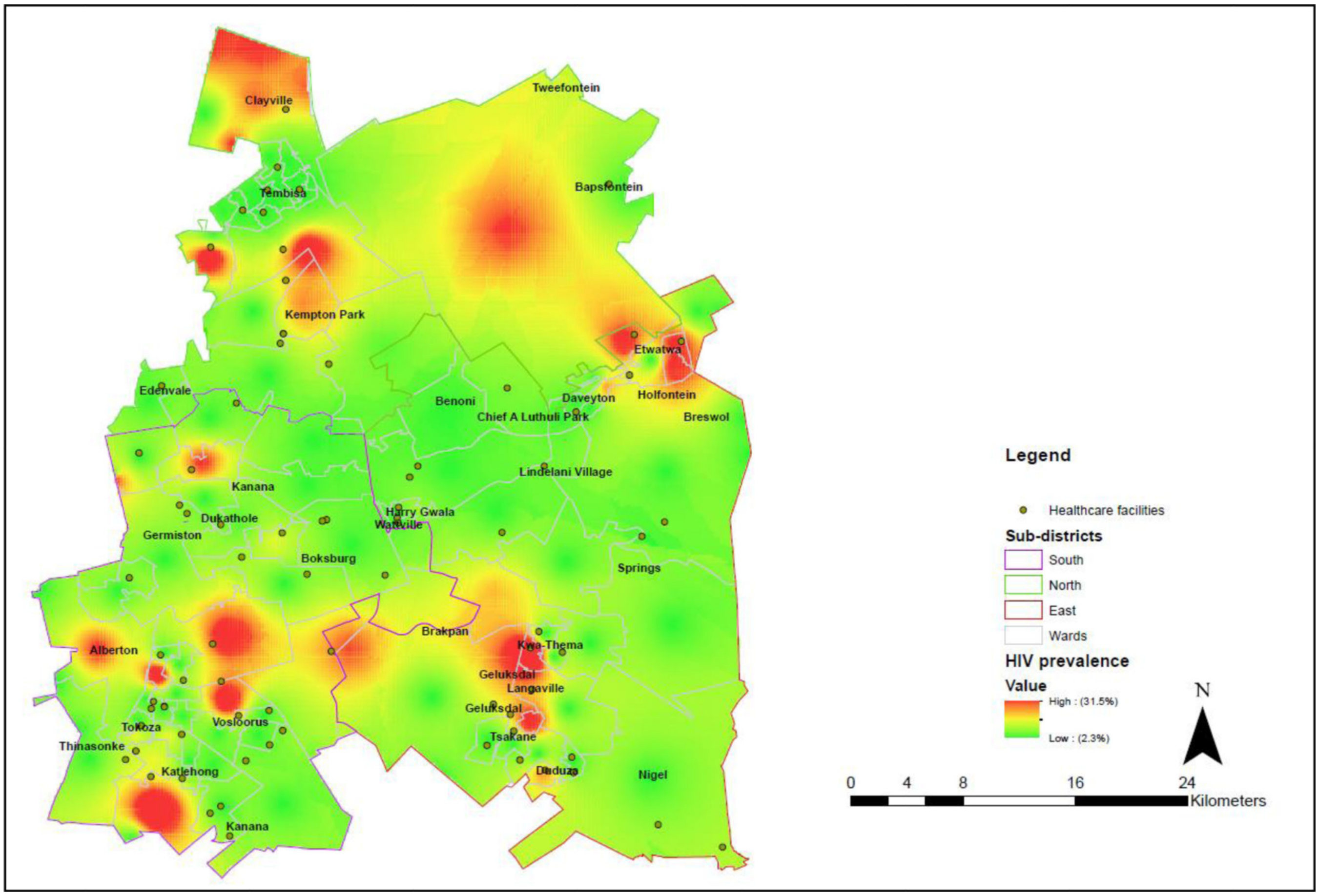

Figure 1: A smoothed HIV prevalence map of Ekurhuleni Metropolitan Municipality, South Africa

Based on 2012 HSRC national survey

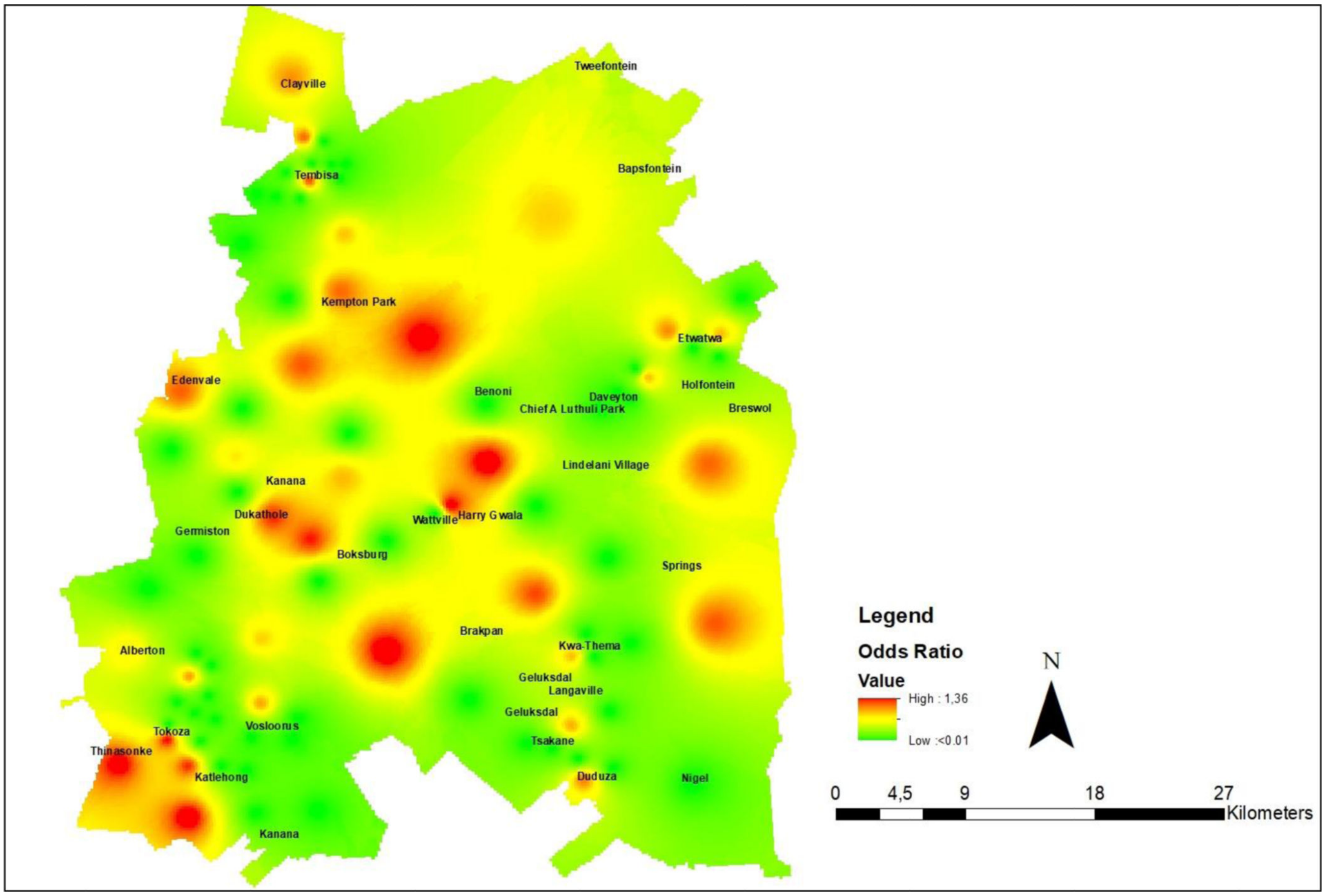

Figure 2: A smoothed map showing the expected Posterior Odds Ratio HIV infection in Ekurhuleni Metropolitan Municipality, South Africa

Based on the 2012 HSRC national survey

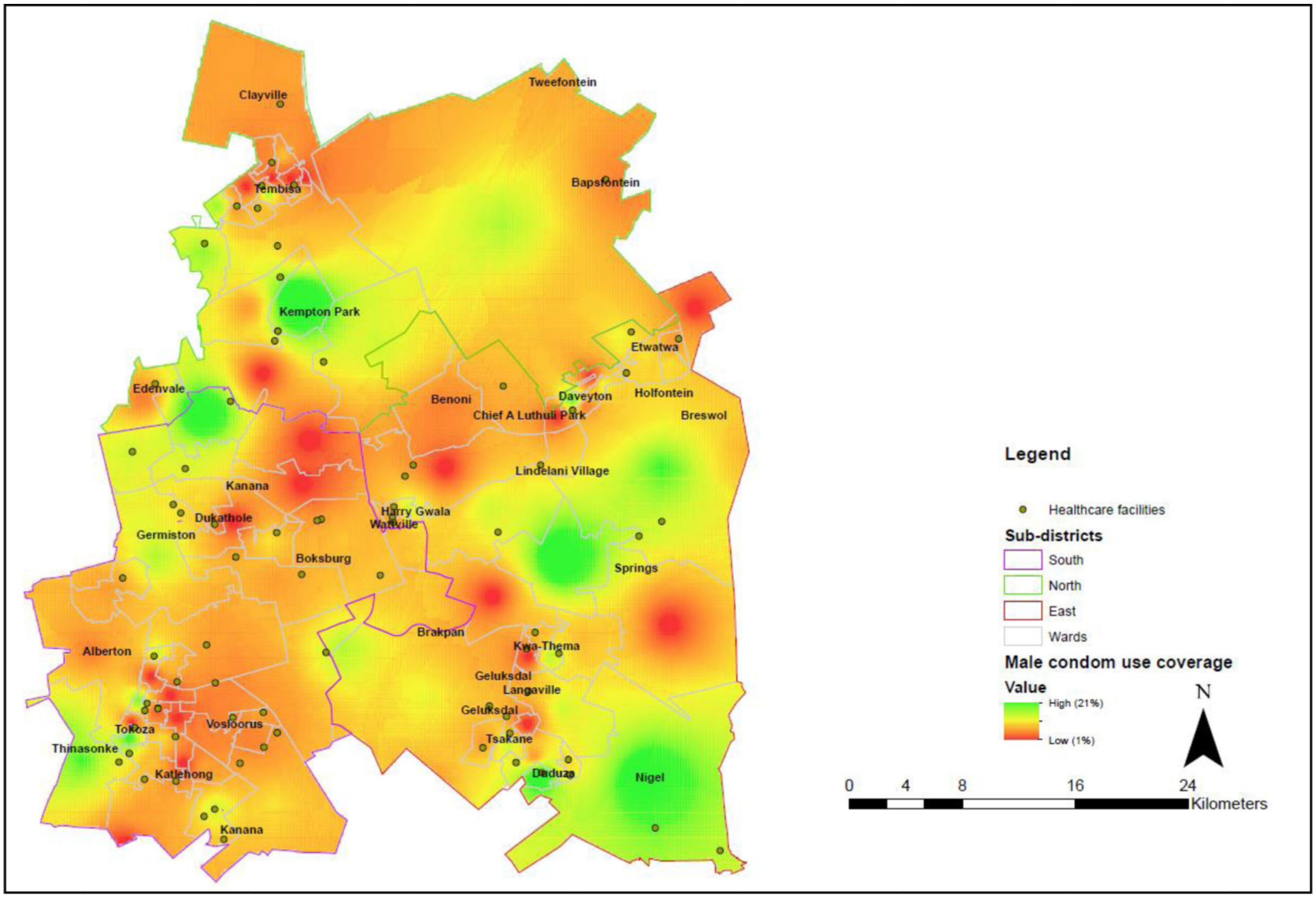

Figure 3: A smoothed distribution of male condom coverage in Ekurhuleni Metropolitan Municipality, South Africa

Based on routinely collected programmatic data

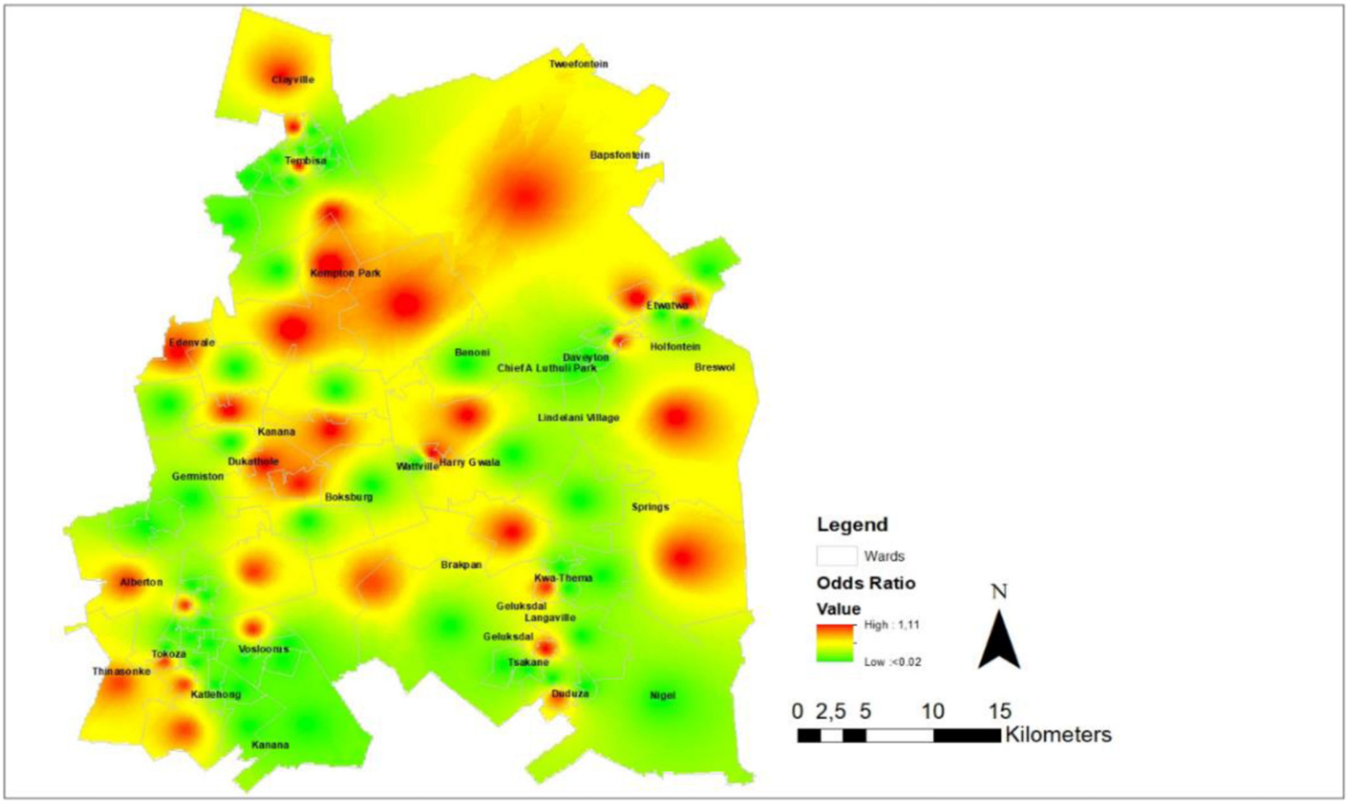

Figure 4: A smoothed map showing the expected Posterior Odds Ratio sub-optimal condom use in Ekurhuleni Metropolitan Municipality, South Africa

Based on the 2012 HSRC national survey

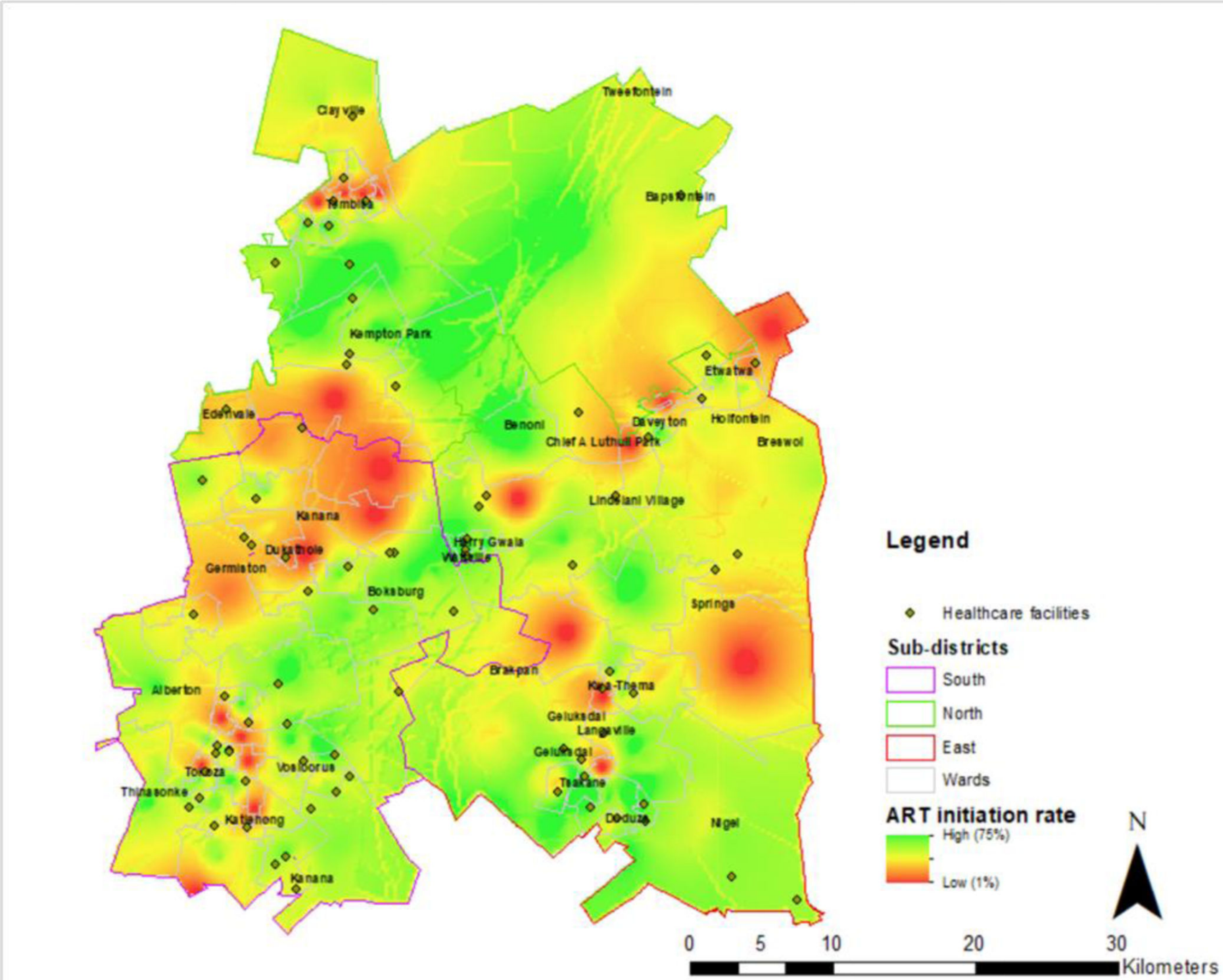

Figure 5: A smoothed map showing the distribution of ART initiation rates in Ekurhuleni Metropolitan Municipality, South Africa

Based on routinely collected programmatic data.

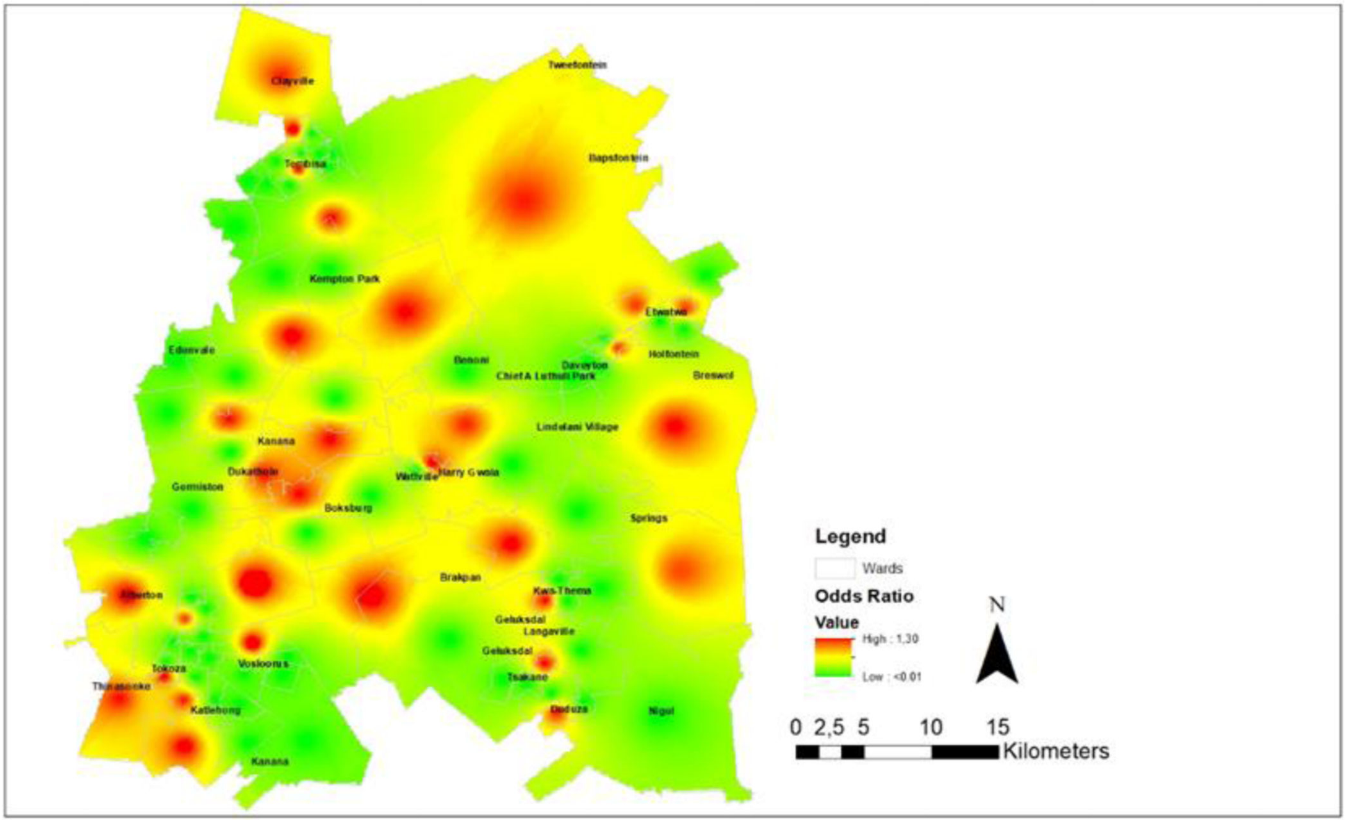

Figure 6: A smoothed map of showing expected Posterior Odds Ratio for non-ART use in Ekurhuleni Metropolitan Municipality, South Africa

Based on the 2012 HSRC national survey

Table 1:

Posterior summaries of Odds Ratio for HIV infection in Ekurhuleni, South Africa

Factor		Standard logistic regression model POR (95% CI)	Random effects logistic regression model POR (95% CI)	Spatial effects logistic regression model POR (95% CI)
Employment status	Unemployed	1	1	1
	Employed	1.26 (0.76–2.08)	1.32 (0.78–2.17)	1.33 (0.73 – 2.12)
	Student	**12.74 (3.29–95.01)**	**19.37 (3.39–81.70)**	**19.53 (3.22– 84.93)**
Level of education	Primary	1	1	1
	Secondary	0.55 (0.24–1.42)	0.66 (0.24–1.52)	0.65 (0.25–1.52)
	Tertiary	0.67 (0.37–1.20)	0.68 (0.34–1.16)	0.70 (0.35–1.19)
Condom use in past one month	No	1	1	1
	Yes	**0.46 (0.25–0.85)**	**0.48 (0.25–0.87)**	**0.48 (0.24–0.87)**
	Sometimes	**0.31 (0.17–0.56)**	**0.34 (0.17–0.67)**	**0.34 (0.18–0.63)**
Lifetime sexual Partners (no.)		0.97 (0.94–1.01)	0.97 (0.94–1.00)	0.97 (0.94 – 1.01)
Deviance information criteria		480.3	457.7	456.7

Table 2:

Posterior summaries of Odds Ratio for sub-optimal condom use in Ekurhuleni, South Africa

Factor		Standard logistic regression model POR (95% CI)	Random effects logistic regression model POR (95% CI)	Spatial effects logistic regression model POR (95% CI)
Age (years)		**1.09 (1.06–1.12)**	**1.09 (1.06–1.11)**	**1.09 (1.06–1.11)**
Sex	Female	1	1	1
	Male	**0.52 (0.32–0.78)**	**0.51 (0.32–0.78)**	**0.53 (0.33–0.80)**
Marital status	Not married	1	1	1
	Currently married	**3.19 (1.23–4.12)**	**3.78 (1.24–4.06)**	**4.14 (1.23 – 4.28)**
	Previously married	**0.27 (0.07–0.76)**	**0.28 (0.07–0.79)**	**0.28 (0.07 – 0.79)**
Media exposure	Frequent	1	1	1
	Not frequent	1.90 (0.95–3.57)	1.95 (0.95–3.49)	1.97 (0.95 – 3.49)
Deviance information criteria		523.7	530.8	528.5

Table 3:

Posterior summaries of Odds Ratio for non-ART initiation in Ekurhuleni, South Africa

Factor		Standard logistic regression model POR (95% CI)	Random effects logistic regression model POR (95% CI)	Spatial effects logistic regression model POR (95% CI)
Age (years)		0.94 (0.88–1.00)	0.95 (0.88–1.01)	0.95 (0.90–1.00)
Drug use in past 3 months	No	1	1	1
	Yes	6.72 (0.69–32.01)	7.03 (0.71–34.91)	7.17 (0.74–32.21)
Marital status	Not married	1	1	1
	Currently married	**6.12 (1.37–20.28)**	**7.18 (1.57–22.75)**	**6.79 (1.43–22.43)**
	Previously married	5.37 (0.38–28.71)	6.19 (0.37–33.96)	5.68 (0.33–25.98)
Media exposure	Frequent	1	1	1
	Not frequent	2.14 (0.52–6.39)	2.44 (0.54–7.98)	2.45 (0.59–8.24)
Deviance information criteria		107.4	109.0	107.8