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Planning area-specific prevention and intervention programs for HIV using spatial regression analysis

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ABSTRACT

Objective: The study was conducted to inform area-based prevention intervention programs and plan resource allocation to reduce new infections in the District of Columbia (DC), United States of America.

Study design: The analysis used spatial regression to evaluate the spatial heterogeneity of the new HIV rate and its association with sexually transmitted infection repeaters (STIREPs) and socio-economic as well as demographic characteristics. The HIV and STIREP data were obtained from the DC Department of Health surveillance data (2010–2016). Other covariates were obtained from the American Community Survey, 2016.

Methods: Ordinary least squares (OLS) and geographically weighted regression (GWR) were used to compare global and local relationships. GWR-computed robust results were compared with other spatial regression methods such as spatial lag or spatial error methods.

Results: For the OLS model, age, high school dropouts (NHSD), and the black population had an association with new HIV diagnoses ($HIVDV_i$). The results from the GWR model demonstrate spatial variations of association of STIREPs; mean age of each block group; and percentage of female population, NHSD, unemployment, and poverty with $HIVDV_i$. Akaike information criterion (AICc) value for the global model was 2770.99, and R^2 was 0.54 (54%). The R^2 and AICc of the GWR model was 0.81 (81%) and 2580.84, respectively, where the latter showed a 0.27 (27%) increase in R^2 and a decreased AICc.

Conclusion: These results will assist in planning HIV prevention and intervention strategies. These results will also be used for targeted testing, planning pre-exposure prophylaxis, and access to health care. The results will help plan resource allocation to community-based providers for prevention intervention programs and fund public health programs such as condom distribution, mobile vans, and youth-based sex education.

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Introduction

The Joint United Nations Program on HIV and AIDS (UNAIDS) launched the 90-90-90 plan in 2014, which aimed to end the AIDS epidemic by 2020 across the world. Reducing new transmission of HIV was one of the recommended goals for effective implementation of prevention and treatment programs under the UNAIDS plan. Since 2010, the annual number of new HIV infections (all ages) in the world declined by 16% to 1.8 million,[1] which is far less than the rate recommended by the United Nations General Assembly to reach the Fast Track target of 500,000 new infections by 2020.[2] In the United States of America (US), the number of new HIV infections fell by 18% from 2008 to 2014; this was the first substantial drop in new infections in the country in two decades.[3] The District of Columbia (DC) has experienced a constant decrease of new HIV infections over the last decade.[4] However, after these large declines, there is an indication of a plateau effect in reductions, which has been seen globally. The DC has proposed a plan (90/90/90/50)[4] concurrent with the UNAIDS plan, which seeks to reduce new HIV infections by 50% by 2020. An essential part of the DC's 90/90/90/50 plan was the implementation of area-specific intervention programs based on risk clusters to reduce new HIV diagnoses ($HIVDV_i$). To aid the area-specific prevention programs and optimize resource allocation, it is imperative to identify factors that may have an association with new HIV infections. Although there are studies that have evaluated various factors that may have an association with HIV, there has been little research that examines the spatial dimension of these associations, and this analysis fills that gap. The analysis is recommended for the health department aiming to inform HIV prevention programs based on their local surveillance data.

HIV and its relationship with the social determinants of health and sexually transmitted infections (STIs)[5–9] is well-documented research. However, these relationships are most often analyzed using national and provincial data by applying global regression. By using global regression models, researchers implicitly rely on the assumption of a stationary relationship, which means parameter estimates describe an invariant relationship across space,[10] thus masking any local area variation, which in turn leads to misinterpretation of the underlying spatial patterns.[10–13]

Therefore, public health researchers have begun to counter stationary assumptions by using spatial regression modeling such as geographically weighted regression (GWR) which allows for spatial variations in parameter estimates.[14] These localized spatial models allow researchers to recognize the association between local patterns of disease prevalence and the covariates. The spatial models help in planning prevention efforts,[13] planning resource allocation,[15,16] inferring gaps in service provision,[16] understanding biases of surveillance data,[17] adapting services, and targeting interventions.[12] It is critical for planners to have an understanding of the local variations of the intensity of the epidemic, and spatial methods make this feasible.

In this study, we sought to answer the following questions: (1) do the relationships between $HIVDV_i$ and sexually transmitted infection repeaters (STIREPs) vary across places?; (2) do the relationships between $HIVDV_i$ and block group (BG)–level socio-economic characteristics vary across places?; and (3) how do local relationships explain health outcomes when compared with global analysis?

Methods and data

Data sources

The DC has an estimated 2016 population of 659,009 according to the American Community Survey (ACS) estimates. Administrative and statistical divisions of the DC include eight wards, 179 census tracts, and 450 Block Groups (BGs). The US Census Bureau BGs are statistical divisions of census tracts, which are defined to contain between 600 and 3000 people, and are used to present data and control block numbering. The DC cartographic boundary shapefile of BGs was obtained from the Master Address File/Topologically Integrated Geographic Encoding and Referencing database of the DC Office of the Chief Technology Officer for analysis (Fig. 1).

HIV data

HIV surveillance data used in this analysis are collected routinely by the HIV/AIDS, Hepatitis, sexually transmitted disease (STD), and tuberculosis (TB) Administration (HAHSTA) within the DC Department of Health (DOH). Newly diagnosed HIV cases reported from providers and laboratories were collected and managed in the Enhanced HIV/AIDS Reporting System. The total number of newly diagnosed HIV infections from 2010 to 2016 used for this analysis was 4237. The cases were geo-coded using Maptitude and then aggregated by BGs. The incidence rates for $HIVDV_i$ for each BG were calculated using Equation (1).

$$HIVDV_i = (TNI_i / POPULATION_i) \times 1000 \quad (1)$$

where $HIVDV_i$ is the rate of the diagnosed cases from 2010 to 2016 and TNI_i is the total number of HIV diagnoses in the DC BG from 2010 to 2016. The population was obtained from the ACS 2016 estimate for each BG.

STI data

Repeaters are individuals who acquire more than one non-viral STI in a specified period,[17] which, for this analysis, was 6 months or more. The STI data were regularly collected in the Sexually Transmitted Diseases Management Information System (STD*MIS) which were later transferred to the DC Public Health Information System (DCPHIS). Providers and laboratories report STI data which are routinely collected in the DCPHIS. The data for this study were obtained from the DCPHIS. There were 54,266 incidences identified using patient ID as well as the first name, last name, date of birth, and date of diagnosis between 2010 and 2016, of which 12,347 repeaters were identified using an algorithm of first name, last name, date of birth, and date of diagnosis. Repeaters are individuals who had more than any one of the reportable STIs diagnosed

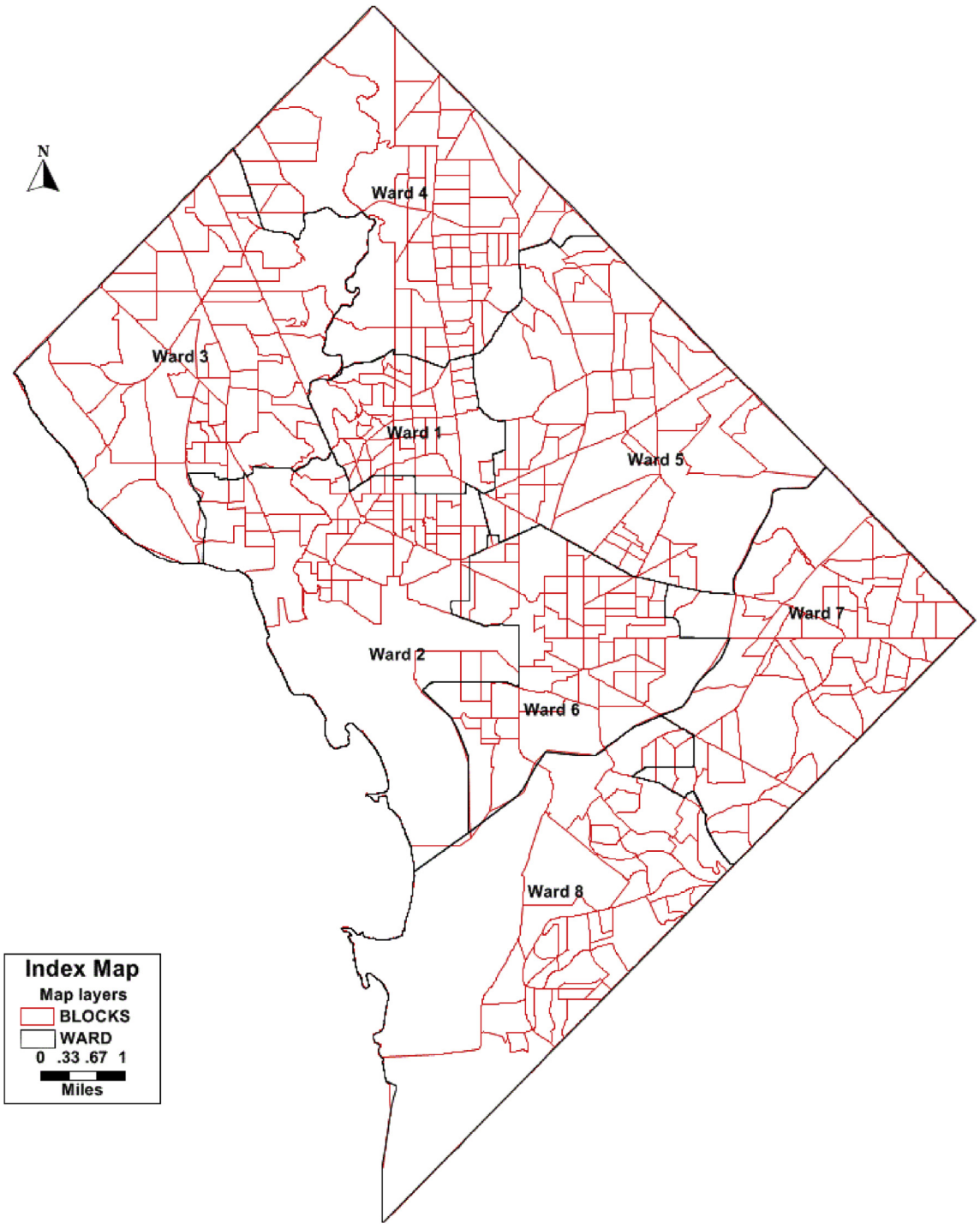

Fig. 1 – The boundary map of the District of Columbia. The red lines demarcate the block groups, and the black lines, the ward boundaries. (For interpretation of the references to color, the reader is referred to the Web version of this article.)

between 2010 and 2016. The geographic coordinates associated with each case of infection were assigned using Maptitude Geographic Information System software. In this study, three of the reportable STIs—chlamydia, gonorrhea, and syphilis—were combined. The model was applied using each of the STIREPs separately in the ordinary least squares (OLS) model, but the variance inflation factor (VIF) indicated multicollinearity. Thus, the STIREPs were combined into the STI repeat incidence rate variable to be included as an explanatory variable in the study. The incidence rates of STIREPs in each BG were calculated using Equation (1) as well.

Other variates

The other covariates used in the study were obtained from the ACS for each BG. The ACS is conducted each year to provide up-to-date information about the social and economic

variables of communities. The census is conducted once every 10 years to provide an official count of the entire US population to the US Congress. The study aims to inform policies in the DC; thus, current estimates of population from the ACS were used instead of the US census data.

There were six covariates used in the model for each BG: (1) mean age of people (AGE); (2) percentage of the female population (FEM); (3) percentage of people who are black (BLACK); (4) percentage of people who are high school dropouts (NHSD); (5) percentage of the unemployed (UNEM); and (6) percentage of people below the poverty line (POV). The variables were selected based on the literature[18–20] and VIF as well as correlation association analysis of the independent variables.

Statistical analyses

Global regression

The global linear regression (OLS) was computed using R software, version 3.3.4.

$$y_i = \alpha + \beta x_i + \varepsilon_i \quad (2)$$

where α and β are the intercept and slope of the true regression line, respectively. Each observation,y_i, may be viewed as the sum of a component that predicts the value of y_i on the basis of the value of x_i (using true coefficients α and β) and some random error (ε_i).

Spatial regression

Spatial regression analyses (GWR) were performed using *spgwr package* of R software, version 3.3.4 , to account for the spatial non-stationarity of these relationships. Rather than calculating global parameter estimates based on one regression analysis, GWR extends OLS by allowing regression coefficients to vary spatially within a study area. Unlike OLS, GWR assumes that relationships between exposure and health outcomes may vary over space; it generates a set of local regression coefficients for each observation point in the BG.[21] An established form of the GWR model is described in the following paragraphs.

$$yi = \beta_{i0}(u_i, v_i) + \sum_{k=1}^{p} \beta_{ik}(u_i, v_i)x_{ik} + \varepsilon_i \quad i = 1, \ldots..n, \quad (3)$$

where y_i is the dependent variable at point i, $\beta_{i0}(u_i, v_i)$ is the intercept parameter at point i, $\beta_{ik}(u_i, v_i)$ is the local regression coefficient for the kth independent variable at point i, and (u_i, v_i) is the coordinate of the ith point in the study area. In our study, the x and y coordinates are given in miles through geographic coordinate system World Geodetic System 1984 projection system. GWR requires assigning a specific x and y coordinate to each observation, i.[14,21,22]

GWR used equation (3) to generate separate regression equations for each observation, with a search window also known as spatial kernel,[23] deciding which adjacent observations were involved in the regulation of each regression. The spatial kernel also defined how the adjacent observations were weighed based on Gaussian distance decay.[12,23] These functions give most weight to the observations that were nearest to the one at the center. The weights were based on the supposition that the nearby observations are more related to each other than the distant ones (Tobler's law). The spatial kernel area was based on a method of calibration to choose an 'optimal' bandwidth.[23] This study applied adaptive kernel where the size would vary depending on the neighbors. Because the regression equation was calibrated independently for each observation, a separate parameter estimate, *t-value*, and goodness of fit were calculated for each observation.[23] Local values of *t-statistics* were calculated by dividing each local regression coefficient by the corresponding local standard error. These values were mapped for the graphical interpretation of the spatially varying association.

Akaike information criterion (AICc) values reported for both global regression and GWR models were used to compare the performance of the models.[23] The model with the lower AICc was considered to have a better fit. Spatial autocorrelation of standardized residuals was checked for both global regression and GWR models, using Moran's *I* in R. The global spatial clustering of $HIVDV_i$ was also checked using global Moran's *I*. Global Moran's *I* is a tool that measures spatial autocorrelation based on both feature locations and feature values simultaneously.[24]

Results

Descriptive analyses

In total, 23% of the population were female compared with 73% male (the ramianing data were missing). Blacks or African Americans represented the majority of the new cases (approximately 69%) diagnosed in the DC. New diagnoses decreased from 20% in 2010 to 8% in 2016. The global Moran's *I* of $HIVDV_i$ is 0.0802 ($P < 0.001$) and demonstrates spatial autocorrelation, which makes GWR a relevant statistical analysis (Table 1).

Global regression analyses

The results of the OLS multiple regression analysis indicated that STIREPs had an association with $HIVDV_i$ ($\beta = 0.118$, 95% confidence interval [CI]: 0.107, 0.129) (Table 2). NHSD also showed an association with $HIVDV_i$ ($\beta = 0.482$, 95% CI: 0.091, 0.872), and UNEM ($\beta = 0.269$, 95% CI: 0.099, 0.439). FEM ($\beta = -0.071$, 95% CI: −0.143, −0.0002) had a negative association with $HIVDV_i$. R^2 for the OLS model was 0.54, and the AICc, was 2770.99 (Table 2).

Local regression analyses

The summary results showed that R^2 and AICc of the GWR model was 0.81 and 2580.84, respectively, thus a better fit than the OLS global regression model. The global Moran's I of the GWR residuals is 0.03 ($P > 0.1$), showing no spatial autocorrelation. The lack of spatial autocorrelation of the residuals indicates that the residuals are independent and normally distributed.

Fig. 2(a–g) showed the maps of coefficients of each explanatory variables and the corresponding *t-values*. The pseudo *t-values* for each variable were mapped to represent the fitting level for each specific variable under GWR analysis.

Table 1 – Characteristics of new HIV diagnoses ($HIVDV_i$) in the District of Columbia (2010–2016).

Variables	Number (N)	Percent (%)
Year of diagnosis		
2010	883	21
2011	724	17
2012	709	17
2013	604	14
2014	481	11
2015	489	12
2016	347	8
Total	4237	
Age group at diagnosis		
0–14 years	17	1
15–24 years	882	21
25–49 years	2569	60
≥50 years	769	18
Total	4237	
Race/ethnicity		
White	606	14
Black	2946	69
Hispanic	378	8
Other	110	2
Unknown	197	1
Total	4237	
Sex at birth		
Male	3103	73
Female	976	23
Missing	158	3
Total	4237	
Global Moran's I of new HIV diagnoses	0.0802***	

*P ≤ 0.05, **P ≤ 0.01, ***P ≤ 0.001.

The *t-values* indicated that the parameter estimations in these areas were reliable.

AGE coefficients showed higher coefficient values in the southern parts of the DC in the BGs within wards 6 and 8 extending into few BGs in ward 7. Few BGs in ward 4 showed higher coefficients as well. Lowest values were located in the BGs within ward 7 (Fig. 2a) for AGE. FEM coefficients had higher values in wards 1 and 7; few BGs in wards 4 and 5 showed higher values as well. Lowest FEM values were located in the BGs of ward 8 (Fig. 2b). NHSD showed clustering of higher coefficient values in the BGs within wards 7 and 8 and in few BGs within ward 1 (Fig. 2c). BLACK had the lowest coefficients in few BGs of ward 7 (Fig. 2d). POV had higher coefficients in wards 4 and 8 and the lowest values in ward 7 (Fig. 2e). UNEM had higher coefficients clustered in wards 2 and 8 (Fig. 2f). STIREP (Fig. 2g) coefficients showed higher values clustering in ward 4 and the lowest values clustered in the southern BGs of the DC.

Supplement Fig 1 showed the maps of the locally weighed R^2 between the observed and fitted values, which indicated how well the GWR model replicated the local $HIVDV_i$ around the covariates selected for this analysis. It is evident that the value of R^2 was not homogeneously distributed all over the DC, and the overall GWR model fitted best in the BGs of wards 1, 5, and 8 ($R^2 > 0.83$).

The map of the intercept term represented the distributions of $HIVDV_i$ when the covariates equaled zero (Supplement Fig. 2). It was observed higher intercept values clustered in wards 7 and 8 and in few BGs within ward 5.

Discussion

This analysis provided further indications that the relationships of $HIVDV_i$–STIREP and the socio-economic variables are spatially non-stationary in the DC. From the GWR model, it is clear that the intensity and directions of the influence of STIREPs and other covariates on $HIVDV_i$ are spatially heterogeneous. The result can thus be adapted to plan for area-specific prevention and intervention strategies to control new HIV infections.

The 90/90/90/50 plan suggests treatment as prevention, which means preventing new infections by increasing the

Table 2 – Global regression results of $HIVDV_i$ with explanatory variables.

	OLS global regression results					GWR results
	Estimate	Standard error	*T-value*	Lower limit 95% CI	Upper limit 95% CI	β range
Intercept	5.648	1.898	2.976**	1.9182	9.3770	−5.726, 28.168
STIREPs	0.118	0.006	20.895***	0.107	0.129	0.0373, 0.4327
AGE (ages 15 to 24 years)	−0.022	0.020	−1.119	−0.0617	0.0169	−0.348, 0.1912
ELSEAGE (ages below 15 and above 24 years) (REF)	–	–	–	–	–	–
FEM	−0.071	0.036	−1.970*	−0.1426	−0.0002	−0.327, 0.1669
NHSD	0.482	0.199	2.424*	0.0911	0.8720	−0.751, 1.881
BLACK	0.000	0.009	−0.046	−0.0173	0.0165	−0.306, 0.0703
UNEM	0.269	0.086	3.121**	0.0997	0.4389	−0.126, 1.466
POV	0.046	0.049	0.930	−0.0511	0.1427	−0.462, 0.408
R^2	0.54					0.81
AICc	2770.99					2580.84
Global Moran's I standard residuals	−0.011					−0.007

AGE, mean age of people; AICc, Akaike information criterion; BLACK, black population; CI, confidence interval; FEM, female population; GWR, geographically weighted regression; $HIVDV_i$, new HIV diagnoses; NHSD, high school dropouts; OLS, ordinary least squares; POV, people below the poverty line; STIREP, sexually transmitted infection repeater; UNEM, unemployment.
*P ≤ 0.05, **P ≤ 0.01, ***P ≤ 0.001.

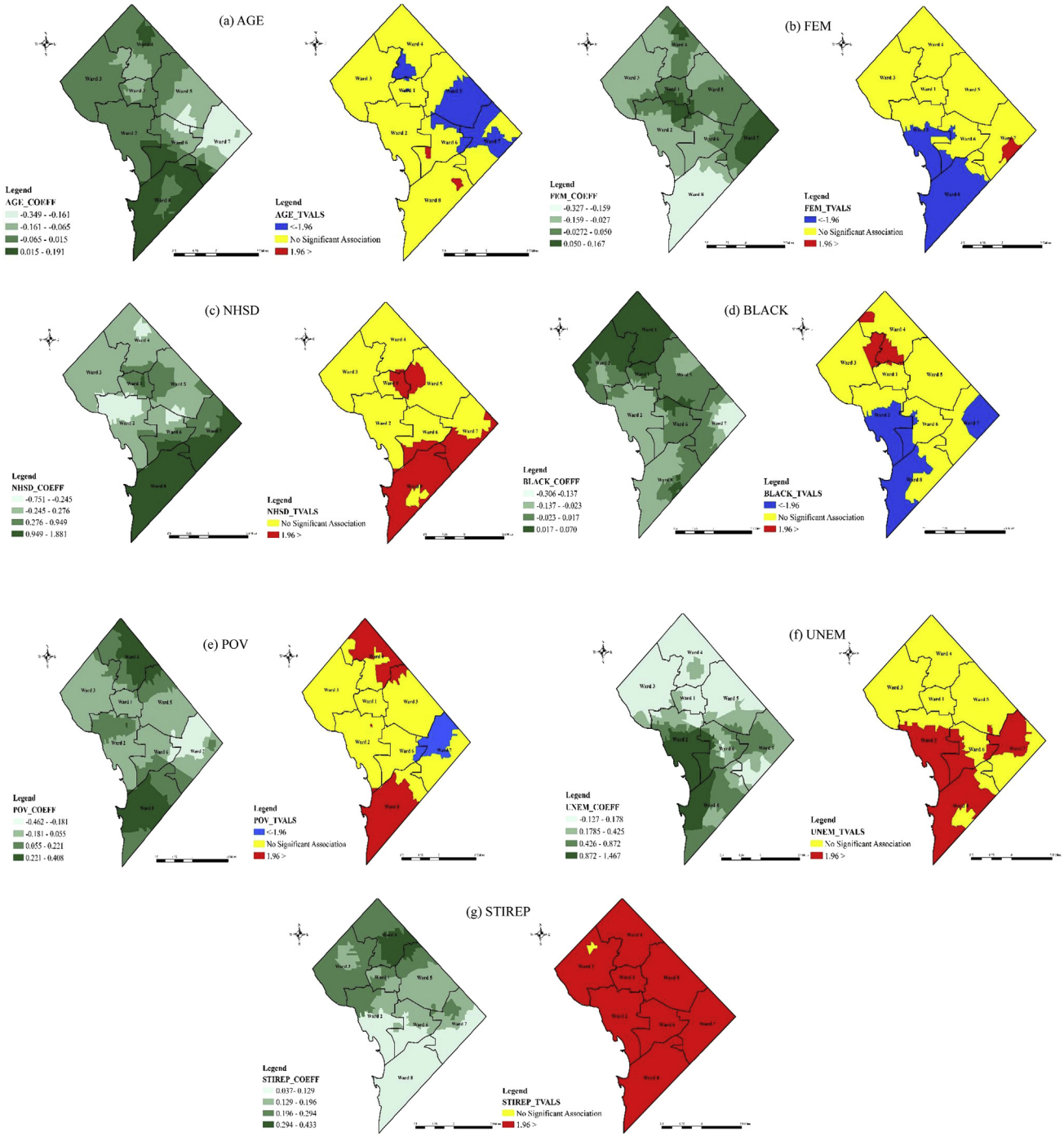

Fig. 2 – Spatial mapping of coefficients and the corresponding *t-values*. The dependent variable was new HIV diagnoses ($HIVDV_i$) in the District of Columbia (DC) from 2010 to 2016. (a) Age (15–24 years) coefficients and the *t-values* (AGE), (b) female coefficients and the *t-values* (FEM), (c) high school dropouts coefficients and the *t-values* (NHSD), (d) black population coefficients and the *t-values* (BLACK), (e) Poverty coefficients and the *t-values* (POV), (f) unemployment coefficients and the *t-values* (UNEM), and (g) STI coefficients and the *t-values* (STIREP). AGE, mean age of people; BLACK, black population; FEM, female population; NHSD, high school dropouts; POV, people below the poverty line; UNEM, unemployment; STIREP, sexually transmitted infection repeater.

number of people who reach viral suppression and are unlikely to pass on the virus has the potential to reduce new infections by 50% by 2020.[25] In 2012, the Food and Drug Administration approved a treatment regimen that is widely used to prevent HIV infection among high-risk HIV negatives. This treatment is called pre-exposure prophylaxis, or PrEP, and is the first novel strategy introduced since the start of the epidemic that is explicitly targeted at preventing sexual HIV

transmission. Previous studies have shown that PrEP has been successful in preventing HIV acquisition.[26] The challenge is access to PrEP; the results of this analysis will be used to plan for providing PrEP through community-based organizations or health department clinics to areas which are vulnerable.

The analysis found higher coefficients of STIREPs in the northern parts of the DC, although the *t-values* were more than 1.96 in all wards. It is well known that STIs increase the risk of HIV,[27] and controlling for repeat STIs has always been considered a significant step to prevent new HIV infection transmission.[28] Repeat STIs double the risk of new HIV infection and can be used to identify risk in HIV-negative individuals.[25] The high-risk areas which show significant association of STIs and HIV will be targeted for providing interventions, such as STI treatment, PrEP and postexposure prophylaxis use, and elimination of needle sharing through syringe access programs, to interrupt HIV transmissions.

Women showed higher values clustered in central DC and ward 7. There are disparities in the degree of variations which calls for a deeper understanding of the burden of HIV diagnoses among women in the DC. Although PrEP for women has been an essential step in the community, it is also important to pay attention to the women's ability to negotiate safe sexual practices, particularly condom use.[29] Apart from condom use, attention needs to be paid to the association of HIV risk with awareness, outlooks, peer encouragements, and perception of self-worth among women.[29–31]

Unlike OLS, GWR showed a spatial association of AGE with $HIVDV_i$. According to Center for Disease Control and Prevention, United States (CDC) (2015), 22% of all $HIVDV_i$ in the US were between ages 15 and 24 years.[32] Of any age group, youths with HIV are least likely to be linked to care and have a suppressed viral load (i.e., having a low level of the virus in the body, which helps the person to stay healthy and reduce the risk of transmitting HIV to others). Addressing HIV in youths required them to be provided with information and tools needed to reduce their risk, make healthy decisions, and get treatment and care if needed.[32]

The global regression model also showed a positive association of $HIVDV_i$ with lack of high school education (NHSD). The spatial regression analysis found spatial heterogeneity in the association of NHSD with $HIVDV_i$ in southern DC and few BGs spread across wards 1 and 5. High schooling years have shown to decrease the risk of HIV.[33] On a worldwide level, it has been observed that lower education and lack of sexual health education in school is related to a higher risk of HIV epidemics.[34,35] The DOH formed a collaboration across healthcare providers, researchers, district government agencies, community organizations, and young people to develop the 2016–2020 Youth Sexual Health Plan to address sexual health among younger people. Programs need to be extended to include initiatives that support students absent from in-school sessions. The DOH will continue to work in concert with public education efforts and school-based sexual health education.

Unemployment and poverty show spatial variation in association with $HIVDV_i$, which points out areas where poverty and unemployment may need to be addressed. Employment benefits in the past have been shown to improve HIV health outcomes,[36–38] and the DC provides employment assistance, financial services, utility assistance, and rental assistance to those in need and has special programs for HIV patients. There are also studies that have shown that employment benefits HIV health outcomes. Employed people were 39% more likely to have achieved optimal adherence to antiretroviral medications (reaching better than 95% adherence), which in turn helps curtail new infections.[39] However, it also needs to be acknowledged that employment generation does not always lead to poverty alleviation, particularly in areas where disease stems from disparity.[37] Many researchers have often described HIV as a 'disease of poverty'.[38] Thus, health departments should consider poverty and its impact on HIV-related health outcomes.

Geographical heterogeneity was detected by the GWR method in the relationship of new HIV infections with STIs and other economic and demographic variables. The analysis used GWR because conventional regression analysis, OLS, cannot discriminate the spatial variation in relationships if geographical non-stationarity exists. The results of adjusted R^2 and AICc indicated GWR was a better model to explain the dataset. GWR analysis and its application to HIV and STI research have been gradually gaining significance, and this analysis is a significant step towards that.

Conclusion

As a methodology, GWR has some limitations. Non-linear terms cannot be added to the GWR models, and the model inferences cannot be conducted in this model.[12] However, despite the limitations, the article is an important contribution toward understanding the underlying etiology that may have an impact on new HIV infections. The article also opens avenues such as access to PrEP, HIV risk among women, and space-based networks for research that await to be explored. Future research using Bayesian additive regression models, which are based on Markov chain Monte Carlo algorithms, for parameter estimations and inferences to overcome the mentioned problems is underway.

Author statements

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Ethical approval

The DC surveillance receives electronic reports from providers and laboratories for HIV, gonorrhea, chlamydia, and syphilis. The studies published from the District of Columbia Department of Health do not require any IRB clearance unless they have to identify information. Our article does not have any identifying information; the cases/events are aggregated by census tracts, thus geo-masked.

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Competing interests

The authors do not have any known competing interests. The authors do not have anything to declare.

REFERENCES

1. Unaids. *Ending Aids Progress Towards the 90-90-90 Targets*. Global Aids Update; 2017. p. 198. Available from: http://www.unaids.org/sites/default/files/media_asset/Global_AIDS_update_2017_en.pdf.
2. Unaids. *90-90-90 An ambitious treatment target to help end the AIDS epidemic*. 2014. p. 40. http://WwwUnaidsOrg/Sites/Default/Files/Media_Asset/90-90-90_En_0Pdf.
3. CDC. *HIV incidence: estimated annual infections in the U.S., 2008–2014. Atlanta, GA*. 2017.
4. HAHSTA DC Department of Health. *Annual Epidemiology & Surveillance Report*. 2017.
5. Marmot M. Social determinants of health inequalities. *Lancet* 2005;**365**(9464):1099–104. Available from: http://www.sciencedirect.com/science/article/pii/S0140673605711466.
6. Takarinda KC, Madyira LK, Mhangara M, Makaza V, Maphosa M, Rusakaniko S, et al. *Factors associated with HIV testing in the 2010-11 Zimbabwe Demographic and Health Survey. DHS Working Papers No. 110 (Zimbabwe Working Papers No. 11)*. Rockville, Maryland, USA: ICF International; 2014. Available from: http://dhsprogram.com/pubs/pdf/WP110/WP110.pdf.
7. Ward H, Rönn M. The contribution of STIs to the sexual transmission of HIV. *Curr Opin HIV AIDS* 2010;**5**(4):305–10.
8. Weber JN, McCreaner A, Berrie E, Wadsworth J, Jeffries DJ, Pinching AJ, et al. Factors affecting seropositivity to human T cell lymphotropic virus type III (HTLV-III) or lymphadenopathy associated virus (LAV) and progression of disease in sexual partners of patients with AIDS. *Genitourin Med* 1986;**62**(March):177–80. Available from: http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&list_uids=3015772.
9. Piot P, Taelman H, Bila Minlangu K, Mbendi N, Ndangi K, Kalambayi K, et al. Acquired Immunodeficiency Syndrome in a Heterosexual Population in Zaire. *Lancet* 1984;**324**:65–9.
10. Clary C, Lewis DJ, Flint E, Smith NR, Kestens Y, Cummins S. The local food environment and fruit and vegetable intake: A geographically weighted regression approach in the ORiEL study. *Am J Epidemiol* 2016;**184**(11):837–46.
11. John Tukey. *Statistical mapping: What should not be mapped? Collect Work*. Belmont, CA: Wadsworth; 1988.
12. Fotheringham AS, Brunsdon C, Charlton M. *Geographically Weighted Regression: The Analysis of Spatially Varying relationships*. John Wiley & Sons; 2003.
13. Weir SS, Boerma T. *From People to Places : Overview of the PLACE Method and Lessons Learned Background : Evaluation*, vol. 4; 2002. p. 1–6.
14. Fotheringham A. Stewart et al. Geographically Weighted Regression : The Analysis of Spatially Varying Relationships. John Wiley & Sons, Incorporated,;
15. Auerbach JD, Stall R, Herrick A, Guadamuz T E, Friedman M S, Fenton KA, et al. *HIV Prevention. HIV Prevention*. Elsevier; 2009 [cited 2016 Mar 23]. Available from: http://www.sciencedirect.com/science/article/pii/B9780123742353000170.
16. Wilson DP, Blower SM. Designing equitable antiretroviral allocation strategies in resource-constrained countries. *PLoS Med* 2005;**2**(2):0132–41.
17. Montana LS, Mishra V, Hong R, Montana LS. Comparison of HIV prevalence estimates from antenatal care surveillance and population-based surveys in Sub-Saharan Africa . DHS Working Papers No 47. *Calverton, Maryland, USA : Macro International* 2008;**84**(Suppl 1):i78–84. Available from: http://dhsprogram.com/pubs/pdf/WP47/WP47.pdf.
18. Delpierre C, Cuzin L, Lauwers-Cances V, Datta GD, Berkman L, Lang T. Unemployment as a risk factor for AIDS and death for HIV-infected patients in the era of highly active antiretroviral therapy. *Sex Transm Infect* 2008;**84**:183–6.
19. Krueger LE, Wood RW, Diehr PH, Maxwell CL. Poverty and HIV seropositivity: the poor are more likely to be infected. *AIDS* 1990;**4**(8). Available from: http://journals.lww.com/aidsonline/Fulltext/1990/08000/Poverty_and_HIV_seropositivity__the_poor_are_more.15.aspx.
20. Gregson S, Waddell H, Chandiwana S. School education and HIV control in sub-Saharan Africa: from discord to harmony?. John Wiley & Sons, Ltd. *J Int Dev* 2001;**13**(4):467–85. Available from: https://doi.org/10.1002/jid.798.
21. Gebreab SY, Diez Roux AV. *Exploring racial disparities in CHD mortality between blacks and whites across the United States: A geographically weighted regression approach. Health and place***18 5**. Elsevier; 2012. p. 1006–14. Available from: https://doi.org/10.1016/j.healthplace.2012.06.006.
22. Brunsdon C, Fotheringham S, Charlton M. *Geographically weighted regression- modelling spatial non-stationarity*. 1998. p. 431–43.
23. Tsiko R. Geographically Weighted Regression of Determinants Affecting Women's Access to Land in Africa. *Geosciences* 2016;**6**:16. Available from: http://www.mdpi.com/2076-3263/6/1/16.
24. Anselin L. Local Indicators of Spatial Association - Lisa. *Geogr Anal* 1995;**27**(2):93–115.
25. *HAHSTA DC DEPT OF HEALTH, DC Appleseed WA partnership. 90-90-90-50 Plan*. 2016.
26. McCormack S, Dunn DT, Desai M, Dolling DI, Gafos M, Gilson R, et al. Pre-exposure prophylaxis to prevent the acquisition of HIV-1 infection (PROUD): Effectiveness results from the pilot phase of a pragmatic open-label randomised trial. McCormack et al. Open Access article distributed under the terms of CC BY *Lancet* 2016;**387**(10013):53–60. Available from:, https://doi.org/10.1016/S0140-6736(15)00056-2.
27. Malek R, Mitchell H, Furegato M, Simms I, Mohammed H, Nardone A, et al. Contribution of transmission in HIV-positive men who have sex with men to evolving epidemics of sexually transmitted infections in England: an analysis using multiple data sources, 2009–2013. *Euro Surveill* 2015;**20**(15). Available from: http://www.eurosurveillance.org/content/10.2807/1560-7917.ES2015.20.15.21093.
28. Lattimore S, Thornton A, Delpech V, Elford J. Changing patterns of sexual risk behavior among London gay men: 1998-2008. *Sex Transm Dis* 2011;**38**(3):221–9.
29. Pulerwitz J, Amaro H, Jong W De, Gortmaker SL, Rudd R. Relationship power, condom use and HIV risk among women in the USA. *AIDS Care* 2002;**14**(May):789–800. Available from: http://www.tandfonline.com/doi/abs/10.1080/0954012021000031868.
30. Gielen AC, Faden RR, O'Campo P, Kass N, Anderson J. *Women's protective sexual behaviors: a test of the health belief model. AIDS education and prevention*, vol. 1. United States: official publication of the International Society for AIDS Education; 1994 Feb;6. p. 1–11.
31. Cynthia A, Vanoss B. *Gender , culture , and power : Barriers to HIV-prevention strategies for women*. 1996.
32. Centre for Disease Control. *HIV Among Youth. Factsheet [Internet]*. 2015 (December 2015):2. Available from: http://www.cdc.gov/hiv/pdf/risk_youth_fact_sheet_final.pdf.
33. Gant Z, Gant L, Song R, Willis L, Johnson AS. A census tract-level examination of social determinants of health among

black/African American men with diagnosed HIV infection, 2005-2009-17 US areas. *PLoS One* 2014;**9**(9):2005–9.
34. Behrman JA. *The effect of increased primary schooling on adult women's HIV status in Malawi and Uganda: Universal Primary Education as a natural experiment*. *Social Science and Medicine*, vol. 127. Elsevier Ltd; 2015. p. 108–15. Available from: https://doi.org/10.1016/j.socscimed.2014.06.034.
35. De Neve JW, Fink G, Suburamanian S, Moyo S, Bor J. Length of secondary schooling and risk of HIV infection in Botswana: evidence from a natural experiment. *Lancet Global Health* 2015;**3**(8):470–7.
36. Nachega JB, Uthman OA, Peltzer K, Richardson LA, Mills EJ, Amekudzi K, et al. Association between antiretroviral therapy adherence and employment status: systematic review and meta-analysis. *Bull World Health Organ* 2015;**93**(October):29–41. Available from: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=4271680&tool=pmcentrez&rendertype=abstract.
37. Gutierrez C, Carlo O, Pierella P, Pieter S. *Does Employment Generation Really Matter for Poverty Reduction? Policy Research Working Paper 4432 [Internet]* (December). 2007. p. 4–33. Available from:, http://elibrary.worldbank.org/doi/pdf/10.1596/1813-9450-4432.
38. Gillies P, Tolley K, Wolstenholme J. Is AIDS a disease of poverty? *AIDS Care* 1996;**8**(3).
39. Nachega JB, Uthman O a, Mills EJ, Peltzer K. *The Impact of Employment on HIV Treatment Adherence*. 2013.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2019.01.009.