ART coverage and viral load suppression rates as correlates to HIV positivity in Kenya; Spatial-temporal analyses 2015-17

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Abstract

Introduction

High antiretroviral therapy (ART) coverage and high rates of viral load suppression (VLS) should reduce transmission of HIV, and ultimately, HIV incidence and the number of new HIV diagnoses out of the number tested (HIV positivity). We used 3 years of HIV program data in Kenya to assess whether trends in the number of new HIV diagnoses were associated with ART coverage and VLS rates and spatial-temporally auto-correlated at county level.

Methods

We analyzed routine program county-level aggregate data on ART coverage and VLS (proportion of persons on ART with VL<1000 copies/mL) from 3 years (2015-2017). We examined the association between ART coverage and VLS rates to HIV positivity by fitting spatial and spatial-temporal semi-parametric Poisson regression models using R-Integrated Nested Laplace Approximation (INLA) package. We used the extended Cochran-Mantel-Haenszel stratified test of association to test for trend for rates across years and Kruskal-Wallis equality-of-populations nonparametric rank test to compare medians for continuous variables. We fit a structural equation model to assess direct and total effects between the two exogenous covariates to adjusted newly HIV-diagnosed as the endogenous variable adjusting for clustering by 47 counties. Finally, we mapped adjusted HIV positivity using QGIS version 3.2.

Results and discussion

A spatial-temporal model with covariates was better in explaining geographical variation in HIV positivity (deviance information criterion (DIC) 381.2), than either a non-temporal spatial model (DIC 418.6) or temporal model without covariates (DIC 449.2). Overall, the adjusted HIV positivity decreased over 3 years from median of 2.9% in 2015, [interquartile range (IQR): 1.9-3.4] to 1.5% in 2017, IQR(1.3-2.0), p=0.032. While adjusting for clustering and covariance, VLS had a direct effect on HIV positivity rates p=0.004, but ART coverage did not, p=0.843.

Conclusions

From 2015-2017, there has been improved ART coverage and sustained VL coverage and suppression rates. We have observed a general decline of rates of HIV positivity associated with VLS rates. To assess the trends and impact of implementation of scaled-up care and treatment, spatial-temporal analyses help to identify geographic areas that need focused interventions.

Background

HIV epidemic control will be attained when persons living with HIV/AIDS (PLHIV) have been identified, put on antiretroviral therapy (ART) t and are virally suppressed. This cascade in HIV diagnoses, engagement in care, initiation on ART and the impact of treatment resulting in viral load suppression (VLS, proportion of persons on ART with VL < 1000 copies/mL)) has been proposed as the UNAIDS fast-track targets referred to as the 90-90-90 or 95-95-95 [1, 2]. It is expected that by the year 2030, 95% of PLHIV will be diagnosed, 95% of them linked to HIV treatment and 95% will be virally suppressed. High ART coverage and high rates of VLS should reduce HIV transmission, and ultimately to a decline in HIV positivity. For example, measures of successful widespread ART coverage have been demonstrated by reductions in new HIV infections in San Francisco [3]. In sub-Saharan Africa (SSA), community viral load is higher compared to other regions and may be the driver of the epidemic [4].

Exploring the association between geographic location and programmatic HIV targets such as 90-90-90 is important to help focus interventions [5]. Based on this chronological relationship from HIV diagnoses, linkage to care, initiation of ART after linkage and VLS, we postulated that ART coverage and VLS can be analyzed as covariates in a structural equation model to explain observed differences in new HIV diagnoses as one of the impact indicators for HIV epidemic control. Such structural equation models provide a quick snapshot of associations between correlates to a phenomenon of interest [6–8] such as in our case, variation in rates of HIV positivity. Covariates measured at the individual level have been demonstrated as associated with access to HIV care, ART uptake, adherence and better outcomes. These include; age, sex, location, having experienced previous illness or health conditions or symptoms of disease, disclosure and a supportive family [9–11]. These are useful covariates but may not be easy to summarize and analyze at geographical level.

We used 3 years of HIV program data in Kenya to assess whether trends in the number of new HIV diagnoses were associated with ART coverage and VLS rates, and explored spatial-temporal autocorrelation at county-level.

Methods

Program setting and data sources

In Kenya, HIV program planning is done using the county level as the planning unit. There are 47 counties in Kenya with wide ranging HIV burden from the highest in Homabay County at 26.0%, which is about 4.5 times higher than the national prevalence to < 1% in Wajir County [12]. The estimated number of PLHIV in Kenya was 1,517,707, 1,587,840, 1,493,381 while ART coverage 61.3, 68.6 and 74.6% in 2015, 2016 and 2017, respectively [13]. We aggregated ART coverage and VLS data for 3 years (2015–2017). By 2017, there were 10 VL testing laboratories in Kenya. These laboratories receive dried blood spot (DBS) samples from HIV care and treatment sites from all over the country. The hub laboratories are organized such that they receive samples from the facilities closest to them. HIV testing and treatment data were downloaded from the data for accountability, transparency and impact (DATIM) repository < https://www.datim.org/>. These data come from all geographic regions providing HIV care and treatment services in the country.

Shape polygons used in the manuscript were downloaded from a public repository < http://data.ilri.org/geoportal/catalog/main/home.page>.

Measures

We defined ART coverage as the estimated ratio of persons currently on ART out of the estimated number of PLHIV for a particular year according to national HIV estimates in Kenya [14]. Viral load was measured in copies/mL of viral load ribonucleic acid (HIV RNA) measured after 6 of follow-up after initiation of ART according to Kenyan guidelines [15]. VLS rates were directly calculated from PLHIV with VL < 1000 cells per mL out of persons on ART with a VL result. The number of HIV-positives identified during the reporting period were recorded, and the crude positivity rate was defined as the proportion of tests performed that were reactive. Fitted estimates were derived after spatial-temporal analyses.

Statistical analyses

We examined the association between ART coverage and VLS rates to HIV positivity by fitting spatial and spatial-temporal semi-parametric Poisson regression models using R-Integrated Nested Laplace Approximation (INLA) package [16, 17] and mapped adjusted HIV positivity using QGIS version 3.2. To assess spatial relationships, we fitted these semi-parametric Poisson regression models: (1) spatial-temporal model without covariates;

(2) a spatial non-temporal model with covariates; and (3) a spatial-temporal model with covariates as proposed by Blangiardo, Cameletti and Rue [18]. For each of these spatial models we used Bayesian Deviance Information Criterion (DIC) according to Spiegelhalter et al., [19, 20] to assess the strength of the fit. Since Bayesian analyses are based on an assumed probability model. Appropriateness of these models can be assessed using DIC.

We used the extended Cochran-Mantel-Haenszel stratified test of association to test for trend across the three years for fitted rates of HIV positivity, Kruskal-Wallis equality-of-populations nonparametric rank test to compare medians for continuous variables and a structural equation model implemented in Stata version 14.1, (Stata Corp, College Station, TX, USA) to assess direct effects between the two exogenous covariates to fitted newly HIV-diagnosed as the endogenous variable (ε_1) adjusting for clustering by 47 counties. We assessed for goodness of fit for the model using the standardized root mean squared residual and coefficient of determination. We also used the equation-level goodness of fit to assess for correlation between endogenous variables and their predictions using the Bentler-Raykov squared multiple correlation coefficient. We then looked for modification indices to ascertain that the model was correctly constructed. We reported direct and total effects and described associations using a path diagram.

Results

Overall summary of covariates, their rates and outcomes are presented in Table 1. Although the HIV testing services (HTS) targets stabilized in 2016-17, there was a steep rise from 2015 to 2016 in median

number of persons tested (99,255 in 2015, 172,981 in 2016) to 153,330 in 2017 (p = 0.04). However, the number on ART has remained constant through 2017 (p = 0.769) and ART coverage has slightly increased in the three years (p = 0.468).

Table 1
County aggregated median and interquartile range values for covariates, exogenous variable and test for trends, 2015–2017, Kenya

Data	2015	2016	2017	p-value
ART coverage (%)	52.8 (40.7–63.5)	59.3 (41.5–69.7)	65.4 (47.2–74.1)	0.242†
# on ART	10540 (4538–20866)	11648 (4955–25737)	12970 (4880–27901)	0.769‡
VL coverage rates	74.1 (65.1–84.7)	74.1 (65.1–84.7)	74.1 (65.1–84.7)	1.0†
VLS* rates (%)	81.1 (78.9–83.2)	81 (78-84.9)	81.3 (77.6–84.5)	0.424†
Number tested	99255 (38765–193834)	172981 (76586–301680)	153330 (57542–312865)	0.040‡
Number HIV positive	2661 (907–5395)	3033 (1375–5227)	2268 (814–4118)	0.566‡
Raw positivity rate (%)	2.6 (1.8–3.5)	1.7 (1.2–2.2)	1.5 (1–2)	0.445†
Fitted positivity rate (%)	2.9 (1.9–3.4)	1.8 (1.5–2.3)	1.5 (1.3-2)	0.037†
*VLS = Viral load suppression				
†Cochrane Mantel- Haenszel test				
‡Kluskal-Wallis equality of populations rank test				

Output from various model comparisons are presented in Table 2. A spatial-temporal model with covariates was better in explaining geographical variation in HIV positivity DIC 381.3), than either a non-temporal spatial model (DIC 444.3) or temporal model without covariates (DIC 449.2). Our best fitting model was a spatial-temporal model with covariates and had DIC lower by greater than 10 points from the next model of a different nature (spatial non-temporal model).

Table 2
Model comparison using deviance information criterion (DIC) to identify best fitting model

Model type	DIC	Effective parameters	Model choice
Model 1: Spatial model without covariates	449.2	35.4	Third
Model 2: Spatial non-temporal model with covariates	444.3	36.3	Second
Model 3: Spatial-temporal model with covariates	381.3	37.3	Best*
*Best fitting model with lowest DIC (> 10) from the next model of a different nature is model 3			

There was a strong correlation between number of HIV tests and number of PLHIV in counties across the years (r^2 = 0.95, 0.93 and 0.95 in 2015, 2016 and 2017 respectively), $p < 0.001$ for the three years (data not shown). In contrast, spatially-adjusted positivity does not necessarily follow the preceding assumption that positivity would correlate to the number of PLHIV in a county (Fig. 1). For example, 2 of the 5 high burden counties (Homabay and Migori) were no longer among the leading 5 counties in terms of positivity given their HIV burden.

Figure 2 shows the spatial-temporal trend of fitted HIV positivity from 2015 to 2017. When we compared raw to fitted HIV positivity rates, only 3 counties had increased positivity in 2017 compared to 2016 but in adjusted rates, seven had higher positivity in 2017 compared to 2016. Whereas the raw rates of HIV positivity apparently remained about 2.1% across the three years, the fitted rates showed a constant decline.

To validate the structural equation model, we assessed the goodness of fit. The standardized root mean squared residual value was significant $p < 0.001$, and the coefficient of determination was 0.099. There were no modification indices to report, since all modification index values were less than 3.84. The direct relationship between individual correlates and HIV positivity showed a strong association between VLS rates and HIV positivity, $p = 0.001$, and the direct relationship between VLS and HIV positivity remained significant, $p = 0.004$ (Fig. 3b). Out of the 6 worst performing counties, 5 are in remote areas of Kenya (Turkana and West Pokot) and both border neighboring countries.

Discussion

Overall, the adjusted HIV positivity decreased over 3 years from 2015 to 2017. While adjusting for spatial clustering and covariance, viral load suppression had a direct effect on decreasing HIV positivity rates but ART coverage did not. Our analyses show that a spatial-temporal model with covariates was better in explaining geographical variation in HIV positivity or temporal model without covariates. In SSA, ART coverage had been associated with prevalence but not national income, healthcare expenditure nor number of health care workers [21]. Although ART coverage is driven by program targeting based on HIV

prevalence estimates, the question of inappropriate targeting due to poor HIV prevalence estimations remains unanswered. For greater HIV epidemic control impact, it is ideal to see an increase of VL coverage and VLS with optimized ART over time. Our analyses show that VL coverage and suppression rates have been constant across the years. This may be indicative of strong VL networking and uniform use of HIV treatment guidelines across the country. Whereas there has been no change in raw positivity rates through the three years, there were differences in the spatially-adjusted HIV positivity rates with a decline from 2.9% in 2015 to 1.5% in 2017, indicating the role of spatial approach in providing better estimates. Thus, while the raw rates of HIV positivity apparently remained about 2.1% across the three years, the fitted rates showed a constant decline. We were able to better understand where the declines in HIV positivity are using geospatial analyses than would have been identified using unadjusted analyses. Although the decline in positivity has generally been uniform across most counties, there were some reversals or increases observed in 6 out of 47 counties by the end of 2017. Kisumu, Siaya, Nakuru, Turkana, Narok, and West Pokot counties had higher positivity rates in 2017 than in either 2015 or 2016.

Targets set by the HIV program in Kenya were driven by the desire to find more positives especially in 2016 after the renewed commitment and a call for HIV epidemic control [22]. However, location based programming has been on high HIV burden counties and not driven by other geo-spatial criteria including spatial-temporal and covariates considerations. Our analyses show that there has been a strong correlation between number of HIV tests and number of PLHIV in counties across the years. Assuming that strategies for HIV testing have been applied consistently in line with current guidelines through the years, this raises the question why the positivity rates were higher in 2017 for these counties. It is possible that the health workers strike that was experienced in 2017 may have led to lowered availability of testing and thereby presentation of sicker patients who got tested using a provider initiated testing approach, resulting in higher overall positivity, including that of infants [23]. Additionally, strategies for HIV case finding have changed over time to more targeted approaches for testing e.g., index testing possibly attributing to greater identification in 2017.

The tipping point description for epidemic control and ending AIDS is related to declining positivity rates as seen by a fall in the number of new (incident) HIV infections to the point where they are below the number of all-cause deaths among PLHIV [22]. This can be achieved with scaled-up ART and sustained adherence for those on treatment. Although we refer to new HIV diagnoses as HIV positivity, these rates may be indicative of actual incident HIV infections. Challenges towards ending AIDS including the need for improved access to ART, HIV prevention through bio-behavioral interventions, and a greater understanding of populations that may be left out undiagnosed is still relevant [24]. We postulated that ART coverage should lead to higher rates of VLS taking into account that positivity rates are a function of the two covariates, and ultimately fewer new infections. This tripartite relationship indicates that rates of VLS may play a bigger role than ART coverage in determining HIV positivity, whose role is masked due to good coverage. Given the majority (> 80%) of VL tests are conducted for routine monitoring [25], our findings suggest that the potential of investing in improved VLS rates to reduce HIV positivity. In a mixed HIV epidemic like Kenya's, reduced sexual transmission of HIV with sustained and improved ART coverage and suppressed viral loads may be leading to declines in HIV positivity. Such associations have

been demonstrated by others [26]. The direct relationship between individual correlates and HIV positivity showed a strong association between VLS rates and HIV positivity, while the direct relationship between VLS and HIV positivity remained significant. The relationship between ART coverage to VLS rates was equally significant validating our assumptions that ART coverage leads to improved VLS suppression rates. These gains in the HIV program in Kenya however need to be maintained. Our analyses help identify geographic disparities, and calls for re-programming of HTS alongside linkage to ART to address county inequalities. Continued exploration of the interaction of population dynamics and programmatic interventions such as VL testing access or coverage and enhanced adherence for individuals on treatment and those with virologic non-suppression are needed. Out of the 6 worst performing counties, 5 are in remote areas of Kenya (Turkana and West Pokot) and both border neighboring countries. While keeping an eye on programmatic interventions, cross-border migration and tracking of defaulters may require collaboration between countries necessitating greater collaboration and tracking of patients and allocation of shared health resources.

We acknowledge that ecological analyses are flaunt with biases due to inherent individual-level characteristics that may be sufficiently accounted for. Our data are aggregated at county level therefore it is not possible to do more granular analyses e.g., by age and other classifications for example by HIV testing strategies, sex etc. Although similar spatial-temporal reduction in transmission rates among infants has been demonstrated in a prevention of mother to child transmission (PMTCT) setting [27], VLS rates for mothers was not a factor in these analyses, and neither was it possible to relate the impact of virally suppressed mothers and PMTCT. Finally, we assumed that the numbers reported as newly diagnosed were indeed new diagnoses yet retesting of previously diagnosed may happen to some unknown extent. Although these results may be triangulated with population-level HIV impact assessments (PHIAs) whenever available, PHIAs are conducted every 5 years yet HIV programs in the era of epidemic control need fast and robust analyses.

Conclusions

Our analyses demonstrate the possibility of using programmatic data in a spatial context to describe outcomes that are associated with HIV epidemic control. The value of our analyses lies in HIV planning including forming a basis for the purposes of targeting interventions during country operational plans. While in a duration of 3 years of improving ART coverage in Kenya a general decline of HIV positivity rates associated with improved VLS rates was observed, we have however noted differences in HIV case finding at county level. To assess the trends and impact of implementation of scaled-up HIV care and treatment, spatial-temporal analyses help to identify geographic areas that need greater attention.

List Of Abbreviations

AIDS acquired immunodeficiency syndrome

ART antiretroviral therapy

CDC US. centers for disease control and prevention

DBS dried blood spot

DIC Bayesian deviance information criterion

HIV human immunodeficiency virus

HTS HIV testing services

INLA integrated nested laplace approximation

MOH ministry of health (Kenya)

NASCOP national AIDS and STI control program (Kenya)

PEPFAR president's emergency plan for AIDS relief

PHIA public-health impact assessments

PLHIV people living with HIV/AIDS

PMTCT prevention of mother to child transmission of HIV

RNA ribonucleic acid

SSA sub-Saharan Africa

UNAIDS joint united nations programme on HIV/AIDS

VL viral load

VLS viral load suppression

Declarations

Ethics approval and consent to participate

The MOH, National AIDS and STI Control Programme (NASCOP), and President's Emergency Plan for AIDS Relief (PEPFAR) funding agencies provided concurrences. The protocol was reviewed in accordance with the US Centers for Disease Control and Prevention (CDC) human research protection procedures and was determined to be nonresearch, public health program activity.

Consent for publication

All the PEPFAR funding agencies, the Kenya ministry of health and All authors read the manuscript, provided feedback, and approved the final version for publication.

Availability of data and materials

HIV testing and treatment data are available from the data for accountability, transparency and impact (DATIM) repository <https://www.datim.org/>, and are available to authorized persons within the US government agencies. The same data are available from DHIS 2 and can be requested from the ministry of health. Viral load (VL) data are available from the Ministry of Health (MOH) VL dashboard <https://viralload.nascop.org/>. Shape files used in the manuscript for mapping are freely available from a public repository hosted at <http://data.ilri.org/geoportal/catalog/main/home.page> and are covered under the creative commons license CC BY 4.0.

Competing Interests

The authors declare that they have no conflict of interest(s).

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Authors' contributions

AW conceived the idea for this manuscript and prepared the concept, data analyses and wrote the first and subsequent drafts of the manuscript. JW, MK, KM, FB, SO, LN, EZG, SN, KMD and TT helped with results interpretation provided insights on HIV programmatic implications and recommendations. TNOA, JMK, and JLT helped with analytic methods and data interpretation. CM helped with data acquisition.

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Authors' Information

"Not applicable"

References

1 Joint United Nations Programme on HIV/AIDS (UNAIDS). UNAIDS 2016-2021 Strategy: On the Fast-Track to end AIDS 2015:1–120.

2 UNAIDS (Joint United Nations Programme on HIV/AIDS). Fast-Track Ending the AIDS epidemic by 2030. Unaids 2014:1–40. doi:ISBN 978-92-9253-063-1.

3 Das M, Chu PL, Santos G, Scheer S, Vittinghoff E, Colfax GN. Decreases in community viral load are accompanied by reductions in new HIV infections in san Francisco. PLoS One 2010;5. doi:10.1371/journal.pone.0011068.

4 Abu-Raddad LJ, Barnabas R V., Janes H, Weiss HA, Kublin JG, Jr IML, Wasserheit JN. Have the explosive HIV epidemics in sub-Saharan Africa been driven by higher community viral load? 2015;6:790–5. doi:10.1016/j.pmrj.2014.02.014.Lumbar.

5 Joint United Nations Programme on HIV/AIDS (UNAIDS). On the Fast-Track to end AIDS by 2030: Focus on location and population 2015:1–260.

6 Amorim LDAF, Fiaccone RL, Santos CAST, Santos TN dos, Moraes LTLP de, Oliveira NF, Barbosa SO, Santos DN dos, Santos LM dos, Matos SMA, Barreto ML. Structural equation modeling in epidemiology. Cad Saúde Pública 2010;26:2251–62. doi:10.1590/S0102-311X2010001200004.

7 Sánchez BN, Budtz-JØrgensen E, Ryan LM, Hu H. Structural equation models: A review with applications to environmental epidemiology. J Am Stat Assoc 2005;100:1443–55. doi:10.1198/016214505000001005.

8 In'nami Y, Koizumi R. Structural equation modeling in educational research: A primer. Appl Struct Equ Model Educ Res Pract 2013:23–51. doi:10.1007/978-94-6209-332-4.

9 Gari S, Doig-Acuña C, Smail T, Malungo JR, Martin-Hilber A, Merten S. Access to HIV/AIDS care: A systematic review of socio-cultural determinants in low and high income countries. BMC Health Serv Res 2013;13. doi:10.1186/1472-6963-13-198.

10 Sanga ES, Mukumbang FC, Mushi AK, Lerebo W, Zarowsky C. Understanding factors influencing linkage to HIV care in a rural setting, Mbeya, Tanzania: qualitative findings of a mixed methods study. BMC Public Health 2019;19:1–15. doi:10.1186/s12889-019-6691-7.

11 Lubogo D, Ddamulira JB, Tweheyo R, Wamani H. Factors associated with access to HIV care services in eastern Uganda: the Kumi home based HIV counseling and testing program experience. BMC Fam Pract 2015;16:1–9. doi:10.1186/s12875-015-0379-6.

12 National AIDS and STI Control Programme (NASCOP), National AIDS Control Council (NACC). Kenya HIV County Profiles. 2016.

13 National AIDS Control Council (NACC). Kenya HIV Estimates Report 2018 2018:1–34. doi:10.1111/j.1365-2664.2007.0.

14 National AIDS and STI Control Programme Ministry of Health, National AIDS Control Council (NACC). Kenya HIV estimates 2015. 2015.

15 Ministry of Health National AIDS & STI Control Programme. Guidelines on Use of Antiretroviral Drugs for Treating and Preventing HIV Infection in Kenya. NASCOP; 2016.

16 Blangiardo M, Cameletti M, Baio G, Rue H. Spatial and spatio-temporal models with R-INLA. Spat Spatiotemporal Epidemiol 2013;7:39–55. doi:10.1016/j.sste.2013.07.003.

17 Lindgren F, Rue H. Bayesian Spatial Modelling with R-INLA. J Stat Softw 2015;63:1–25. doi:10.18637/jss.v063.i19.

18 Blangiardo M, Cameletti M, Baio G, Rue H. Spatial and spatio-temporal models with R-INLA. Spat Spatiotemporal Epidemiol 2013;7:39–55. doi:10.1016/j.sste.2013.07.003.

19 Spiegelhalter DJ, Best NG, Carlin BP, van der Linde A. Bayesian measures of model complexity and fit. J R Stat Soc Ser B (Statistical Methodol 2002;64:583–639. doi:10.1111/1467-9868.00353.

20 Spiegelhalter DJ, Best NG, Carlin BP. Bayesian deviance, the effective number of parameters, and the comparison of arbitrarily complex models 2013.

21 Furuoka F, Hoque MZ. Determinants of antiretroviral therapy coverage in Sub-Saharan Africa 2015:1–17. doi:10.7717/peerj.1496.

22 Office of the Global AIDS Coordinator. PEPFAR 3.0. Controlling the Epidemic: Delivering on the Promise of an AIDS-Free Generation 2014:1–32.

23 Kabale N. Striking nurses cause surge in mother to child HIV infection 2017. https://www.standardmedia.co.ke/health/article/2001243275/striking-nurses-cause-surge-in-mother-to-child-hiv-infection (accessed November 29, 2018).

24 Friends of the global fight against TB HIV and Malaria. At the tipping point n.d.

25 Mwau M, Syeunda CA, Adhiambo M, Bwana P, Kithinji L, Mwende J, Oyiengo L, Sirengo M, Boeke CE. Scale-up of Kenya's national HIV viral load program: Findings and lessons learned. PLoS One 2018;13:1–13. doi:10.1371/journal.pone.0190659.

26 Attia S, Egger M, Müller M, Zwahlen M, Low N. Sexual transmission of HIV according to viral load and antiretroviral therapy: Systematic review and meta-analysis. Aids 2009;23:1397–404.

doi:10.1097/QAD.0b013e32832b7dca.

27 Waruru A, Achia TNO, Muttai H, Ng'ang'a L, Zielinski-Gutierrez E, Ochanda B, Katana A, Young PW, Tobias JL, Juma P, De Cock KM, Tylleskär T. Spatial–temporal trend for mother-to-child transmission of HIV up to infancy and during pre-Option B+ in western Kenya, 2007–13. PeerJ 2018;6:e4427. doi:10.7717/peerj.4427.

Figures

Order‖	SNU	PLHIV* (2015)	ART coverage (%)			VLS† rates (%)			Positivity trend‡	Positivity trend§	
			2015	2016	2017	2015	2016	2017	2015-2017	2015-2017	Order△
1	Nairobi	171510	67.3	71.6	74.1	86.7	84.6	85.2			3
2	Homa Bay	158077	51.5	59.2	70.9	83.2	84.7	85.7			6
3	Kisumu	144303	55.5	67	80.1	84.7	84.8	85.9			1
4	Siaya	126411	50.9	53.1	64.1	79.3	79.9	80.9			2
5	Migori	83603	61.5	62.1	75.3	84.9	87.6	87			7
6	Kiambu	70971	38.6	46.3	59.7	87.3	87.8	88.4			9
7	Mombasa	54310	67.2	83.4	103.4	81.3	80.7	85.8			14
8	Kakamega	50844	59.6	80.2	72.6	82.2	79.9	81.3			5
9	Nakuru	41217	63.4	53	71.7	81.5	82.4	82.7			4
10	Busia	38549	72.5	92.9	83.9	83	79.2	81.6			23
11	Kisii	34014	61.3	60.4	73.7	77.5	81.8	87.4			32
12	Machakos	32611	58.1	69.3	73.3	83.2	85.3	82.6			30
13	Kilifi	31630	53	70	62.6	81.3	81.6	81.8			23
14	Bungoma	30091	63.8	84.7	73.8	81.1	79.5	77.1			17
15	Makueni	29370	45.3	59.3	62	83.1	86.2	83.7			32
16	Kitui	28918	52.8	58.6	61	80.7	84.9	83.2			17
17	Murang'a	27245	40.7	46	42.7	85.5	85.4	88.4			23
18	Uasin Gishu	26771	96.4	69.1	90.4	78.9	75.2	81.3			11
19	Trans Nzoia	26164	59	36.4	47.2	80	77.5	80.3			10
20	Meru	26019	59.3	69	70.8	86.3	87.6	82			13
21	Nyamira	24357	43.3	57.4	68.7	81.4	79.4	77.2			40
22	Kwale	23902	35	33.8	41.8	77	78.8	79			17
23	Turkana	22523	22.2	21.3	31.2	64.8	64.3	62.9			11
24	Kajiado	20268	40	34.8	43.4	80.5	83.3	80.3			8
25	Vihiga	19381	58.6	76.1	65.4	82.8	81.1	81.8			15
26	Nyeri	18662	73.6	84.4	74.2	86.7	86	88.9			23
27	Kericho	16382	82.6	63	88.9	80.5	82.5	84.5			40
28	Narok	15890	38.6	32.2	42.7	75.4	78	79.2			15
29	Nyandarua	12754	48	44.3	45.6	84.3	88.1	84.4			32
30	Kirinyaga	12323	68.4	69.7	62.6	86.5	88	88.7			32
31	Taita Taveta	11788	38.5	42.1	47.8	81	81	77.6			17
32	Nandi	11215	81	60.2	80.8	78.9	78.1	81.3			40
33	Bomet	11144	63.5	69.7	104.4	78.4	79.2	81.6			23
34	Embu	11141	64	74.4	74.1	83.2	83.4	81.1			23
35	Tharaka Nithi	9093	60.6	67.5	70.4	80.4	85.1	80.4			40
36	Laikipia	7770	75.9	60.4	82.9	83.4	86.6	83			17
37	Baringo	5586	51.5	41.5	53.9	72.3	79.2	75.9			38
38	West Pokot	4790	31.3	36.7	53.2	80.2	76.7	80.7			17
39	Elgeyo Marakwet	4381	47.2	41	56.8	83.7	74.1	73.5			32
40	Isiolo	3616	47.1	64.8	69.3	80.8	77.8	75.3			30
41	Mandera	3385	9.6	21.3	52	60.9	66.7	68			46
42	Samburu	2965	33	28.9	45.6	68.3	64.7	57.9			32
43	Marsabit	2841	43.4	56.7	46.8	79.2	77.6	76.5			38
44	Tana River	2792	33.4	34.8	45.1	72.8	70.9	67.7			44
45	Garissa	2534	43.4	72.9	40.1	80.2	81.8	81.3			45
46	Lamu	2319	44.2	42.3	46.2	81.6	77.2	74.2			23
47	Wajir	1277	16	29.1	77.6	71.4	78.7	84.6			47
	Sum/average(%)	**1,517,707**	**52.6**	**56.4**	**64.4**	**80.2**	**80.5**	**80.4**			

Figure 1

County-level variations in ART and VL coverage and fitted positivity rates, Kenya, 2015-2017 Caption: The figure lists 47 counties in order of declining HIV burden (PLHIV), covariates and HIV positivity. The last column lists the 20 topmost counties in HIV positivity in 2017 (highlighted in red). *PLHIV=People living with HIV (estimates for 2015) † VLS=Viral load suppression (expressed as rates in percentage) ‡ Raw positivity trends § Fitted positivity trends ‖ Descending order of PLHIV (HIV burden) Δ Descending order of HIV positivity by 2017 and top 20 counties highlighted in red Positivity trend: Green marker means the

lowest value, red maker means highest value and black means a value that is in between the lowest and highest in the three years

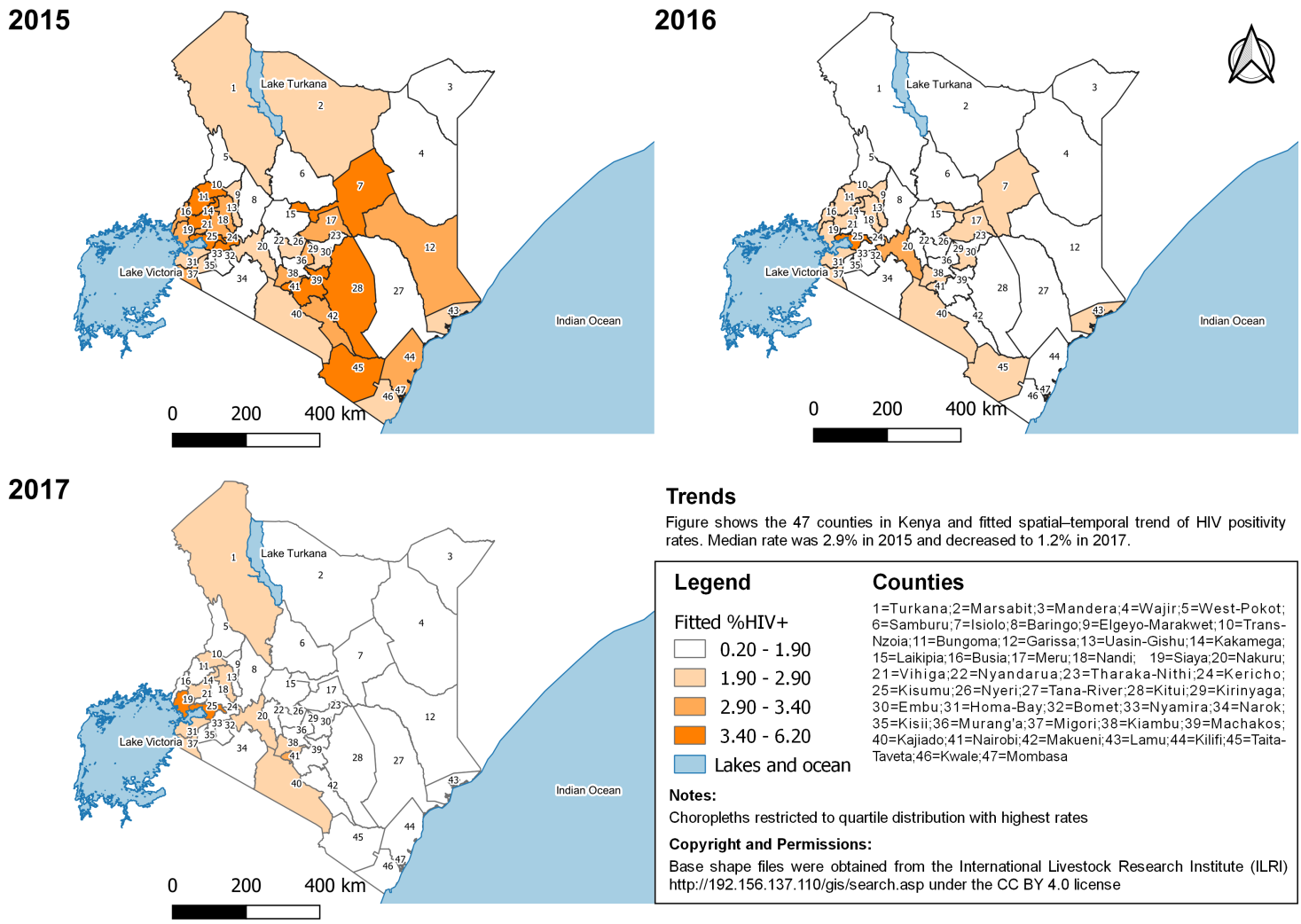

Figure 2

Spatial-temporal trend of new HIV positivity rates, Kenya, 2015-2017 Caption: Spatial temporal trend of HIV positivity rates from 2015 to 2017. The darker shades of the choropleths show higher HIV positivity and lighter shades low HIV positivity.

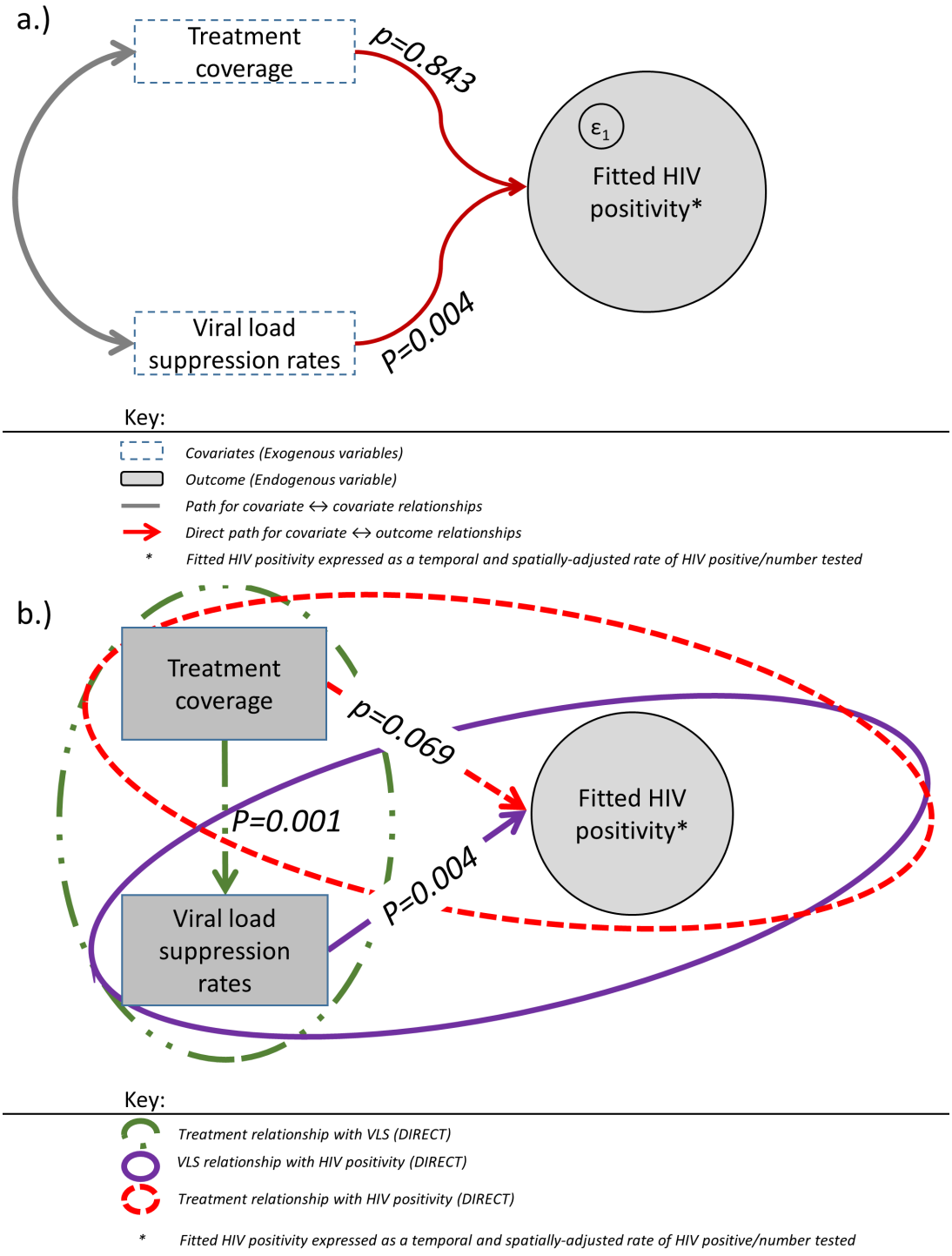

Figure 3

Structural equation model and path diagram of treatment coverage and viral load suppression as correlates of HIV positivity rates, Kenya, 2015-2017 Caption: Figure 3a shows the two correlates (treatment coverage and viral load suppression) and relationship paths as related to HIV positivity rates; Figure 3b shows the direct relationship between correlates and HIV positivity rates.