Bayesian Modeling of Space and Time Dynamics: A Practical Demonstration in Social and Health Science Research

Ding-Geng Chen *University of North Carolina at Chapel Hill*
David Ansong *University of North Carolina at Chapel Hill*

ABSTRACT ***Objective:*** This article introduces Bayesian spatial–temporal modeling for social and health science research. We use the World Bank's *World Development Indicators* data on youth unemployment and HIV risk in Africa to illustrate the utility of the Bayesian paradigm in modeling space–time changes in outcomes. ***Method:*** Data on adolescents and young adults were collected in 36 African countries from 1991 to 2014. We examined associations between HIV risk and youth unemployment rates using 16 Bayesian Poisson models incorporating spatial and temporal autocorrelations. ***Results:*** The best fit to the data was the model with spatially uncorrelated heterogeneity, temporally correlated random-walk autocorrelation, and spatial–temporal interaction. HIV risk factors are spatially uncorrelated across 36 countries but temporally correlated (i.e., country and time interaction) over the data collection period. The relationship between HIV risk and unemployment rate is statistically nonsignificant because of large spatial–temporal variations. ***Conclusions:*** This article demonstrates the capacity of Bayesian modeling to incorporate spatial (neighborhood) and temporal (historical) information to reflect not only the influences of space and time but also their interactions on the phenomenon of interest. The Bayesian framework holds great promise for improving the dynamic targeting of interventions and strategies to achieve desired outcomes.

KEYWORDS: HIV risk, spatial autocorrelation, temporal autocorrelation, Bayesian modeling

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The application of spatial techniques in social work research and social services delivery is not new. As early as the 1800s, social workers such as Jane Addams and Frances Kelley used hand-drawn maps and foot surveys to shed light on the socioeconomic and demographic composition of communities (Felke, 2006; Hillier, 2007). More than a century later, spatial mapping became prominent in social work theorization, discourse, and practice (Spatscheck, 2012). The German tradition of social work is best known for fostering the idea of Sozialräume (i.e., concept of social spaces) and application of spatial analytic approaches in the 1990s (Spatscheck & Wolf-Ostermann, 2009).

In part, the increased application of advanced spatial approaches in social work research has been fostered by the wide availability of geographic information system (GIS) technology, open-source software (e.g., QGIS), and geographically referenced data (e.g., census data; Felke, 2015; Teixeira, 2018). This shift to greater use of spatial approaches is characterized by the movement away from graphical display of data, such as choropleth maps, toward applications that include spatial inferential modeling, such as geographically weighted regression and hotspot analysis (see, e.g., Ansong, Ansong, Ampomah, & Adjabeng, 2015; Ansong, Ansong, Ampomah, & Afranie, 2015; Ansong, Renwick, Okumu, Ansong, & Wabwire, 2018; Felke, 2015; Freisthler, Lery, Gruenewald, & Chow, 2006; Wolf, Freisthler, Kepple, & Chavez, 2017). As evident in these studies, advances in the ability to statistically analyze spatial distributions, patterns, processes, and relationships have enabled social work researchers and practitioners to rigorously apply a spatial perspective, allowing them to not only understand and predict social problems affecting individuals and communities but also to inform program and policy development (Knight, 2016).

Social work research often involves applying longitudinal and location data to test hypotheses of outcome change trajectories; therefore, the need for social work researchers to use advanced statistical models has become increasingly apparent (Guo, 2013). Thus far, the advances in longitudinal and spatial analysis in social work research have been overwhelmingly based on the *frequentist paradigm* (i.e., conventional statistical approaches). The goal of this article is to draw attention to the utility of the alternative Bayesian paradigm in modeling spatial–temporal changes in outcomes. Notably, despite the promise that the Bayesian framework holds as a more intuitive and practical approach to spatial statistical modeling, social work researchers have not yet adequately explored the combination of temporal and spatial modeling, particularly from a Bayesian framework.

With recent advances in computation and simulation methods, the application of Bayesian methodology has become mainstream in spatial statistical and epidemiological inferences (Congdon, 2010; Lawson, 2006, 2013; Lawson, Banerjee, Haining, & Ugarte, 2016; Lesaffre & Lawson, 2002), and the popularity of Bayesian methodology is growing in social work research (D. Chen & Fraser, 2017a, 2017b; D. Chen, Fraser, & Cuddeback, 2018). Thus, this is an opportune time for social work researchers to seriously consider the application of Bayesian methodology. To further advance the application of Bayesian methods in social work and related fields, we draw on practical examples from space and time patterns in HIV prevalence and youth unemployment in Africa. We show how researchers might apply spatial statistics from a Bayesian framework to better understand how real-world phenomena and social problems (e.g., young Africans' HIV risk) and predictive factors (e.g., unemployment rates) evolve across space and time.

Without discounting the emotional, sexual, psychological, structural, and other strong determinants of HIV risk, the present study focuses on unemployment and its possible connections to HIV risk factors primarily to illustrate how Bayesian spatial–temporal modeling can be applied to social research to support evidence-based programs and policies. For a more in-depth review of the relevant literature on HIV and unemployment, we encourage readers to consult the large body of relevant empirical studies, systematic reviews, and meta-anlayses; in particular, we recommend Arndt and Lewis (2001), Baral et al. (2012), Oldenburg et al. (2014), and Zanoni, Archary, Buchan, Katz, and Haberer (2016). Additionally, we offer a brief review of the literature on HIV prevalence and unemployment in Africa to help readers put the methodogical application into context.

A Real-World Motivation for Bayesian Spatial–Temporal Modeling

Although rates of new HIV infections in Africa have declined in recent years, HIV is still a major public health concern on the continent and remains one of the leading causes of death in many areas of sub-Saharan Africa (Kabiru, Izugbara, & Beguy, 2013; Kharsany & Karim, 2016; United Nations Programme on HIV/AIDS [UNAIDS] & World Health Organization [WHO], 2003; United Nations Children's Fund [UNICEF], 2016). Additionally, improved access to antiretroviral treatment means more Africans are living with HIV. For example, from 2005 to 2015, the number of young people in Africa living with HIV rose by 28% (UNICEF, 2016). Beyond global trends in HIV infections, Africa has regionalized spatial clustering of HIV infections. For instance, seven countries in Eastern and Southern Africa account for two thirds of the global total of people living with HIV (Kharsany & Karim, 2016).

Because real-world phenomena and social problems often evolve conjointly, exploring spatial trends in isolation from temporal trends can be problematic. Although Africa's Eastern and Southern regions have the highest concentration of HIV cases, focusing only on the spatial clustering is often inadequate. Indeed, the history of HIV in Africa hints at changing trends across time and geographies (Denis & Becker, 2006; Shilts, 2007). Epidemiological data suggest the spread of HIV in Africa started in the 1960s and 1970s (Kagaayi & Serwadda, 2016). While the HIV epidemic quickly spread across Western, Eastern, and Central Africa in the early 1980s, Northern and Southern Africa were largely unscathed (UNAIDS & WHO, 2003). However, this status changed in the late 1980s when the infection hotspot shifted to Southern Africa. By the late 1990s, Africa's Southern region had become the epicenter of the global HIV epidemic, and more people in South Africa were living with HIV/AIDS (approximately 5 million) than any other country in the world (UNAIDS & WHO, 2003). Around the same time, the highest prevalence of HIV was recorded in two other southern countries: Botswana (38%) and Swaziland (33%). This geo-historical overview of HIV prevalence on the African continent suggests a *dynamic geographical clustering*—a phenomenon that the present study examines simultaneously from the spatial and temporal dimensions.

An essential benefit of Bayesian spatial–temporal modeling is the ability to incorporate spatial (neighborhood) and temporal (historical) information in ways that not only reflect the influences of space and time but also reflect the interactions of space and time on the phenomenon of interest. In the case of HIV infections, despite the significant advances in the fight against HIV made over the past two decades, the progress has been uneven across Africa's countries and regions. Although HIV has touched every area of the continent, Eastern and Southern Africa have had higher concentrations of HIV historically; consequently, those regions have not only experienced some of the most severe effects of the HIV pandemic but also experienced higher prevalence of HIV than other regions of sub-Saharan Africa. Moreover, vast disparities remain at the regional level, with 2% of adults infected with HIV in West and Central Africa compared to 7% of adults in Eastern and Southern Africa (UNAIDS, 2017). Even more nuanced is the disparity within regions. Western Africa is a case in point: During 2000–2016, new HIV infections among children decreased in 13 countries but increased in five other countries in the region (UNAIDS, 2017). This complex interaction between geography and time in the prevalence of HIV mirrors nuanced trends in other social phenomena; thus, understanding these complex interactions provides the impetus for social work researchers and practitioners to use advanced analytical approaches and frameworks capable of unearthing the spatial and temporal patterns of complex phenomena such as emotions, perceptions, attitudes, and behavior.

Motivation for Incorporating Predictor/Covariates into Bayesian Spatial–Temporal Modeling

Although understanding the space–time patterns in health outcomes and other developmental outcomes is critically important for policymakers, practitioners, and funding agencies, such understanding might be inadequate without insights into predictors and determinants. In the HIV example, perhaps the more important aspects are clarifying the malleable determinants and correlates of HIV outcomes and identifying how those factors differ across space and time. Such insights would inform the dynamic targeting of interventions and strategies to achieve desired outcomes, such as reductions in new HIV infections. Therefore, this study demonstrates how a predictor or covariate could be incorporated into Bayesian spatial–temporal modeling.

In this example, we used the unemployment rate as a covariate. It is worth noting that in a typical HIV risk study, the unemployment rate might not be the preferred variable of interest because the literature often focuses on HIV infection as the antecedent in the connection between HIV and unemployment. Nonetheless, given data constraints and our purposes for this demonstration, we have focused on unemployment as a variable of interest to demonstrate whether the role of unemployment in HIV infection, if any, was fixed across space and time. We encourage readers who are interested in the methodological application and the substantive role of unemployment as a correlate of HIV prevalence to consult the substantive literature. (For an overview of unemployment as an HIV risk factor, see Austin, Choi, & Berndt, 2017; Delpierre et al., 2008; Maruthappu, Zhou, Williams, Zeltner, & Atun, 2017).

Analogous to HIV prevalence in Africa, unemployment rates remain a primary concern for many African governments. For decades, the African continent—especially sub-Saharan Africa—has experienced enormous increases in the working-age population. By 2013, the continent's working-age population stood at 466 million people. Given the large upswell of youth entering the workforce, many African countries have struggled to create enough employment opportunities; high unemployment rates have resulted, especially among adolescents and young adults. Since the 2000s, the unemployment rate in sub-Saharan Africa has hovered around 7.5%, and the labor force participation rate has stagnated around 70% (Bhorat, Naidoo, & Ewinyu, 2017). This problem is so widespread it warrants a special label for unemployed youth: NEET, or youth who are not engaged in employment, education, or job training (Organisation for Economic Co-operation and Development, 2016). However, from a spatial perspective, significant variations exist in youth unemployment rates (Baah-Boateng, 2016). For instance, at the regional level from 2010 to 2014, North Africa had the largest share of NEET youth (World Bank, 2016). The increasing numbers and locations of NEET youth are important because these individuals lack skills to improve their economic well-being and therefore face a higher risk of becoming excluded from mainstream society and trapped in a cycle of poverty.

In addition to social exclusion, NEET youth face other risks related to unemployment. Austin and colleagues (2017) suggested that when extended unemployment creates a sense of economic insecurity, young people—especially girls in developing countries—become more susceptible to keeping concurrent partners or "sugar daddies" and engaging in transactional sex, invariably risking HIV infection. For intervention researchers, critical empirical questions might include the following: To what extent might youth unemployment rates predict HIV transmission across space? How robust is the association between youth unemployment and HIV prevalence when unemployment rates are appropriately accounted for as a time-varying phenomenon? In this article, we demonstrate how Bayesian spatial–temporal modeling can be applied to address such questions with space–time dimensions. Using the example from the HIV–unemployment connections, we address two research questions:

1. Are space–time trends observable in HIV incidence in Africa?
2. Are unemployment rates among adolescents predictive of the space–time trends in HIV prevalence?

Bayesian Spatial–Temporal Models

General Spatial–Temporal Model

When using spatial–temporal data to study occurrences such as diseases, researchers are often interested in both the spatial and temporal aspects of these data. For instance, researchers might want to investigate disease location and time of diagnosis along with the disease counts. This goal could be achieved by modeling the disease counts as a Poisson process while concurrently incorporating the space and time data with all other risk covariates. Because of the spatial–temporal autocorrelations, spatial–temporal disease data are typically modeled as multivariate with correlated observations of Poisson disease counts at a fixed spatial location that evolves over time.

For the present study, we specifically focused on HIV data from 36 African countries collected over a 24-year period (1991–2014). Thus, i denotes the spatial location among 36 countries ($i = 1 \ldots i = 36$), and t denotes years ($t = 1 \ldots t = 24$). HIV disease incidence (y_{it}) is modeled as a Poisson spatial–temporal model with the expected incidence (E_{it}) and the associated risk (θ_{it}). Therefore, the spatial–temporal model can be characterized as

- Data distribution:

$$y_{it} \sim \text{Poisson}(E_{it} \times \theta_{it}), \tag{1}$$

- Mixed-effects regression model:

$$\log(\theta_{it}) = \beta_0 + \beta_1 x_{1it} + \ldots + \beta_p x_{pit} + S_i + T_t + ST_{it}\,. \tag{2}$$

S, T, and ST are random-effects components representing the random spatial effect, the random temporal effect, and the random spatial–temporal interaction, respectively. The fixed-effects component is $\beta_0 + \beta_1 x_{1it} + \ldots + \beta_p x_{pit}$, where $x1_{it} \ldots x_{pit}$ are the risk factors to be modeled with the disease risk (θ_{it}). Because only UEM_{it} (i.e., unemployment) is available, the model is simplified as

$$\log(\theta_{it}) = \beta_0 + \beta_1 UEM_{it} + S_i + T_t + ST_{it}\,. \tag{3}$$

In the data distribution, E_{it} is the expected incidence; several methods can be used to estimate these values. The most commonly used method is the *overall average from the population*, which is calculated as

$$E_{it} = p_{it} \times \sum_{i=1}^{L} \sum_{t=1}^{T} y_{it} \Big/ \sum_{i=1}^{L} \sum_{t=1}^{T} p_{it} \tag{4}$$

where p_{it} is the population at the ith location (i.e., country) and tth time point (i.e., year) in this HIV data.

HIV Spatial–Temporal Models

We fit eight spatial–temporal models to the African HIV data (see Table 1) with the goal of modeling the spatial–temporal heterogeneity in the data. As seen in Table 1, we explored three groups of models: Group 1, which includes Models 1 and 2, models only spatial heterogeneity; Group 2, which includes Models 3–6, extends the Group 1 spatial models by incorporating temporal heterogeneity; and Group 3, which includes Models 7 and 8, assesses the spatial–temporal interaction.

Model 1 is the simplest. It includes the spatial dimension only with uncorrelated heterogeneity (UH)—that is, identically independent distributed (IID) errors among the 36 African countries. Note that Model 1 is oversimplified as it assumes that no spatial and temporal correlation exists; such an assumption is unrealistic. Thus, we include Model 1 only as a reference. Extending Model 1 to incorporate spatial autocorrelation, Model 2 includes spatial components with the standard Besag, York,

Table 1

Specific Spatial–Temporal Models and Associated Fit Statistics

Model	Details	DIC	pD
1	Spatial Only (UH)	1,635.964	6.313
2	Spatial Only (UH + CH)	1,698.169	37.405
3	Spatial (UH + CH) + Temporal Trend	1,700.178	38.402
4	Spatial (UH + CH) + Temporal (UH)	1,744.839	59.443
5	Spatial (UH + CH) + Temporal (CH)	1,727.136	51.888
6	Spatial (UH + CH) + Temporal (UH + CH)	1,710.549	43.597
7	Spatial (UH) + Temporal (CH) + ST	1,646.630	11.646
8	Spatial (UH + CH) + Temporal (CH) + ST	1,708.228	42.436

Note. DIC = deviance information criterion; pD = effective number of parameters; ST = spatial–temporal. Spatial: UH = uncorrelated heterogeneity or identically independent distributed (IID); CH = standard Besag, York, and Mollié (BYM) model (Besag et al., 1991). Temporal: UH = uncorrelated heterogeneity or IID; CH = random walk, spatial–temporal interaction, or IID.

and Mollié (BYM) model (Besag, York, & Mollié, 1991) to assess the spatial autocorrelation among the 36 African countries.

Group 2 includes two models that account for the temporal heterogeneity in the data. First, Model 3 includes a linear time trend from 1991 to 2014 as a regression term, whereas Model 4 assumes an uncorrelated (i.e., IID) temporal heterogeneity. Next, Model 5 includes a random-walk correlated temporal correlation. The last step in the progression of Group 2 models is Model 6, which includes the convoluted spatial and temporal autocorrelations.

The demonstration concludes with Models 7 and 8 in Group 3, both of which explore possible spatial–temporal interactions.

Furthermore, to evaluate the regional effects, the spatial–temporal model in Equation 3 is extended to include the five African regions:

$$\log(\theta_{it}) = \beta_0 + \beta_1 UEM_{it} + \beta_2 Region_{it} + S_i + T_t + ST_{it}\,. \tag{3}$$

Therefore, eight additional spatial–temporal models are included, yielding 16 fitted spatial–temporal models.

We used goodness-of-fit measures to compare how well these models fit the data. The most commonly used goodness-of-fit measures in Bayesian modeling include the deviance information criterion (DIC) and the effective number of parameters (pD); smaller values for the DIC and pD indicate a better model fit with the data (as detailed in Lawson et al., 2016). When fitting a series of models, a 3- to 5-point difference in DIC is considered a significant model improvement.

Implementation of Bayesian Spatial–Temporal Modeling

Typically, spatial–temporal disease mapping and modeling are conceptually complicated and computationally intensive due to the autocorrelation from both spatial and temporal aspects. Traditional statistical modeling techniques were developed principally to use spatial neighborhood information with assumed positive spatial autocorrelation between observations. The disease mapping approach is credited to Clayton and Kaldor (1987), who defined the empirical Bayesian methods from Poisson regression with random effects based on spatial correlation. This hierarchical modeling is a natural framework that incorporates spatial correlation in the estimation of disease rates. Besag and colleagues (1991) later extended this model to a full Bayesian framework with Markov chain Monte Carlo (MCMC). Since then, Bayesian spatial–temporal disease mapping with MCMC has become the default and is a popular method of modeling disease prevalence, as summarized in Congdon (2010), Lawson (2006, 2013), and Lawson and colleagues (2016).

Notwithstanding the method's popularity, Bayesian spatial–temporal disease mapping with MCMC is extremely intensive computationally, and thus, very expensive (D. Chen & Chen, 2017). A new alternative to this approach uses *integrated nested Laplace approximations* (INLA), which is much less computationally expensive. Most

MCMC software, such as BUGS and JAGS, samples from the posterior distribution of parameters, which results in significant computations. However, INLA accurately approximates to the posterior marginals in significantly less time. Although Laplace approximations have been known in mathematical and statistical computation for a long time, the method is now sufficiently developed for accurate statistical computing (Rue, Martino, & Chopin, 2009). Because INLA does not rely on sampling, this approach is often much faster than MCMC in BUGS or JAGS, making INLA highly suitable for large, high-dimensional computation in complex spatial and spatio-temporal modeling. For our analyses, INLA was implemented in the R package "INLA" (R-INLA), which can be downloaded from http://www.r-inla.org. (The website also provides extensive examples and documentation.)

Application to HIV Data

Data

We extracted time-series data from 1991 to 2014 from the *World Development Indicators* collated by the World Bank (2016) for all countries in the African continent (Figure 1). Although HIV risk on the continent dates back to at least the late 1970s, HIV data prior to 1991 are not available for many African countries; therefore, the present study limited analyses to data collected in 1991 or later. We also excluded countries with large amounts of missing data and countries that are not contiguous. Because the spatial aspect of the analyses assesses the influence of neighboring countries, nations that did not share a boundary with at least one other country were excluded from the analyses, which led to 36 countries as shown in Table 2. In Table 2, we grouped the 36 African countries into five regions (i.e., Northern, Southern, Eastern, Western, and Central Africa) to investigate regional differences.

The *World Development Indicators* database contains nearly 1,500 indicators across several development domains for data collected from more than 200 countries starting in the 1960s (World Bank, 2016). The United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics works with individual countries to compile the indicators. We extracted the HIV prevalence for all 15- to 24-year-old males and females. To obtain the HIV incidence, we merged these data with world population data to calculate the associated HIV incidence (y_{it}) and the expected incidence (E_{it}) for use in Equations 1 and 4.

As acknowledged earlier, HIV can be related to many risk factors. Epidemiologically, HIV risk includes factors such as the number of immigrants and in-country migrants, number of men who have sex with men, rates of prostitution, rates of illegal drug use/drug trafficking, rates of condom use, amount of government expenditures for HIV prevention and treatment, education background, and socio-economic and employment status, among others. The *World Development Indicators* database (World Bank, 2016) includes an extensive list of risk covariates that could

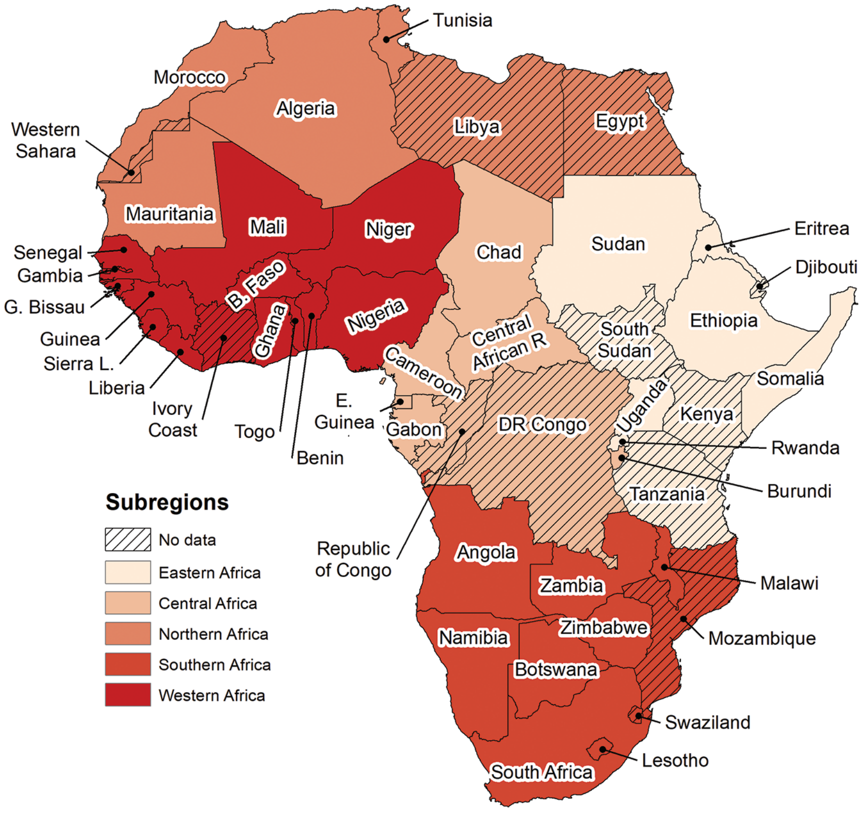

Figure 1. Map of the African continent. Countries shaded with hash marks were excluded from analyses because of incomplete data.

be used to model the predictability of these risk factors to HIV prevalence; however, most of the covariates have a significant amount of missing data (> 80%). For demonstration purposes and based on the reviewed literature, we selected the unemployment rate as a possible risk covariate.

Preliminary Data Analysis

As part of our preliminary data analysis procedures to explore the spatial–temporal structure, we analyzed the temporal trend for HIV incidence for all African countries included in our study. Although many of the results had high probability values ($p > .05$), we chose to explain the results to help readers understand how the parameters could be interpreted. As seen in Figure 2, we modeled the log-transformed HIV incidence from 1991 through 2014 for the 36 countries in our sample. We found that 12 countries had positive trends and 24 countries had negative trends,

Table 2

List of 36 African Countries and Associated Country Codes

RegionNum	RegionName	CountryName	CountryCode	RegionCode
1	Central Africa	Burundi	BDI	1.BDI
1	Central Africa	Cameroon	CMR	1.CMR
1	Central Africa	Central African Republic	CAF	1.CAF
1	Central Africa	Chad	TCD	1.TCD
1	Central Africa	Equatorial Guinea	GNQ	1.GNQ
1	Central Africa	Gabon	GAB	1.GAB
2	Eastern Africa	Eritrea	ERI	2.ERI
2	Eastern Africa	Ethiopia	ETH	2.ETH
2	Eastern Africa	Rwanda	RWA	2.RWA
2	Eastern Africa	Somalia	SOM	2.SOM
2	Eastern Africa	Sudan	SDN	2.SDN
2	Eastern Africa	Uganda	UGA	2.UGA
3	Northern Africa	Algeria	DZA	3.DZA
3	Northern Africa	Mauritania	MRT	3.MRT
3	Northern Africa	Morocco	MAR	3.MAR
3	Northern Africa	Tunisia	TUN	3.TUN
4	Southern Africa	Angola	AGO	4.AGO
4	Southern Africa	Botswana	BWA	4.BWA
4	Southern Africa	Lesotho	LSO	4.LSO
4	Southern Africa	Malawi	MWI	4.MWI
4	Southern Africa	Namibia	NAM	4.NAM
4	Southern Africa	South Africa	ZAF	4.ZAF
4	Southern Africa	Zambia	ZMB	4.ZMB
4	Southern Africa	Zimbabwe	ZWE	4.ZWE
5	Western Africa	Benin	BEN	5.BEN
5	Western Africa	Burkina Faso	BFA	5.BFA
5	Western Africa	Ghana	GHA	5.GHA
5	Western Africa	Guinea	GIN	5.GIN
5	Western Africa	Guinea-Bissau	GNB	5.GNB
5	Western Africa	Liberia	LBR	5.LBR
5	Western Africa	Mali	MLI	5.MLI
5	Western Africa	Niger	NER	5.NER
5	Western Africa	Nigeria	NGA	5.NGA
5	Western Africa	Senegal	SEN	5.SEN
5	Western Africa	Sierra Leone	SLE	5.SLE
5	Western Africa	Togo	TGO	5.TGO

Note. These 36 countries are grouped into five regions (RegionNum) under the region names (RegionName). For ease of representation in Figures 2 and 3, we created the RegionCode abbreviation that combines the RegionNum and the CountryCode.

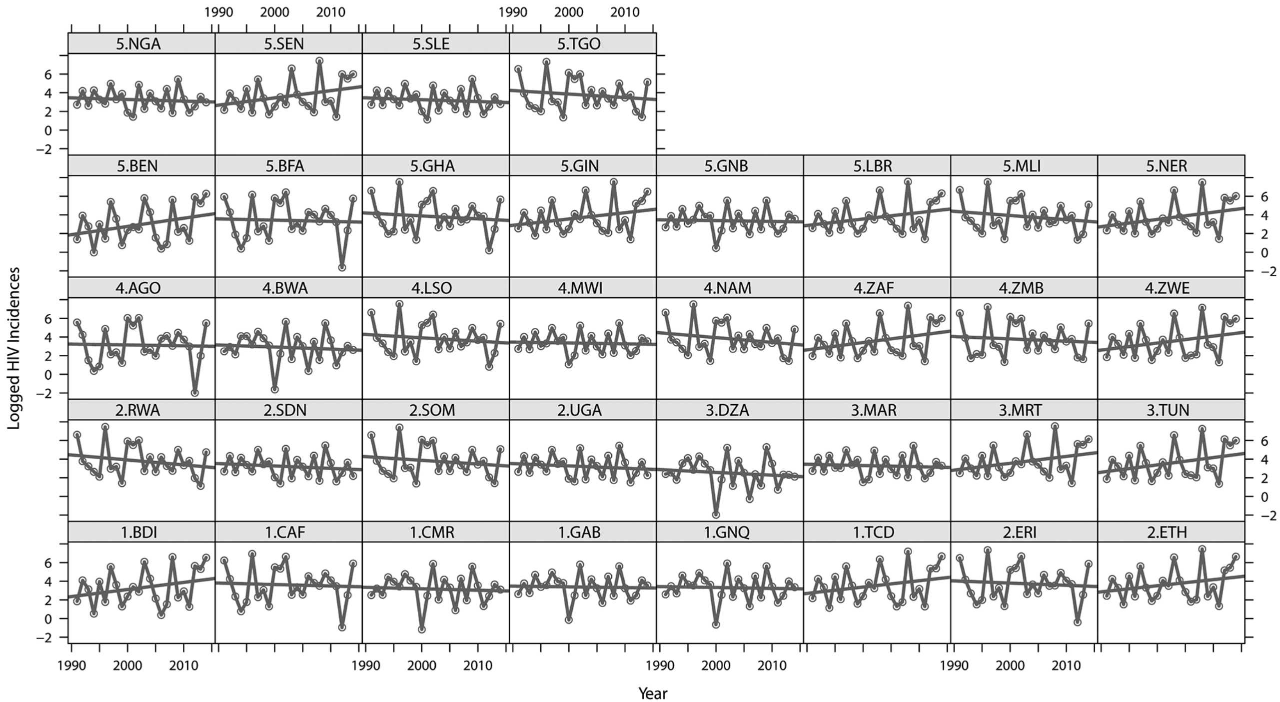

Figure 2. Temporal trends for HIV incidence (logged) for 36 African countries from five regions. See Table 2 for the list of country name abbreviations used here.

but due to large variations, none of these temporal trends were statistically significant. The average slope was 0.0086 ($p = 0.46$). Had this finding been significant, it would indicate that HIV incidence increased by about 0.86% per year, on average, from 1991 to 2014.

We further examined the HIV incidence using the risk covariate of unemployment rate. As seen in Figure 3, of the 36 countries in our sample, 26 had positive correlations and 10 had negative correlations; none of the correlations reached statistical significance. The average slope was 0.0091 ($p = 0.64$). This increase in HIV incidence was not statistically significant due to large variation. If this finding were significant, one would back-transform the log-transformed variable and interpret the slope as follows: For every additional 10% increase in the unemployment rate, the HIV incidence increases by about 9.1%.

Spatial–Temporal Modeling

As a comprehensive analysis, we incorporated all the spatial–temporal data from 36 countries collected from 1991 to 2014 for a unified Bayesian spatial–temporal model. The principle of the Bayesian spatial–temporal model is to use a convolution of spatial correlated heterogeneity (CH) and uncorrelated heterogeneity (UH) to model the HIV incidence within a fixed spatial (i.e., African countries) and temporal period (i.e., years) along with the spatial–temporal interactions. We fitted the first eight of 16 models without regional effect and the second eight models with regional effects. Testing of the regional effect was necessary to account for the fact that the Eastern and Southern regions had disproportionally high prevalence compared to the other regions. We found that the regional effects were not statistically significant, and therefore, Table 1 reports results for only the models without regional effects.

As seen in Table 1, a series of spatial–temporal models were fitted with the R-INLA package. Model selection was based on the DIC and pD values, where smaller DIC and pD values indicate a better model fit to the data. The smallest of all DIC and pD values produced Model 1 (see Table 1), but this model assumes that no spatial and temporal correlation exists; therefore, this model is overly simplified and unrealistic. We selected Model 7 as the most appropriate model for these data, for which HIV risks are spatially uncorrelated among 36 countries but temporally correlated over the 24-year period (1991–2014) with country and time interaction. In Model 7, the estimated $\hat{\beta}_0 = -3.293$ with a 95% credible interval of $[-3.304, -3.282]$ translates into a statistically significant overall HIV risk rate of 3.7% for the African continent. The estimated $\hat{\beta}_1 = 2.306 \times 10^{-7}$ with a 95% credible interval $[-0.0004, 0.0004]$ means that HIV risk is not statistically significantly related to unemployment rate.

With Model 7, we concluded that HIV risk rates lacked spatial autocorrelation among the 36 countries. A reviewer pointed out that as an infectious disease, HIV usually shows a pattern of transmission across geographic neighborhoods, which is

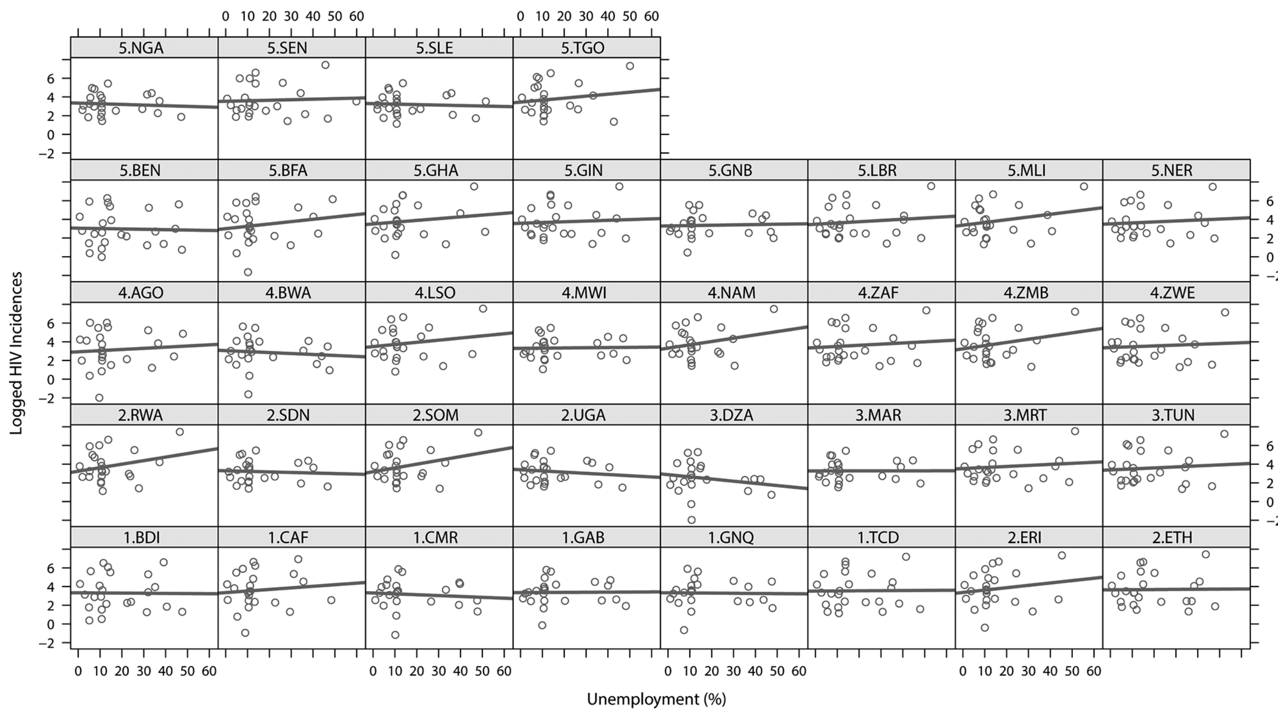

Figure 3. HIV incidence versus unemployment rates for 36 African countries from five regions. See Table 2 for the list of country name abbreviations used here.

intuitively true epidemiologically. With careful investigation, we found that this lack of significant spatial autocorrelation was mainly due to high variations in the HIV rates within these 36 countries. In fact, even though there are no statistically significant spatial patterns, the HIV rates as depicted in Figures 4 and 6 show some signs of spatial trends.

The map in Figure 4 illustrates the estimated overall pattern in the spatial random-residual effects showing spatial autocorrelation (indicated by S_i in Equation 3). The map suggests that over time, all five regions—Eastern, Central, Northern, Southern, and Western Africa—have had a mix of high and low HIV rates, which is indicated by the random effects (S_i) and fixed effects ($\beta_0 + \beta_1 UEM_{it}$) in Equation 3. In some circumstances, researchers may find global and continent-wide snapshots useful; however, we caution against sole reliance on maps that offer a cross-sectional snapshot of predicted prevalence (which is an aggregation of the temporal data) because such maps do not fully account for the longitudinal nuances of the prevalence. In the present study, although Figure 4 offers useful information about how each of the five regions has had countries with high prevalence, the map also masks the his-

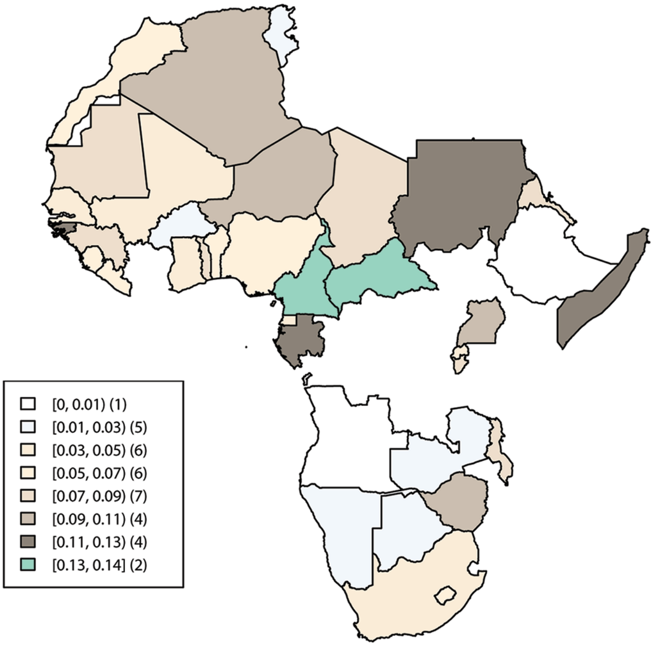

Figure 4. Spatial random-residual effects showing spatial autocorrelation as indicated by S_i (i = the spatial effects from the 36 countries) in Equation 3. In the legend, spatial effects are displayed in eight categories from the lowest (0) to the highest (0.14) residuals; the second number in parentheses signifies the number of countries in that category.

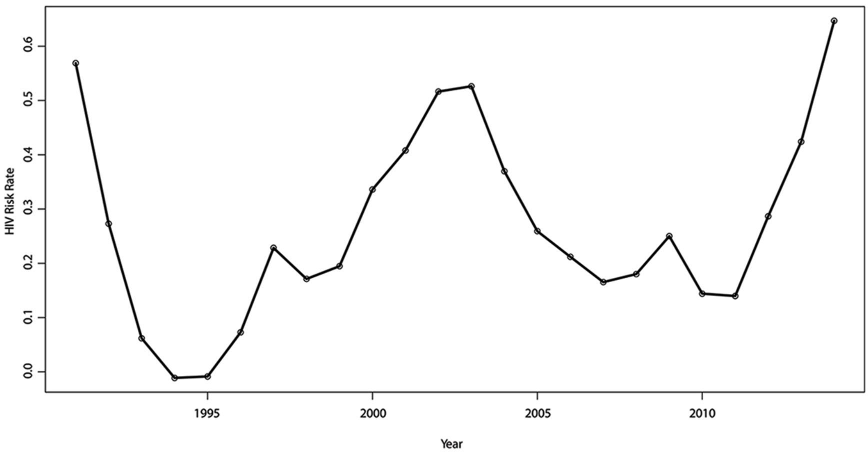

Figure 5. Temporal random-residual effects showing temporal autocorrelation as indicated by T_t in Equation 3.

torical reality that some regions (e.g., Eastern and Southern Africa) have had disproportionally high rates. Figure 5 has a similar drawback because it depicts only the overall temporal pattern of the HIV risk rates as indicated by T_t in Equation 3; this suggests that the African continent as a whole experienced uneven risk of HIV infection over the study period without offering information about differences across countries or regions. Therefore, at the very least, the interpretation of spatial-only patterns (Figure 4) should go hand-in-hand with interpretation of temporal-only trends (Figure 5).

For a comprehensive graphical representation of space–time patterns, we encourage researchers to opt for space–time interaction maps such as those featured in Figure 6 because this type of map is more nuanced and superior to either spatial-only (Figure 4) or temporal-only (Figure 5) illustrations. As shown in Figure 6, the interaction of spatial–temporal factors during the 1991–2014 period shows the presence of convoluted spatial and temporal autocorrelation as indicated by ST_{it} in Equation 3. In addition, Figure 6 shows subtle region-wide trends. For instance, in 1991, 1996, 2000, 2001, and 2011, the Southern Africa region reported comparatively lower HIV prevalence than the other four regions.

Discussion

In this article, we introduced the method of Bayesian spatial–temporal mapping using R-INLA. A series of Bayesian spatial–temporal HIV risk models and the predictive role of the unemployment rate were presented to shed light on the trajectories of HIV risk among African adolescents and young adults. We processed country-level data from the World Bank to obtain the HIV incidence for youth (ages 15–

24 years) for 1991–2014. Using a hierarchical approach to model building, we used data from 36 African countries to test a series of Poisson spatial–temporal models from the Bayesian perspective, starting with the simplest model (null model). In all, we tested 16 spatial–temporal models, which we then sorted into three groups based on how the models accounted for spatial and temporal autocorrelations. In addition to modeling the spatial–temporal correlations in HIV prevalence, we assessed for possible links between HIV risks and unemployment rates in the 36 African countries over the study period (1991–2014).

Results suggest that during the 24-year period starting in 1991, overall HIV risk among the 36 countries was *spatially uncorrelated* but *temporally correlated*. This means that when viewed from a historical perspective at the country level, HIV infection rates are geographically heterogeneous. Figure 6 illustrates that HIV prevalence tends to be spatially dispersed over time. For example, even though HIV prevalence is comparatively higher in specific Eastern and Southern African countries, country-level analysis suggests that HIV prevalence is not spatially concentrated in statistically significant numbers but rather somewhat dispersed, particularly across regions. The lack of evidence in the data to support spatially correlated trends at the country level does not mean the theories of neighborhood influence and geographical bands do not apply to HIV infections and transmission. Instead, traces of country-level spatial clustering might be temporary and dissipate over time. This finding might also be a reflection of the unique experience of each country and each country's level of success in efforts to address the HIV epidemic.

Regardless of the possible reasons for the nonsignificant results, this finding should caution researchers about the issue of modifiable areal unit problem (MAUP) when interpreting spatial results. MAUP is a major problem in spatial inferential modeling that occurs when data are aggregated and reported at a scale that biases (i.e., overestimates or underestimates) results. For researchers interested in applying Bayesian spatial–temporal modeling in their work, the MAUP challenge has implications for the choice of an appropriate geographical unit of analysis. It is possible that the data used in the present study contain spatially correlated HIV prevalence trends at the district, town, or census-tract level that are not visible at the country level. When conducting Bayesian spatial–temporal modeling, if it is possible to analyze the data at higher and lower levels of aggregation, we recommend conducting sensitivity tests to assess whether the results vary at different geographical scales. When results differ, researchers should be prepared to discuss the research, policy, and practice implications. In addition, an emerging body of work in the field of spatial ecology explores how Bayesian estimation can be used to address MAUP. For insights into the Bayesian estimation approach, refer to Hui (2009).

When using Bayesian spatial–temporal methods to research incidence, researchers should note a caveat related to measurement. Researchers must make theoretically and conceptually driven decisions regarding whether to calculate the incidence

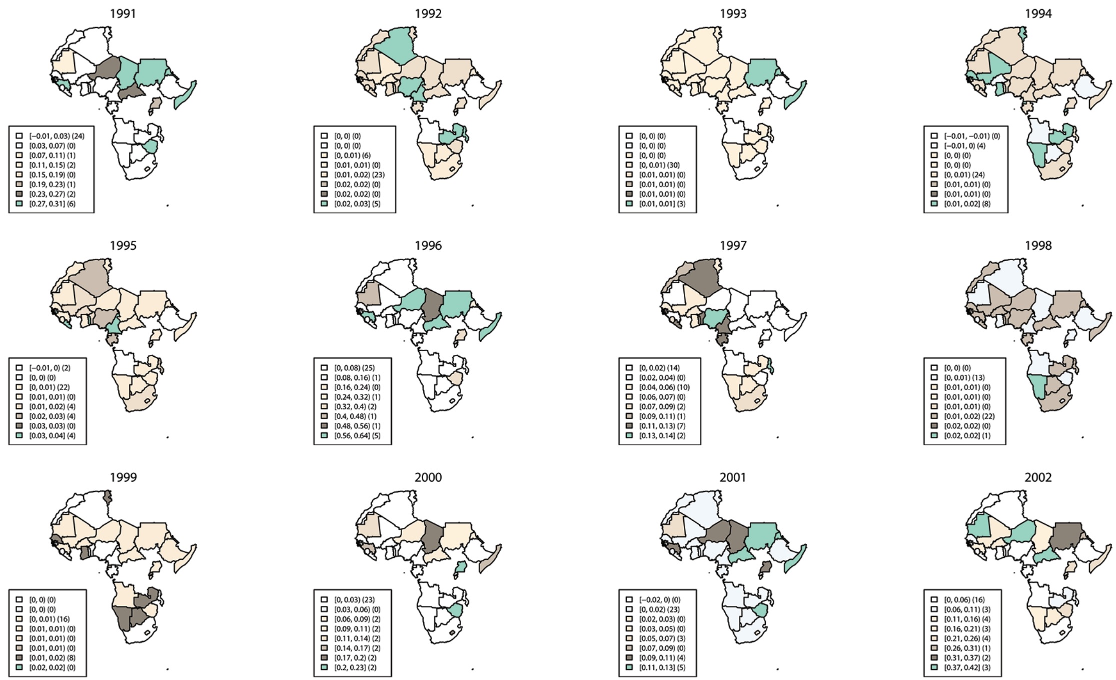

Figure 6. Spatial and temporal random-residual effects showing the spatial–temporal interaction effects indicated by ST_{it} (i = the spatial effects from the 36 countries, and t = the temporal effects from 1991 to 2014) in Equation 3. In the legend, the spatial–temporal interaction effects are displayed in eight categories for each year from 1991 to 2014 for the 36 countries from the lowest to the highest residuals. The second number in parentheses signifies the number of countries in that category.

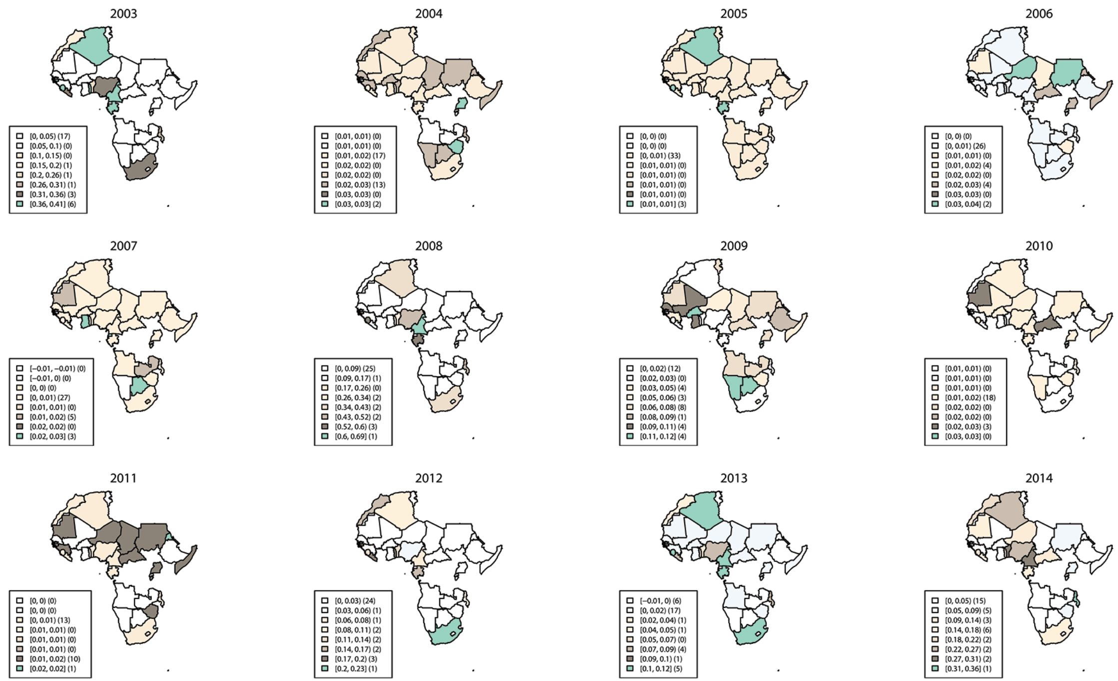

Figure 6 (continued)

as population-based, geographic area-based, or a combination of both. As seen in Equation 4, we used the population-based incidence, which is the most commonly used incidence in spatial–temporal disease mapping as discussed in Lesaffre and Lawson (2002), Lawson (2006, 2013), and Lawson and colleagues (2016). However, a geographic area-based incidence and a combined population area-based incidence have recently been proposed (D. Chen, 2017; X. Chen & Wang, 2017) as two novel indicators to enhance research and precision of intervention for more effective HIV/AIDS control. These newly proposed indictors could be more efficient than the existing population-based approach of characterizing HIV epidemic by country. This alternative approach relies on extensive comparisons with real data and computationally intensive Monte Carlo simulations. We are exploring this alternative approach as our next research direction.

Results from our analyses also suggest that the HIV risk rate in Africa overall is estimated at 3.7%, which is statistically significant, and that HIV risk is *temporally correlated* over the 24-year study period (1991–2014). The extent of correlation between consecutive years of HIV prevalence suggests that turning the tide on HIV infections and prevalence takes substantial time. The results presented in Figure 2 show across-the-board volatility in HIV prevalence. Each country represented in the trellis plot (Figure 2) experienced significant declines in their HIV incidence over the 24-year period. These decreases in incidence mean that efforts to uncover spatial patterns would be more robust if viewed from a temporal perspective; such combinations address the fact that some spatial patterns might be nonstationary across time. As best practice, if time data are available, researchers should consider time trends to reveal nuanced interactions between time and space that could be missed if studies do not attend to the mix of subtle and conspicuous variabilities in outcomes across time. From a policy standpoint, the temporal dynamism in the spatial patterns of HIV prevalence suggests that policies and strategies targeted at reducing HIV prevalence or addressing complex social problems could be more effective if designed to account for both short- and long-term changes. For researchers who test adaptive interventions, methodological applications that allow for temporal tracking of outcomes might be useful for developing SMART (sequential, multiple assignment, randomized trials) design to build adaptive interventions. (For more on SMART design, see Lei, Nahum-Shani, Lynch, Oslin, & Murphy, 2012.)

Advantages of Bayesian Spatial–Temporal Modeling

One of the superior capabilities of Bayesian spatial–temporal modeling is the ability to glean insights into geographical and time patterns without aggregating the data over time or across geographical areas. The ease and flexibility with which researchers can incorporate information from neighboring spatial units ("neighborhood effect") and from prior information ("time effect") means the Bayesian method is more realistic because it aligns with how social phenomena and outcomes evolve in the real world. In many cases, people's attitudes, behaviors, and dispositions are, at least in part, a function of their prior and contextual experiences (Meinlschmidt, 2005). Thus, the ability of social and health researchers to draw on spatial priors makes the Bayesian approach more intuitive, credible, and accurate (Wioletta, 2015). Wioletta explained that the accuracy of the Bayesian analysis is a result of *not* being based on asymptotic approximation. The implication for research using the Bayesian approach is that even with limited and incomplete data, Bayesian-based spatial–temporal analysis can produce accurate, reliable inferences to support decisions regarding policies, interventions, and funding priorities.

Furthermore, the Bayesian spatial–temporal framework is more comprehensive, and thus superior, to spatial-only and temporal-only frameworks. The Bayesian approach is robust to outliers and missing data, particularly in the outcome variable. In large part, temporal data can make up for missingness in spatial data, and vice versa. Thus, considerably more information can be drawn concurrently from spatial priors and contexts (neighbors) to make robust predictions. However, some exceptions are worth noting. In the present study, some countries were excluded from the analyses due to lack of shared boundaries (noncontiguous), and others were excluded because of incomplete data. When incomplete cases are overly high, it may be more prudent to exclude variables, although doing so may come at a cost to the fit between the conceptual and statistical models. In our HIV prevalence demonstration, the countries excluded from analysis because of incomplete data fell in two groups: those that did not have a data tracking system or those for which the World Bank could not guarantee the integrity of the data provided. Regardless, the loss of large amounts of data is a reason for concern.

Conclusion

Social phenomena are rarely stationary in space or time. As such, analytic frameworks capable of modeling these space–time variabilities should be used when social work theories and conceptual frameworks suggest the presence of such variabilities. Compared with the frequentist paradigm, the Bayesian spatial–temporal analytic framework is a robust and intuitive framework for space–time data (Carlin & Louis, 2009). Although this Bayesian framework is not entirely new to social science research and practice, the use of Bayesian analysis is uncommon in social work research. However, if researchers in social work and related fields are provided adequate orientation to this analytic approach, the use of Bayesian analysis could gain momentum—particularly in social work—and contribute to the robust analysis of space–time nuances for most outcomes of interest to social workers. As a first step toward achieving this goal, the present study used data on HIV prevalence and unemployment among youth in Africa to demonstrate how spatial–temporal modeling can be conducted using R-INLA. (Interested readers may request the demonstration data and R program from the authors.) With the recent computational advances and availability of geographically referenced longitudinal data, researchers seeking a deeper understanding of spatial–temporal patterns in their data would benefit from the intuitive, concrete, and robust advantages offered by Bayesian spatial–temporal modeling.

Author Notes

Ding-Geng Chen, PhD, is the Wallace H. Kuralt Distinguished Professor at the School of Social Work, University of North Carolina at Chapel Hill.

David Ansong, PhD, is an assistant professor at the School of Social Work, University of North Carolina at Chapel Hill.

Correspondence regarding this article should be directed to Ding-Geng Chen, 325 Pittsboro St., Campus Box 3550, Chapel Hill, NC 27599 or via e-mail to dinchen@email.unc.edu

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References

Ansong, D., Ansong, E. K., Ampomah, A. O., & Adjabeng, B. K. (2015). Factors contributing to spatial inequality in academic achievement in Ghana: Analysis of district-level factors using geographically weighted regression. *Applied Geography*, *62*, 136–146. https://doi.org/10.1016/j.apgeog.2015.04.017

Ansong, D., Ansong, E. K., Ampomah, A. O., & Afranie, S. (2015). A spatio-temporal analysis of academic performance at the Basic Education Certificate Examination in Ghana. *Applied Geography*, *65*, 1–12. https://doi.org/10.1016/j.apgeog.2015.10.003

Ansong, D., Renwick, C. B., Okumu, M., Ansong, E., & Wabwire, C. J. (2018). Gendered geographical inequalities in junior high school enrollment: Do infrastructure, human, and financial resources matter? *Journal of Economic Studies*, *45*(2), 411–425. https://doi.org/10.1108/JES-10-2016-0211

Arndt, C., & Lewis, J. D. (2001). The HIV/AIDS pandemic in South Africa: Sectoral impacts and unemployment. *Journal of International Development*, *13*, 427–449. https://doi.org/10.1002/jid.796

Austin, K. F., Choi, M. M., & Berndt, V. (2017). Trading sex for security: Unemployment and the unequal HIV burden among young women in developing nations. *International Sociology*, *32*, 343–368. https://doi.org/10.1177/0268580917693172

Baah-Boateng, W. (2016). The youth unemployment challenge in Africa: What are the drivers? *Economic and Labour Relations Review*, *27*, 413–431. https://doi.org/10.1177/1035304616645030

Baral, S., Beyrer, C., Muessig, K., Poteat, T., Wirtz, A. L., Decker, M. R., . . . Kwerrigan, D. (2012). Burden of HIV among female sex workers in low-income and middle-income countries: A systematic review and meta-analysis. *Lancet Infectious Diseases*, *12*, 538–549. https://dx.doi.org/10.1016/S1473-3099(12)70066-X

Besag, J., York, J., & Mollié, A. (1991). Bayesian image restoration, with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics*, *43*, 1–20. https://doi.org/10.1007/BF00116466

Bhorat, H., Naidoo, K., & Ewinyu, A. (2017). The tipping point: The youth bulge and the sub-Saharan African labor market. In A. Sy (Ed.), *Foresight Africa, top priorities for Africa in 2017* (pp. 30–45). Washington, DC: Brookings Institution. Retrieved from https://www.brookings.edu/wp-content/uploads/2017/01/global_20170109_foresight_africa_chapter-2.pdf

Carlin, B., & Louis, T. (2009). *Bayesian methods for data analysis* (3rd ed.). Statistical science series. Boca Raton, FL: CRC Press.

Chen, D. G. (2017). Comparing geographic area-based and classical population-based incidence and prevalence rates, and their confidence intervals. *Preventive Medicine Reports*, *7*, 116–118. https://doi.org/10.1016/j.pmedr.2017.05.017

Chen, D. G., & Chen, J. D. (2017). *Monte-Carlo simulation-based statistical modeling*. Singapore: Springer Nature. https://doi.org/10.1007/978-981-10-3307-0

Chen, D. G., & Fraser, M. W. (2017a). A Bayesian perspective on intervention research: Using prior information in the development of social and health programs. *Journal of the Society for Social Work and Research*, *8*, 441–456. https://doi.org/10.1086/693432

Chen, D. G., & Fraser, M. W. (2017b). A Bayesian approach to sample size estimation and the decision to continue program development in intervention research. *Journal of the Society for Social Work and Research*, *8*, 457–470. https://doi.org/10.1086/693433

Chen, D. G., Fraser, M. W., & Cuddeback, G. (2018). Assurance in intervention research: A Bayesian perspective on statistical power. *Journal of the Society for Social Work and Research*, *9*, 159–173. https://doi.org/10.1086/696239

Chen, X., & Wang, K. (2017). Geographic area-based rate as a novel indicator to enhance research and precision intervention for more effective HIV/AIDS control. *Preventive Medicine Reports*, *5*, 301–307. http://dx.doi.org/10.1016/j.pmedr.2017.01.009

Clayton, D. G., & Kaldor, J. M. (1987). Empirical Bayes estimates of age-standardized relative risks for use in disease mapping. *Biometrics*, *43*, 671–681. https://doi.org/10.2307/2532003

Congdon, P. (2010). *Applied Bayesian hierarchical methods*. Boca Raton, FL: Chapman and Hall/CRC Press. https://doi.org/10.1201/9781584887218

Delpierre, C., Cuzin, L., Lauwers-Cances, V., Datta, G. D., Berkman, L., & Lang, T. (2008). Unemployment as a risk factor for AIDS and death for HIV-infected patients in the era of highly active antiretroviral therapy. *Sexually Transmitted Infections*, *84*, 183–186. https://doi.org/10.1136/sti.2007.027961

Denis, P., & Becker, C. (Eds.). (2006). *The HIV/AIDS epidemic in sub-Saharan Africa in a historical perspective* (Online ed.). Retrieved from http://www.dphu.org/uploads/attachements/books/books_1448_0.pdf

Felke, T. P. (2006). Geographic information systems: Potential uses in social work education and practice. *Journal of Evidence-Based Social Work*, *3*, 103–113. https://doi.org/10.1300/J394v03n03_08

Felke, T. P. (2015). The use of geographic information systems (GIS) in conducting a needs assessment of seniors in Collier County. *Advances in Social Work*, *16*(1), 140–153. Retrieved from http://journals.iupui.edu/index.php/advancesinsocialwork/article/view/18130/19944

Freisthler, B., Lery, B., Gruenewald, P. J., & Chow, J. (2006). Methods and challenges of analyzing spatial data for social work problems: The case of examining child maltreatment geographically. *Social Work Research*, *30*, 198–210. https://doi.org/10.1093/swr/30.4.198

Guo, S. (2013). Quantitative research. In C. Franklin (Ed.), *Encyclopedia of social work*. New York, NY: Oxford University Press. https://doi.org/10.1093/acrefore/9780199975839.013.333

Hillier, A. (2007). Why social work needs mapping. *Journal of Social Work Education*, *43*(2), 205–222. https://doi.org/10.5175/JSWE.2007.200500524

Hui, C. (2009). A Bayesian solution to the modifiable areal unit problem. In A-E. Hassanien, A. Abraham, & F. Herrera (Eds.), *Foundations of computational intelligence, Volume 2* (pp. 175–196). Berlin, Germany: Springer. https://doi.org/10.1007/978-3-642-01533-5

Kabiru, C. W., Izugbara, C. O., & Beguy, D. (2013). The health and wellbeing of young people in sub-Saharan Africa: An under-researched area? *BMC International Health and Human Rights*, *13*(11), 1–7. https://doi.org/10.1186/1472-698X-13-11

Kagaayi, J., & Serwadda, D. (2016). The history of the HIV/AIDS epidemic in Africa. *Current HIV/AIDS Reports*, *13*(4), 187–193. https://doi.org/10.1007/s11904-016-0318-8

Kharsany, A. B. M., & Karim, Q. A. (2016). HIV infection and AIDS in sub-Saharan Africa: Current status, challenges and opportunities. *Open AIDS Journal*, *10*, 34–48. https://doi.org/10.2174/1874613601610010034

Knight, S. A. (2016). Social services software: Integrating GIS software with social work practice. *Social Work Today*, *16*(1), 8. Retrieved from http://www.socialworktoday.com/archive/011716p8.shtml

Lawson, A. B. (2006). *Statistical methods in spatial epidemiology* (2nd ed.). West Sussex, UK: John Wiley & Sons. https://doi.org/10.1002/9780470035771

Lawson, A. B. (2013). *Bayesian disease mapping: Hierarchical modeling in spatial epidemiology* (2nd ed.). Interdisciplinary statistics series. Boca Raton, FL: CRC Press.

Lawson, A. B., Banerjee, S., Haining, R. P., & Ugarte, M. D. (Eds). (2016). *Handbook of spatial epidemiology*. Boca Raton, FL: Chapman and Hall/CRC Press.

Lei, H., Nahum-Shani, I., Lynch, K., Oslin, D., & Murphy, S. A. (2012). A "SMART" design for building individualized treatment sequences. *Annual Review of Clinical Psychology*, *8*, 21–48. doi:10.1146/annurev-clinpsy-032511-143152

Lesaffre, E., & Lawson, A. B. (2002) *Bayesian biostatistics*. West Sussex, UK: John Wiley & Sons. https://doi.org/10.1002/9781119942412

Maruthappu, M., Zhou, C., Williams, C., Zeltner, T., & Atun, R. (2017). Unemployment and HIV mortality in the countries of the Organisation for Economic Co-operation and Development: 1981–2009. *Journal of the Royal Society of Medicine Open*, *8*(7), 1–11. https://doi.org/10.1177/2054270416685206

Meinlschmidt, G. P. (2005). *Long-term psychobiological consequences of adverse childhood experiences: Implications for vulnerability and resilience*. Göttingen, Germany: Cuvillier Verlag.

Oldenburg, C. E., Perez-Brumer, A. G., Reisner, S. L., Mattie, J., Bärnighausen, T., Mayer, K. H., & Mimiaga, M. J. (2014). Global burden of HIV among men who engage in transactional sex: A systematic review and meta-analysis. *PLoS ONE*, *9*(7), e103549. https://doi.org/10.1371/journal.pone.0103549

Organisation for Economic Co-operation and Development. (2016). *Youth not in employment, education or training (NEET)*. Paris, France: Author. Retrieved from https://data.oecd.org/youthinac/youth-not-in-employment-education-or-training-neet.htm

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society*, *Series B*. *Statistical Methodology*, *71*, 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Shilts, R. (2007). *And the band played on: Politics, people, and the AIDS epidemic*. New York, NY: St. Martin's Griffin.

Spatscheck, C. (2012). Socio-spatial approaches to social work. *Social Work & Society*, *10*(1), 1–13. Retrieved from http://www.socwork.net/sws/article/view/314

Spatscheck, C., & Wolf-Ostermann, K. (2009). *Social space analyses and the socio-spatial paradigm in social work* (Working Paper 2009-1). Lund, Sweden: Lund University, School of Social Work. Retrieved from https://www.soch.lu.se/sites/soch.lu.se/files/wp2009-1.pdf

Teixeira, S. (2018). Qualitative geographic information systems (GIS): An untapped research approach for social work. *Qualitative Social Work*, *17*(1), 9–23. https://doi.org/10.1177/1473325016655203

United Nations Children's Fund (UNICEF). (2016). *For every child, end AIDS: Seventh stocktaking report*. New York, NY: Author. Retrieved from https://www.unicef.org/publications/index_93427.html

United Nations Programme on HIV/AIDS (UNAIDS). (2017). *UNAIDS data 2017*. Retrieved from http://www.unaids.org/sites/default/files/media_asset/20170720_Data_book_2017_en.pdf

United Nations Programme on HIV/AIDS (UNAIDS) & World Health Organization (WHO). (2003). *A history of the HIV/AIDS epidemic with emphasis on Africa* (UN/POP/MORT/2003/2). Retrieved from http://www.un.org/esa/population/publications/adultmort/UNAIDS_WHOPaper2.pdf

Wioletta, G. (2015). The advantages of Bayesian methods over classical methods in the context of credible intervals. *Information Systems in Management*, *4*(1), 53–63. Retrieved from http://cejsh.icm.edu.pl/cejsh/element/bwmeta1.element.desklight-c2ac1209-674b-46ee-b80f-c3cd4c7f8ae4

Wolf, J. P., Freisthler, B., Kepple, N. J., & Chavez, R. (2017). The places parents go: Understanding the breadth, scope, and experiences of activity spaces for parents. *GeoJournal*, *82*(2), 355–368. https://doi.org/10.1007/s10708-015-9690-y

World Bank. (2016). *World development indicators 2016*. Washington, DC: Author. https://doi.org/10.1596/978-1-4648-0683-4

Zanoni, B. C., Archary, M., Buchan, S., Katz, I. T., & Haberer, J. E. (2016). Systematic review and meta-analysis of the adolescent HIV continuum of care in South Africa: The cresting wave. *BMJ Global Health*, *1*(3), e000004. https://doi.org/10.1136/bmjgh-2015-000004

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