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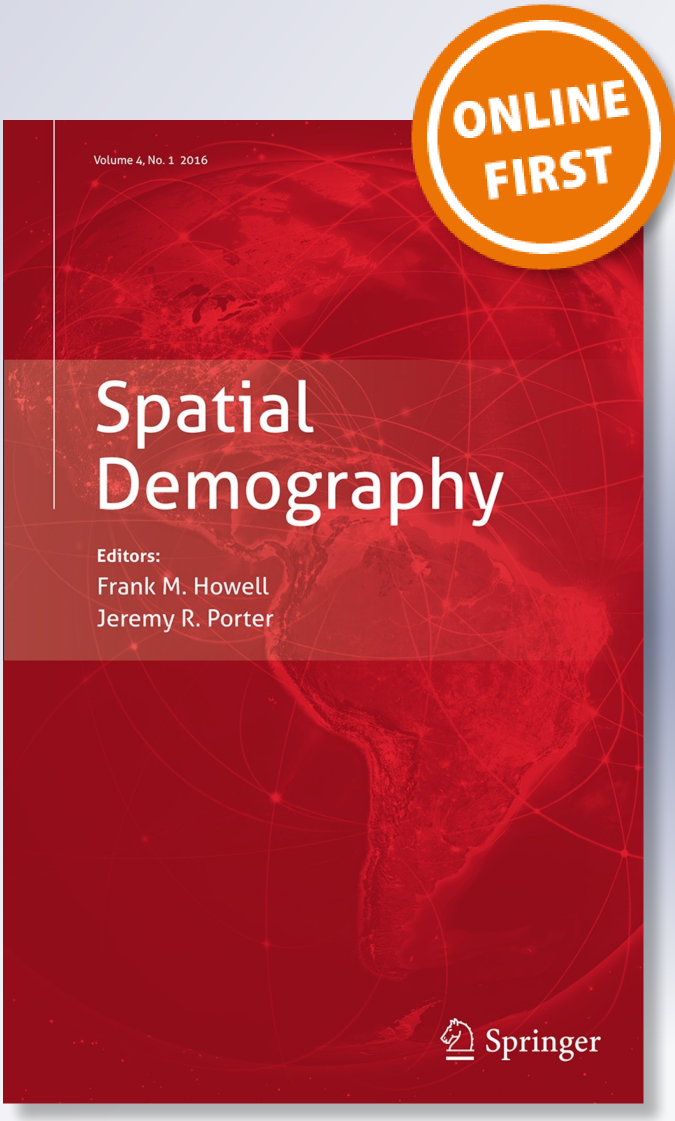

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Latent Trajectory Modeling of Spatiotemporal Relationships Between Land Cover and Land Use, Socioeconomics, and Obesity in Ghana

Stephen E. S. Crook[1] · Li An[1] · John R. Weeks[1] · Douglas A. Stow[1]

Abstract Obesity is a growing public health concern in both developed and developing countries, creating acute challenges in places with scant resources. In Ghana, obesity rates have risen substantially in recent decades, a trend particularly noted in urban areas. However, high levels of migration and urbanization indicate a situation that is more complex than a simple urban/rural distinction may be able to explain. Latent trajectory modeling (LTM) with eigenvector spatial filtering offers a methodology to explore the spatial and temporal patterns of body mass index (BMI) change by going beyond the urban/rural distinction and examining how different environmental, social, and demographic variables contribute to BMI changes over time. Using data from a regional LULC study and the Ghana Demographic Health Survey (1993, 1998, 2003, 2008), the relationship between BMI and the amounts of urban, agricultural, and natural land covers, household size, % of houses with electricity, % houses with flush toilets, and % of houses with no toilets for 845 survey clusters is explored. Our findings suggest higher BMIs in the most urban areas, yet larger BMI increases in peri-urban areas (and lower BMI changes in slums and increasingly rural areas). The LTM modeling indicates a trajectory of BMI growth in the study region, yet one that is slowing over time. Earlier, indicators of higher socioeconomic status and larger households are associated with high BMIs, but these indicators are not associated with rising BMI over the entire study period. Areas with increases in urban land cover show consistent, significant relationships with BMI growth.

Keywords Obesity · Spatial modeling · Eigenvector spatial filtering · Latent trajectory model · Ghana · The urban transition

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1 Introduction

The increasing prevalence of overweight and obese individuals all over the world has become a major public health issue (McLellan 2002). In the last 35 years, the amount of obesity worldwide has doubled, with an estimated 13 % of all people considered obese (World Health Organization 2015). Often thought of as primarily an affliction of developed countries, increasing prevalence of obesity has been shown in developing countries where rates are only expected to continue growing in future decades (Prentice 2006). Indeed, the number of overweight or obese in the developing world has thus far eclipsed the number in the developed world, tripling between 1980 and 2008 (Stevens et al. 2012). In sub-Saharan Africa, the societal impacts of an increase in obesity and overweight populations are of particular concern because of the prevalence of malnutrition in some segments of the population combined with scant financial resources with which to tackle these dual public health issues (Kennedy et al. 2006). This growing problem is a major policy challenge that has been linked to chronic non-communicable diseases such as arthritis, diabetes, heart disease, asthma, and decreasing life expectancies, among other serious health issues (Asfaw 2006; Duda et al. 2008).

A number of recent studies have established that the prevalence of overweight people and obesity (those with a high body mass index (BMI)) within Ghana is substantial, increasing in recent decades, and related to various socioeconomic and demographic factors (Amoah 2003; Dake 2013; Duda et al. 2008). In Greater Accra, data from the Women's Health Study of Accra in 2008–09 showed that among women aged 18 and older, 65 % were either overweight (28 %) or obese (37 %) (Benkeser et al. 2012). No differences were found by education, but obesity increased with age, and with the number of children ever born to a woman. Earlier studies had suggested that older people, those with more education, and those who participated in limited physical activity had higher BMI (Amoah 2003; Biritwum et al. 2005). Of particular importance is the finding from the Demographic and Health Surveys (DHS) that the urban regions of Ghana, especially the Accra Metropolitan Area, have the highest prevalence of overweight and obesity (DHS Program 2015).

1.1 Research Framework

These changes in patterns of obesity are consistent with the overall perspective of the nutrition transition, first proposed by Popkin (1993, 2002, 2009) and Popkin and Gordon-Larsen (2004). Popkin and his associates argue that humans have been going through a dietary transition encompassing five stages: (1) Hunter Gatherer, (2) Early Agriculture, (3) End of Famine, (4) Overeating and Obesity-related Diseases, and (5) Behavior Change. A key difference between developed and developing countries is the speed with which populations have transitioned from stage (3) to stage (4). The shift in diet that took place over a 100-year span in the West is occurring within just a few decades in the developing world. In Ghana, the 1993 DHS revealed that 12.9 % of the female population of reproductive age was overweight or obese (BMI $\geq$ 25.0), while 12.1 % was underweight (BMI $\leq$ 18.5). Yet, scarcely more than two decades later, the 2014 DHS found that 40.1 % was overweight or obese, while the percent underweight had dropped to 6.2 %.

The change in BMI is taking place most quickly in urban areas because these are the places in which people are increasingly exposed to processed and imported foods and where activity levels are lower than in the rural areas, especially those places still associated with subsistence farming. Increases in BMI are initially associated with improved health, but when weight gains are excessive they become a potential health burden to individuals, their families, and to society more generally. Tracking these changes is important in order to generate responsive policies oriented to moving the population as quickly as possible to stage 5 (behavior change) of the nutrition transition. In our understanding of the spatial and temporal trends in obesity, it is clear that the question of "where" is at least as important as the question of "who." Spatial variables such as regions and the distinction between urban and rural are ubiquitous in obesity studies (Abubakari et al. 2008; Neuman et al. 2013; Yadav and Krishnan 2008). Yet Ziraba et al. (2009) lament the lack of a consistent definition of the broad classifications of urban and rural, implying the importance of the concept but current lack of adequate representation. Furthermore, spatial context has been complicated by a number of emerging issues, including the rise of distinct context classes (such as peri-urban) that are difficult to place into the urban–rural dichotomy (Weeks 2010), swiftly changing landscapes in which locations change from one neighborhood type to another, and intra-region connectivity in which we may find a rural farmer regularly attending markets in urban areas (Garrett 2005; McGregor and Simon 2012). Only rarely have studies included the impact of changing biophysical environment on vulnerability, demographics, and health outcomes (Jianchu et al. 2005; Lo and Quattrochi 2003). At the intra-urban scale, specific types of urban design have been linked to public health issues like obesity (Frank et al. 2004), but those studies are from cities in developed countries, where design and infrastructure differ dramatically from cities in West Africa.

Our research to date has suggested that within an urban area such as Accra, land cover and land use (LCLU) classes can serve as proxies for the underlying socioeconomic status of residents within a neighborhood, and associated with that is a profile of health indicators that may be inferred from urban land surface composition and the way in which urban land is being used (Weeks et al. 2012, 2013). LCLU variation within urban areas is hypothesized to be part of a larger gradient of variation ranging from remote rural agricultural areas characterized by open savanna where BMI is low, but people are poor and at relatively high risk of disease and death from communicable disease, to high status urban areas characterized by high levels of impervious surface, where BMI is high and people are at lower risk of communicable disease, but at increasing risk of degenerative disease. That gradient is not static, however. Places are changing over time, and the people within those places are changing over time.

To uncover the relationships between these changes and obesity, we need new transdisciplinary methodologies to analyze the spatial relationships between temporal changes in land cover and land use and changes in obesity. We propose to study these changes by combining data on land cover and land use change (LCLUC) derived from remotely sensed imagery with observed changes in obesity and personal characteristics of people using georeferenced data drawn from a temporal sequence of Ghana Demographic and Health Surveys. Since to our knowledge no previous studies have examined spatio-temporal obesity trends in this manner, our research is exploratory in nature. However, in general we expect to find that BMI will be increasing most rapidly over time in those places that are most rapidly urbanizing, characterized by areas with new built land cover.

1.2 Research Objectives

A space–time analysis framework integrates diverse data along with the impacts of spatial differences into the study of temporal trends of public health issues such as BMI (An et al. 2015; Kwan 2013; Saarloos et al. 2009). Space–time analysis refers to attempts to detect, visualize, explain, and/or predict space–time patterns of human or environmental phenomena that explicitly vary over space and through time (An et al. 2015). Growing largely from the discipline of geography, earlier examples of space–time analysis focused on spatial distributions while neglecting or oversimplifying the details of temporal changes (An et al. 2015).

Employing a latent trajectory modeling (LTM) framework can help in revealing spatially-explicit temporal trends in the public health phenomenon of interest while integrating spatial context data, allowing us to go beyond the simple urban–rural designations that are often used as independent variables. Conceptually, the LTM approach involves three steps: (1) time-wise regression in all values of a certain variable are regressed against time for each geographical unit of analysis to obtain the parameters (e.g., intercept and slope for a linear model of time) and form a trajectory for that unit; (2) trajectory-wise regression in which parameters characterizing the trajectories obtained in Step 1 are regressed against a set of selected covariates; and (3) spatial filtering using the eigenvector spatial filtering (ESF) approach to remove or reduce bias in Step 2 that arises from the spatial autocorrelation among location-specific trajectories (for detail see Section Latent Trajectory Modeling below; Griffith 2000; Tiefelsdorf and Griffith 2007). In our study, this method allows us to establish linear or nonlinear trajectories of change in the dependent variable (BMI in this case), which may reveal the temporal trends of BMI in general or at specific locations. Furthermore, these temporal trends (or trajectories) are explained by a set of covariates, providing insight into mechanisms behind the observed temporally increasing patterns (our hypothesis) (An et al. 2016; Guo and Hipp 2004).

1.3 Study Area

Situated within West Africa, Ghana is a nation of over 25 million people that faces many of the challenges that are present among sub-Saharan countries. This study focuses on analyzing processes of change in health, socioeconomic, and LCLU variables for a four-region area in southern Ghana, including the Greater Accra, Central, Eastern, and Ashanti regions (see Fig. 1 below). This study area is of particular interest because it includes the major urban centers of Accra, Kumasi, Cape

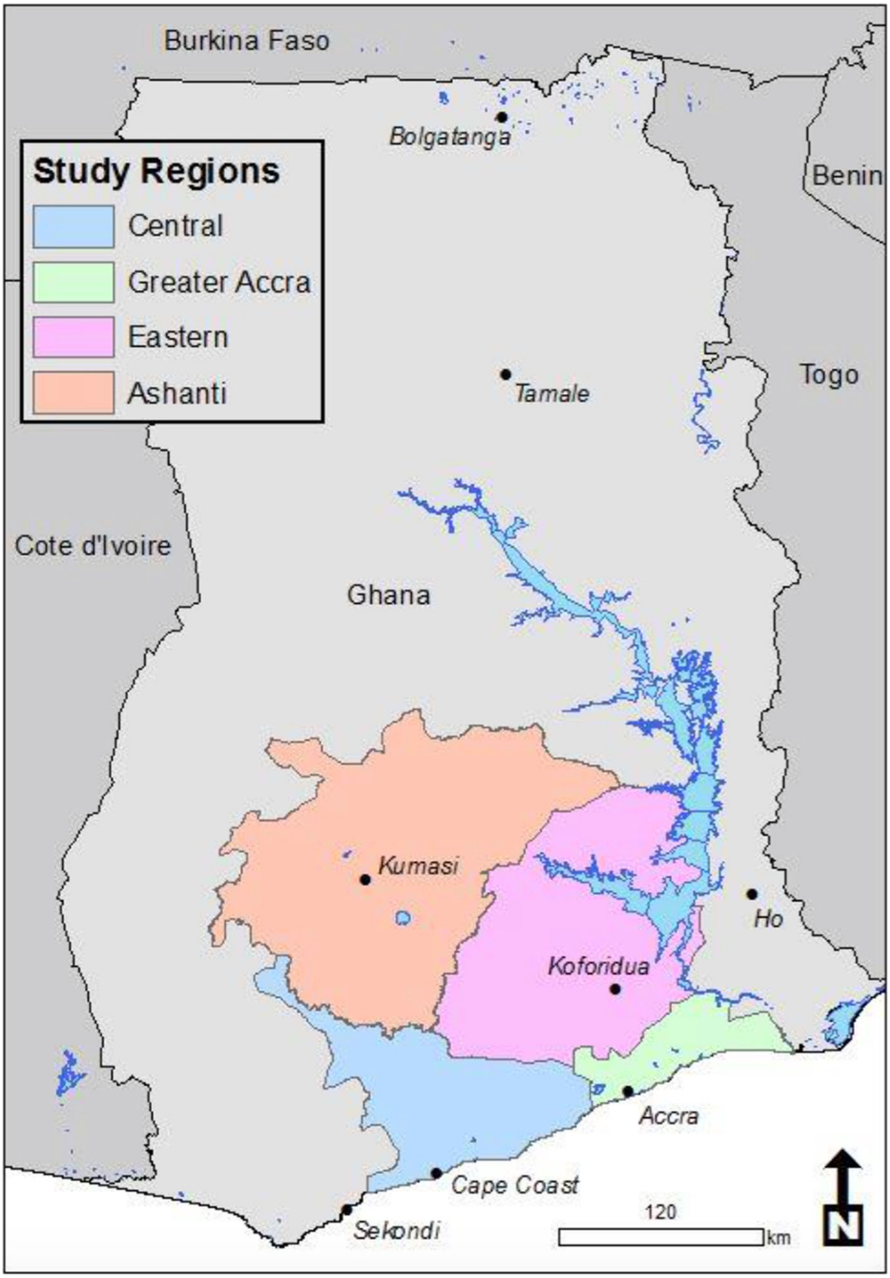

Fig. 1 Study area in Ghana

Coast, and Obuasi, as well as extensive peri-urban and hinterland areas, thus offering insight into a range of diverse landscapes and ways of life. This study area contains just over half of the population of the country (Ghana Statistical Service 2012).

The study area is in the midst of a major transformation associated with rural to urban migration and increasing suburbanization and peri-urbanization encouraged by the densely settled inner city areas becoming too crowded and/or too expensive. These trends contribute to a continual and major set of land cover and lifestyle changes (Weeks et al. 2013). Increasing numbers of migrants from rural areas cause fundamental changes to urban development and configuration of urban areas, likely resulting in the conversion of agricultural land to built land cover and land classes (i.e., through urban densification and sprawl), and potentially changing the fabric of established neighborhoods. Meanwhile, as agricultural land is lost to urban uses, rural areas that may have previously consisted of either natural vegetation or subsistence agriculture are being converted to agriculture to replace the land being built on, and to feed the continually growing population. The relationship between these large-scale physical and social transformations and the health of communities is not only of academic value (e.g., to fill knowledge gaps), but also of practical importance. For instance, the associated information can be used to improve environmental planning or to distribute limited funding for health improvement. As data-scarce as Ghana may be for this type of work, other nearby countries undergoing similar transitions have less data, and insights gained here may be more widely applicable.

2 Methods

2.1 Data

Data used in this project are derived from two principal sources and are listed in Table 1. One source is the Ghana Demographic Health Survey (DHS) and the other

Table 1 Model variables

Variable name	Definition	Years	Source
BMI	Mean BMI (Kg/M^2) in GDHS cluster	1993, 1998, 2003, 2008	GDHS
HHSize	Mean household size in GDHS cluster	1993, 1998, 2003, 2008	GDHS
FlushToilet	Percent of GDHS cluster households with flush toilet	1993, 1998, 2003, 2008	GDHS
NoToilet	Percent of GDHS cluster households with no toilet	1993, 1998, 2003, 2008	GDHS
HasElectricity	Percent of GDHS cluster households with electricity	1993, 1998, 2003, 2008	GDHS
UrbanLandCover	Area in 2500 m buffer of GDHS cluster in urban class	2000, 2010	Landsat classification
AgLandCover	Area in 2500 m buffer of GDHS cluster in agriculture class	2000, 2010	Landsat classification
NatVegLandCover	Area in 2500 m buffer of GDHS cluster in a area natural vegetation class	2000, 2010	Landsat classification

is a set of classified Landsat images covering the vast majority of the four regions of the study site for the years 2000 and 2010. The DHS program conducts surveys in developing countries to gain an understanding of population and health trends. Until the most recent survey, the DHS in Ghana (GDHS) was conducted at 5-year intervals. Here, the DHS surveys from 1993, 1998, 2003, and 2008 were used to derive datasets of socioeconomic and health variables over time (GPS data from the 2014 DHS were not available at the time of our analysis, so we were unable to include data from the 2014 survey). Surveys for individuals and households were aggregated to derive the mean of each variable at the survey cluster level. Survey clusters are defined as groupings of households that participate in the survey (DHS Program 2015). They are typically based on enumeration areas (EAs) defined by Ghana Statistical Service.

NASA Landsat Enhanced Thematic Mapper Plus image data for the years of 2000–2003 and 2010–2013 were used to create image mosaics covering most of the study area. Details of the image classification procedures used to generate LCLU maps for 2000 and 2010 and subsequently data on LCLUC between 2000 and 2010 are provided in Coulter et al. (revised and resubmitted). A multi-temporal compositing approach was used to attain coherent, cloud-free image products from a series of images collected over 5-year periods at the beginning (1999–2003) and end (2009–2013) of the study period. Spectral indices were generated from Landsat 7 ETM + surface reflectance images and used as input to the image classifier. A layered (class-by-class) image classification approach based on threshold values of spectral indices and derived spatial texture products was implemented. The output classification products portray nine LCLU classes: Water, Forest, Built, Agriculture, Secondary/Degraded Forest, Savanna, Commercial Agriculture, Barren, and Mining. Water, Forest, Built, Secondary/Degraded Forest, and Savanna were obtained using semi-automated processing, while Commercial Agriculture, Barren, and Mining were delineated using visual interpretation.

For this study, the areas of three classes within a 2500 m buffer of each cluster were used. The 2500 m buffer size was chosen as a neighborhood distance associated with environs that respondents might occupy on foot on a daily basis, based on research showing: (a) average distance to subsistence agriculture plots are generally within this distance ("usually under 2000 m"); and (b) the World Bank's recommended maximum distance for children to walk to school (before other transport is required) is 2500 m (Dennis 2000). UrbanLandCover and AgLandCover classes consisted of areas of the Built and Agriculture classes, respectively, while NatVegLandCover was comprised of three reclassified categories: Forest, Secondary/Degraded Forest, and Savanna.

2.2 Dependent Variable

Body mass index (BMI) of women surveyed in the GDHS was used as the dependent variable for statistical analyses including LTM. BMI is defined by the World Health Organization as a person's weight in kilograms divided by the square of that person's height in meters, resulting in a measure of kg/m^2. This relatively simple measure is then often used to classify what range of health a person has (e.g.

underweight, normal weight, overweight, or obese). A BMI of less than 18.5 is considered underweight, while over 25 is considered overweight, and over 30 is considered obese (WHO 2004). BMI for each individual DHS survey respondent in a given cluster was averaged over each survey cluster to come up with an average BMI for each survey cluster at each year. In statistical analysis, BMI $\times$ 100 is often used to avoid the need for decimals (resulting in, for example, measures of 2500 and 3000 being considered overweight and obese, respectively).

2.3 Independent Variables

The independent variables used to describe and predict the trajectory of BMI consist of socioeconomic, demographic, and biophysical variables for survey clusters derived from the DHS data and land cover classifications for the 2500 m buffer around each cluster. Percentage of households with electricity and percentage of households with flush toilets were used as proxies for community level socioeconomic status, as seen in previous studies (Houweling et al. 2003). Percentage of respondents with no toilet was included as an indicator of lack of development and low socioeconomic status (Houweling et al. 2003; Unger and Riley 2007). (Note: this measure is not simply the inverse of percent of households with flush toilets because a plurality of respondents had pit toilets). Mean household size was included as a demographic variable that has shown a relationship with health (mortality), and as a surrogate of age and the effects of having multiple children over time (Dake et al. 2011; Rognerud and Zahl 2006). In addition, these indicators fit the suitability criteria for spatial interpolation laid out by USAID by being measurable, not concerning rare events, having spatial distributions, having a specific reference period in which the measures do not vary significantly, and by relating to the current location of the respondents (USAID 2014).

2.4 Derivation of Time Series Data for Each Cluster with EMPIRICAL Bayesian Kriging

Ghana DHS data consist of a separate, geographically varying national sample of survey cluster sites for each survey year. Each cluster point represents the georeferenced centroid of a neighborhood sample with a moderate degree of displacement (0–2 km for urban areas; 0–5 km for rural areas) to preserve privacy with respect to HIV results for each survey cluster for each year it is conducted. Despite the small displacement, the data permit analysis of spatial differences at each time step (USAID 2014). Due to these characteristics, GDHS data do not represent standard time series data, so spatial interpolation was used to create estimates of each health, demographic, and socioeconomic variable at each cluster location over the four survey dates.

Within the study area, approximately 200 DHS survey clusters exist per survey year, covering all areas of human residence proportionate to population size. These survey points, with different locations over the study years, were combined into an ArcGIS shapefile containing a total of 845 survey cluster points. Empirical Bayesian Kriging (EBK) employed in ArcGIS has shown promise as a method of

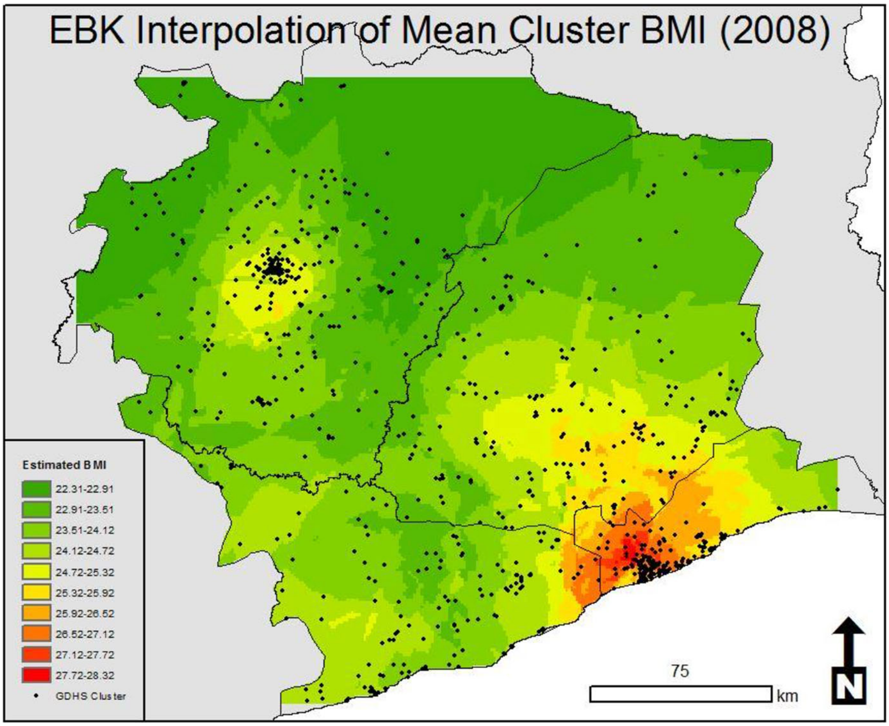

Fig. 2 Example of EBK interpolation results for BMI for 1 year (2008)

interpolation that automatically creates the optimal interpolation surface (Krivoruchko 2012). Therefore we used it to create a surface of estimated variable values at each date. The values of the raster surface at the location of each of the 845 survey cluster centroids were extracted to create new geo-referenced variables, resulting in a final dataset of estimated values for all independent and dependent variables for each time step at each cluster (Fig. 2).

Land cover and land use context for 2000 and 2010 was extracted by computing the area of each LCLU type within a circular buffer with a 2.5 km radius of each survey cluster point (Fig. 3). Then, in order to obtain LCLU estimates at each of four survey dates, the linear rate of change of each class was estimated for each survey cluster. The area of each class at each time step was interpolated using the area at the closest date of classification (2000 or 2010) along with the linear rate of change between the two dates. Temporal interpolation in this manner has been demonstrated as reliable over short time periods (Petit et al. 2001). For example, the equation for 2008 Urban land cover is:

$$\begin{aligned}\mathrm{UrbanLandCover}_{i,2008} = {} & \mathrm{UrbanLandCover}_{i,2010} - 2\left(\mathrm{UrbanLandCover}_{i,2010}\right. \\ & \left. - \mathrm{UrbanLandCover}_{i,2000}\right) / 10\end{aligned}$$

This resulted in an estimate of the area (m^2) of Urban, Agricultural and Natural Vegetation surrounding the cluster at each of the four time steps, included due to the

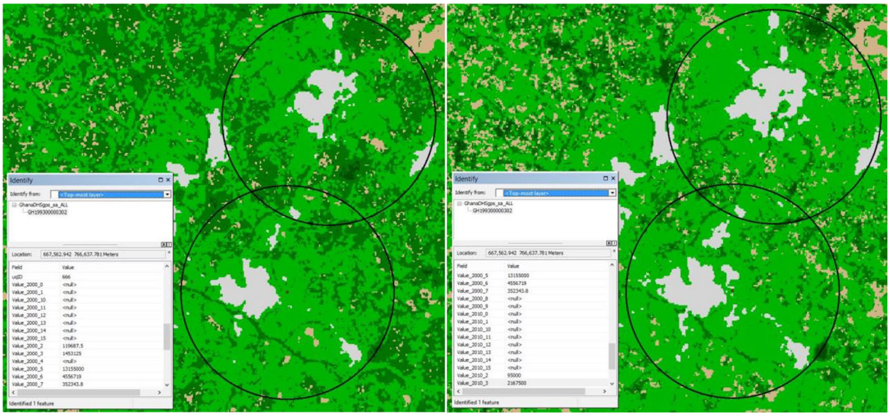

Fig. 3 Example of LCLU data tabulation. Land cover and land use for 2000 on *left* and 2010 on *right*. Data are tabulated from within a circular buffer with a 2500 m radius

noted importance of neighborhood context in investigating health outcomes (Weeks et al. 2004). When using the original values of these land cover and land use variables in the subsequent regression models, the coefficients turned to be very small. We thus standardized all the land cover and land use variables and reported the corresponding coefficients in cases where the values differed.

2.5 Latent Trajectory Modeling

Latent trajectory modeling (LTM), also called latent growth modeling, is a method of modeling time series data (when the same unit of analysis has been measured for more than two times steps) that is popular in various social science contexts (An et al. 2016; Bollen and Curran 2006; Guo and Hipp 2004; Preacher et al. 2008) Specifically, LTM is used to estimate the growth trajectory of each unit for a certain selected variable or phenomenon (such as a child's test scores as they age) over time, rather than determine the influence of specific covariates on the measure of the unit per se, at a specific time as in multivariate regression analysis (An et al. 2016; Guo and Hipp 2004). A growth trajectory, derived from the measures repeated through time, is primarily described by its shape parameters such as intercept and slope (and sometimes the rate of change of slope like slope^2 or other terms that best fit the data or arise from related theories). These parameters reveal essential information about the temporal trend of the variable (phenomenon), and can be influenced by covariates for individual units. In our case, we explore the trajectory of BMI change over time, attempting to describe its growth trajectory (whether rising or falling, and at what rate), but also seeking to understand how environmental, socioeconomic, and demographic factors influence the trajectory in different areas.

2.6 Eigenvector Spatial Filtering

When performing LTM in geospatial applications it is important to account for the influence of spatial autocorrelation on regression results. If not handled properly, it can give rise to negative impacts on regression results such as deflated standard errors and inflated degrees of freedom (Tiefelsdorf and Griffith 2007; Getis and Griffith 2002; Griffith 2000). Between the two major spatial filtering methods developed by Getis (1995), Ord and Getis (2001) and by Griffith (2000), Tiefelsdorf and Griffith (2007), we chose the Griffith et al. eigenvector spatial filtering (ESF) method for two major reasons. First, we have a space–time dataset, i.e., each site (cluster) has four temporal measurements. Using the Getis and Ord method would have required that we calculate the spatial and non-spatial part of each data value of a site at each time. By contrast, the Griffith method requires the derivation of only one set of eigenvectors that is applied to all points in time if we can reasonably assume that the spatial autocorrelation structure is constant over time. This is an efficiency concern. Secondly, and more importantly, each of the top eigenvectors represents an internal structure of spatial autocorrelation in the variable of interest. Using these eigenvectors as filters in regression analysis has been demonstrated to be effective in reducing or eliminating spatial autocorrelation in the variable(s) of interest (Griffith 2000; Tiefelsdorf and Griffith 2007). The related literature suggests a number of ways to choose eigenvectors as predictor variables, such as through stepwise regression. Another approach is to select the top eigenvectors with Moran's I values or adjusted eigenvalues of over 0.25 (the eigenvectors are listed according to a descending order of their corresponding eigenvalues), with the goal of lowering the spatial autocorrelation of the regression residuals to an acceptable level (e.g., the Moran's I's p value > 0.05 or t score < 1.96; Griffith 2000; Tiefelsdorf and Griffith 2007; Chun and Griffith 2011).

We implemented the ESF using a combination of R, SAS, and ArcGIS programs (for detail see http://complexities.org/Methodology/LTMs/LTMs.htm). The top five to ten eigenvectors were used as predictor variables in the models listed below in order to account for spatial autocorrelation in predictor variables. We chose the top five to ten eigenvectors based on our observation that this set of eigenvectors was able to lower the Moran's I's Z-score, consistent with our personal communication with D. Griffith and Y. Chun (developers of the ESF method for geographic data analysis). For more information on the LTM and eigenvector spatial filtering framework, see An et al. (2016).

2.7 Analysis

LTM modeling of BMI in the study area was implemented with Statistical Analysis System (SAS®) statistical software with several configurations, as shown in Table 2. First, a model of just the intercept, slope, and ten eigenvectors was created (M1). A second model of intercept, slope, and slope^2 including ten eigenvectors was created to illustrate the rate of change of the slope (M2). A third model (with versions A and B) incorporate intercept, slope, and all covariates without the top five eigenvectors (M3A) and with the top five eigenvectors (M3B). A fourth model

Table 2 Overview of different models investigated

	Intercept	Slope	Slope^2	Eigenvectors	Covariates
Model 1	x	x	–	10	None
Model 2	x	x	x	10	None
Model 3a	x	x	–	–	All
Model 3b	x	x	–	5	All
Model 4	x	x	x	10	Only land cover
Model 5	x	x	x	10	All minus HasElectricity

(M4) includes intercept, slope, slope^2, 10 eigenvectors, along with only land cover covariates to analyze the influence of land cover variables on BMI (M4). Finally, a fifth model contains intercept, slope, slope^2, covariates, and ten eigenvectors (M5), with one covariate removed to account for possible multicollinearity. Taken together, these models give a comprehensive illustration of the latent trajectory of BMI in the four-region study area of Ghana and the influence of several important covariates. A p value cutoff of $p < 0.05$ is applied for variables to be considered statistically significant predictors, however, we also report the variables that are significant at 0.10 level.

3 Results

3.1 Descriptive Statistics and EBK Validation

BMI and SES data for each year reveal changing patterns in the dependent and independent variables (Table 3). Changing mean values for BMI for the entire study area reveal a large overall increase in BMI (22.88 for 1993 and 24.68 for 2008). Data values extracted from the EBK interpolation surface for each variable at each year allow a comparison of change among given sites over the time period of the

Table 3 Comparison of averages of known cluster means and averages for all EBK estimates for each data cluster for each variable (explained in Table 1) for each year

	1993	1998	2003	2008
MeanBMI	*22.88*	*23.05*	*23.9*	*24.68*
MeanBMI	**22.68**	**23.34**	**23.98**	**24.73**
MeanHSize	*3.45*	*3.37*	*3.76*	*3.47*
MeanHSize	**3.46**	**3.32**	**3.71**	**3.43**
FlushToil (%)	*9.72*	*11.74*	*16.56*	*22.62*
FlushToil (%)	**5.12**	**14.33**	**17.7**	**23.68**
NoToil (%)	*18.04*	*20.6*	*11.91*	*8.7*
NoToil (%)	**17.14**	**20.73**	**11.65**	**8.44**
HasElec (%)	*43.90*	*55.94*	*57.83*	*70.13*
HasElec (%)	**37.99**	**60.22**	**59.66**	**69.75**

DHS values in italics

EBK estimates in bold

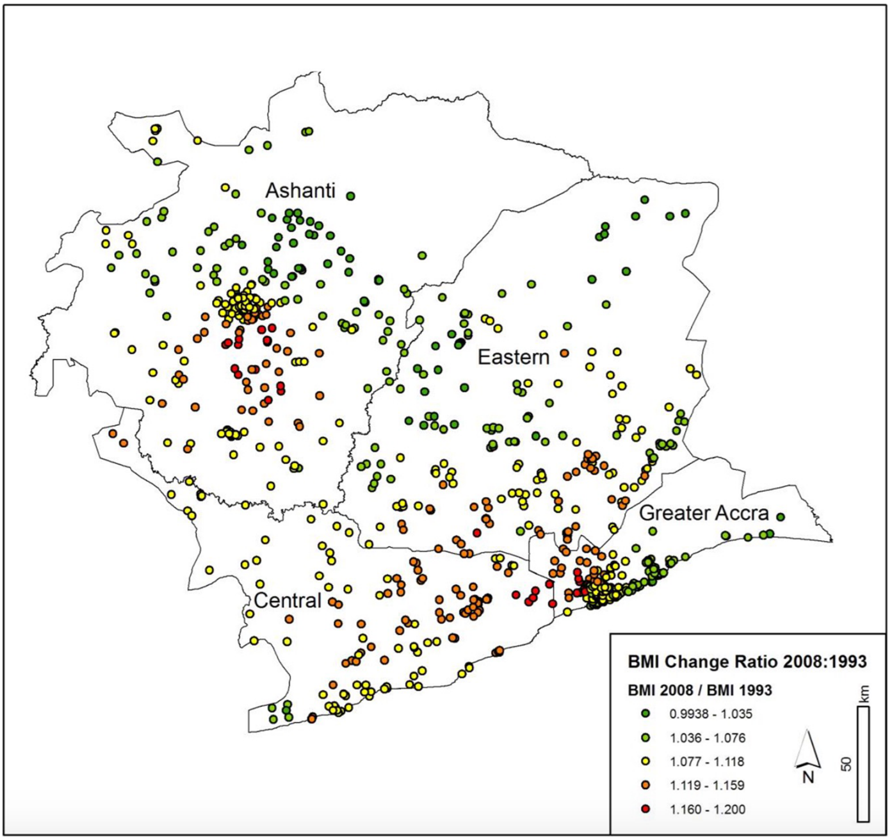

Fig. 4 Mean cluster BMI change: 2008 compared to 1993

study. As seen in Table 3, the averages of estimated values extracted from EBK for all 845 sites are similar to the mean known GDHS survey values at each year. Maps of BMI change ratio shown in Fig. 4 reveal both spatial and temporal trends. There are notable increases in BMI in peri-urban areas while areas previously identified as urban slums show stable (or possibly decreasing BMI).

3.2 Overall Temporal Trend in Data

The latent trajectory model results illustrate the trajectory of change with and without specific combinations of covariates (Table 4). The first model (M1), including just the intercept and slope of the trajectory (along with eigenvectors) estimates a starting BMI of 2219.88 and an increase of 66.61 each time step (5 years), or approximately 13.32 per year. This gives values over time that are very close to the observed mean change values in the study area (Table 4). M2 includes the same features as M1 with the addition of the quadratic term (slope^2) or the rate of change of the slope. For M2, the intercept is a BMI of 2193.73 with a slope of

Table 4 Model results

Models	1	2	3a	3b	4	5
Intercept	2219.88**	2193.73**	1595.41**	1837.93**	2281.97**	1891.83**
T	66.61**	84.66**	304.05**	170.74**	9.9036	379.21**
T^2		−3.44**			4.5021	−67.75**
Intercept Pred						
HHSize			188.08**	89.29**	na	89.40**
FlushToilet			325.70**	−50.93	na	1480.54**
NoToilet			−198.08**	−191.32**	na	−38.91
HasElectricity			234.72**	357.79**	na	na
UrbanLandCover			−0.000000635	−0.00000136**	−0.00000334**	−0.00000292*
AgLandCover			−0.00000385**	−0.00000041**	0.000000873	0.000002795
NatVegLandCover			−0.00001**	−0.00000483**	−0.00001**	−0.00000585**
Slope Pred						
HHSize			−77.19**	−37.41**	na	−80.90**
FlushToilet			−21.40	73.98**	na	−828.64**
NoToilet			49.09**	56.79**	na	−185.10**
HasElectricity			−55.08**	−90.41**	na	na
UrbanLandCover			0.000000853**	0.000001873**	0.000004272**	0.000002858*
AgLandCover			0.000000744**	0.000001304**	−0.00000168	−0.00000355*
NatVegLandCover			0.0000008924**	0.000001691**	0.000007642**	0.00000228
Slope Square Pred						
HHSize					na	14.33**
FlushToilet					na	123.74**
NoToilet					na	68.75**
HasElectricity					na	na
UrbanLandCover					−0.000000459**	−0.0000000281**

Table 4 continued

Models	1	2	3a	3b	4	5
AgLandCover					0.0000006589**	0.000001038**
NatVegLandCover					−0.00000111**	−0.0000000602**
AICc	16532.3	19668.2	16745	16009.7	16152.1	15823.7
−2Log Likelihood	16499.9	19633.8	16696.2	15950.6	16090.8	15743.6

* $p < 0.10$

** $p < 0.05$

84.66. The value of −3.44 for $slope^2$ indicates a subtle deceleration process, with the rate of BMI increase slowing as time progresses. However, the small magnitude of this value indicates a largely linear trajectory.

3.3 Impact of Covariates on Latent Trajectories

The next set of models include different combinations of covariates, where the intercept, slope, and/or quadratic term were altered, showing the type of influence of each covariate has on these parameters. The intercept of M3A and M3B are 1595.41 and 1837.93, with slopes of 304.05 and 170.74, respectively. The model that has no eigenvectors (therefore not accounting for spatial autocorrelation), i.e., M3A, starts with the lowest intercept (1595.41), but has a relatively large, positive slope (304.05), indicating fast BMI growth. The overall model fit increases by including eigenvectors, demonstrated by an AICc change of 16745.0–16009.7. Average household size and the percentage of households with electricity are consistently significantly positive while percentage with no toilets, amount of agricultural land cover, and the amount of natural vegetation land cover show consistent significantly negative impact on the intercept (amount of agricultural land cover is no longer significant in the standardized model). Percentage of households with no toilet, amount of urban land cover, amount of agricultural land cover, and amount of natural vegetation land cover all are consistently associated with increasing slope over the study period (though natural vegetation in the standardized model 3a is not significant and drops to significance at the 0.10 level in model 3b; agricultural land cover is significant at only the 0.10 level in model 3a), while the percentage of households that have electricity and increasing average household size are associated with decreasing slope. The percentage of households with flush toilets is only significantly correlated with intercept in the positive direction when no eigenvectors were included and is correlated with positive slope with eigenvectors, while amount of urban land cover has a significant relationship with the intercept (negative) only in M3B (but it is not significant in either 3A or 3B when land cover variables are standardized).

Model M4 uses only land cover covariates, but was expanded to include the quadratic term ($slope^2$) in addition to intercept and slope. Of these attributes, only the intercept of 2281.97 is significant (though the slope is significant in the model with standardized variables). The amount of urban and natural vegetation land cover exhibit significant negative influences on the intercept. Despite a non-significant slope term, the covariates “amount of natural vegetation land cover” and “amount of urban land cover” have a statistically significant positive influence on the slope. All three LCLU covariates are significant predictors of the quadratic slope variable, with urban and natural vegetation having a negative relationship, and agricultural land cover having a positive relationship (however, in the standardized model, agricultural land cover and natural vegetation land cover are only significant at the 0.10 level while urban land cover is no longer significant).

The final model, M5 is the most comprehensive of the five, and includes intercept, slope, quadratic term, eigenvectors, and all of the covariates (except the percentage of households with electricity, which exhibits moderate correlation with other variables). It has the best fit with AICc at 15823.7, the lowest among all the models. This model has an average intercept of 1891.83, an average slope of 379.21, and an average quadratic term of −67.75. These attributes illustrate an intercept close to (but slightly lower than) the starting mean BMI in 1993, with a rapidly increasing BMI over early time-steps (indicated by the large slope 379.21). However, the upward trajectory is tempered by a fairly large, negative quadratic term −67.75, indicating significant deceleration in the fast BMI growth.

The intercept of M5 is positively predicted by household size and percentage of households with flush toilets, and negatively predicted by urban land cover and natural vegetation land cover, implying that clusters with higher values for household size and ownership of flush toilets have higher BMI at the beginning of the study time period. At the same time, clusters with higher amounts of urban land cover and natural vegetation land cover have lower starting BMI. The slope is positively predicted by the amount of urban land cover (0.000002858), implying that as time goes one, places with higher urban land cover have increasing BMI. Also, the slope is negatively predicted by household size, the percentage of households with flush toilets, the percentage of households with no toilets, and the amount of agricultural land cover, indicating that areas with large amounts of these attributes experienced decreasing BMI over time. The quadratic term is positively predicted by household size, percentage of households with flush toilets, percentage of households with no toilets, and agricultural land cover while being negatively predicted by urban land cover and natural vegetation land cover (though these negative land cover predictors are not significant in the standardized model). This indicates that the increasing trend of BMI observed through the study period may slow down, as would be expected due to the decline of under-nutrition and the human bodily limits on a rise in BMI.

4 Discussion

4.1 Model Implications

The results of the latent trajectory models confirm some findings from previous analysis of survey data and mirror the trends seen in many individual survey sites (see Fig. 5). Average BMI of all the survey clusters for each year show a major overall increase that is similar to the increases seen in other studies, giving some validation of the interpolation methods employed (Amoah 2003; Dake 2013; Duda et al. 2008).

Fractions of land cover types show significant associations with the trajectory of BMI in all models in which those variables were included. To our knowledge, the use of spatial metrics that are more detailed than simple urban/rural differentiation have not been used previously as predictors of BMI. Unsurprisingly, the results here confirm the major impact that urban context had on BMI throughout the nineties. However, it expands on past studies by showing consistent significance of the *amount* of urbanness in the area around a cluster rather than just showing differences between the binary classification of urban and rural derived from survey

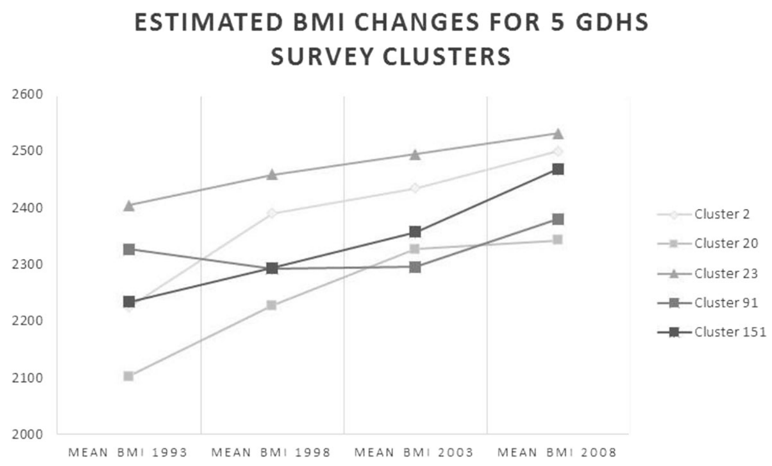

Fig. 5 Exemplar BMI changes in randomly selected survey clusters

data. This supports the idea that resident health is related to the degree to which an area is situated within a continuous urban area. In general, this is what we would expect based on research showing that neighborhoods (broadly defined) affect the health of residents, even when controlling for the individual characteristics of the residents (Kawachi and Subramanian 2007; Weeks et al. 2012). However, we are not aware of other research that has related health specifically to a measure of urbanness as we have done in this paper.

The results of analysis of the spatial distribution of BMI changes (Fig. 4) over time show interesting patterns. While most studies have found major links between overweight prevalence, obesity, and urban areas that this study confirms, our methods allow more detailed analysis of spatial and temporal trends. Most notably, by visualizing the ratio of BMI change between 1993 and 2008, major increases in peri-urban area BMI are noted, while many highly urban areas, including a large number of survey sites in central Accra, show low or no BMI increases (Fig. 2). This suggests that the major increase in BMI is occurring on the urban fringes–areas populated especially by migrants moving to urban areas. Some of this may be a function of underweight migrants from rural areas achieving more normal levels of BMI, but it is also related to the dietary and activity changes that are part and parcel of urban existence, leading to unhealthy levels of overweight and obesity.

Our most comprehensive model (M5) indicates an initial slope (or increase in BMI) of over 3 between study dates (5 years). This can be interpreted as a change of the overall average BMI from normal to obese in a 10-year period. However, the quadratic negative term (−67.75) indicates that the initially very high rate of BMI increase is decreasing. This means that there may be some degree of saturation in the amount of high BMI individuals, as fewer clusters may enter the overweight and obese designations over time. This suggests that Ghana may be on the cusp of following the trend seen in the United States, where obesity rates have remained constant the last several years after decades of substantial growth (Flegal et al. 1998; Ogden et al. 2006). Changes in the future will almost certainly depend upon behavioral changes that are not currently apparent, but may come to the fore as countries deal with the health consequences of obesity.

The most interesting finding in Model M5 is that the only positive predictor of large, significant slopes is the amount of urban land cover in the 2500 m buffer around survey clusters. This implies that between 1993 and 2008, increasingly urban areas had the largest association with increasing BMIs and that none of the other covariates were shown to be associated with the large increases that were observed. This implies that unmeasured aspects of the urban environment are major drivers of the increase in BMI.

The quadratic term also offers interesting insights into population level changes in BMI. The amount of urban and natural vegetation land cover were the only variables negatively impacting the quadratic term, suggesting that the flattening of the increasing rate of change of BMI is being driven by likely demographic changes in highly urban areas and areas with natural vegetation. The impact of highly urban areas could be a result of increasing in-migration of rural and low socio-economic groups that make up the populations of urban slums. Areas with large amounts of natural vegetation may have greater reliance on continued subsistence lifestyles (and associated healthier, traditional diets) and greater physical activity.

Earlier studies found significantly increased BMI not just in urban areas, but among older respondents and wealthier households/areas (Abubakari et al. 2008; Amoah 2003; Biritwum et al. 2005; Dake et al. 2011). In our LTMs, all socioeconomic variables showed at least some significant relationships with BMI, largely corroborating earlier findings for Ghana, but also demonstrating more complex relationships over time. Household size consistently impacted the intercept positively, the slope negatively, and the quadratic term positively. This can be interpreted as areas with more established households and greater numbers of children initially were associated with higher BMI at earlier times. However, areas with these types of households were associated with decreasing rates of BMI (as greater amounts of higher BMI came to be explained by urbanization) over time, but after some tipping time with increasing rates.

Our study assumes that survey clusters with higher proportions of households with flush toilets and electricity are areas of higher socioeconomic status, which Amoah (2003) found to correlate positively with BMI. Our results suggest that these variables have an almost universally significant positive association with the intercept in the models in which either or both were included, indicating an early association with areas of high BMI. Over time, however, these variables had a mostly negative influence on the slope, suggesting that areas of higher socioeconomic status had a decreasing association with high BMIs. This could be related to a possible degree of saturation within the population; wealthier areas that started with high proportions of high BMIs and were unable to match growth rates of areas that started out with lower BMI.

Applying LTM with eigenvector spatial filtering shows promise as a methodology for space–time analysis in public health and geography. The two models that were run with and without eigenvectors show the increase in model fit when using eigenvectors. Even though the Z scores of the corresponding Moran's I values are still greater than 1.96 despite a substantial decrease due to adding the eigenvectors, we see an improvement in overall model fit and the qualitative change in some regression coefficients (e.g., from insignificant to significant or vice versa) due to eigenvector filtering. Most models yield consistent results, with all having a positive intercept within a couple of points of the known mean value for 1993, positive slopes correspond to increasing mean BMI over the past 20 years that have been reported in other studies, and negative quadratic terms. Likewise, few of the independent variables show significant changes in sign.

4.2 Limitations and Further Research Opportunities

There are several limitations associated with aspects of this study. First, it could be beneficial to use more covariates that have shown associations in other studies [e.g. ethnic group or level of physical activity in Biritwum et al. (2005) or education as found in Amoah (2003)], but it was difficult to find consistent data for socioeconomic and demographic variables over the four survey years, as questions included in the GDHS changed over time. Fortunately, as pointed out by Yang and Matthews (2015), the patterns of some top eigenvectors may help researchers further identify important variables that should be included in future analysis. We therefore present a set of eigenvector maps (Fig. 6) for illustration. Secondly, comparing interpolation surfaces over time is generally not recommended but in this study it was the only way to estimate time series data, and results show that the interpolated averages do track closely with observed averages for all variables (Table 2; USAID 2014). Related to this, the geographic displacement of GDHS points introduces some uncertainty, but we believe that the buffers chosen provide a reasonable representation of the context around each cluster.

There is also room for further investigation of different neighborhood definitions. In this case, we used nearest-neighbor based neighborhood definitions that included the 64 closest neighbors for each cluster. One recent study (An et al. 2016) used a number of different neighborhood definitions to minimize the negative impact of

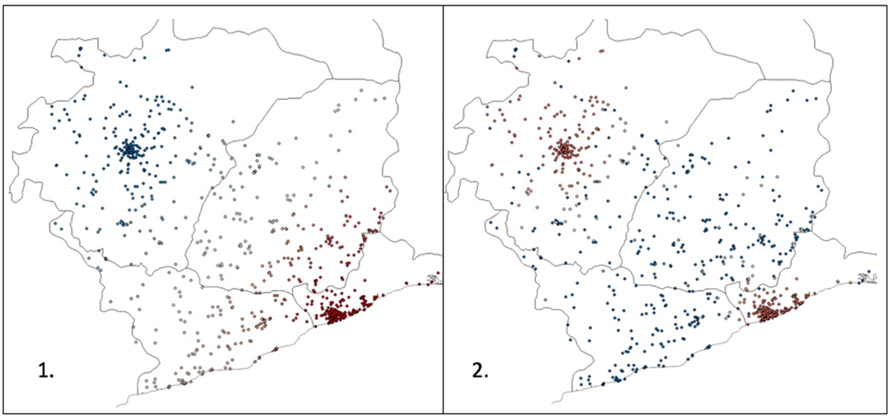

Fig. 6 Top eigenvectors show a northwest-southeast component (eigenvector 1) and an urban rural component (eigenvector 2)

spatial autocorrelation on regression results. Optimizing neighborhood selection for eigenvector spatial filtering is an area for future research. Furthermore, the ESF literature is sparse about the level of spatial autocorrelation that can be allowed so that no serious biased regression outcomes may arise. Further research should be devoted to exploring the complex relationships between the level of spatial autocorrelation that can be allowed (e.g., expressed as Moran's I and its z scores), the influences of various (both spatial and temporal) extent and resolution choices, and the nature of the problem (e.g., dependent or independent variables) under investigation.

5 Conclusion

Our findings give new insight into the spatial and temporal trends of the sustained growth in the proportion of overweight and obese populations in Ghanaian society. Using EBK allowed the creation of spatially dense time series representations that reveal trends in BMI in different areas over time. Highlighted trends include high BMIs in urban centers compared to rural areas, larger BMI increases in peri-urban areas, and lower rates of change in some slums and rural areas.

Our models consistently demonstrate a trajectory of BMI growth (albeit at a slowing rate) in the four-region study area. However, LTM has not just allowed the identification of trends in BMI, but has also highlighted that a number of covariates are associated with this temporal trend. Specifically, areas of higher socioeconomic status and larger households are initially associated with higher BMI, but are not usually positively associated with BMI rise through the study period. Our analysis supports the assertion that increasing urbanization shows the most consistent, significant relationship with the substantial BMI growth shown. In illustrating this point, we have demonstrated that more detailed geographical context (beyond the simple urban–rural designation) can reveal differences when studying health changes.

These results can be helpful in prioritizing health policy for groups, enabling the targeting of areas of high BMI and/or high BMI growth rather than employing a one size-fits all approach. This could include the implementation of programs aimed at promoting physical activity and healthy eating, by taking actions such as building sidewalks in key areas or making high quality foods available while imposing restrictions on unhealthy foods. Such ideas may require large structural changes within society that may not be easily achievable. However, tackling such a pervasive epidemic can be done most effectively by attacking places where the problem is the largest and/or growing the fastest, as identifiable by space–time analysis and latent trajectory modeling. Increased allocation of resources prioritized in this way could significantly aid in managing the obesity epidemic.

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