The Impact of Neighborhood Structure on Health Inequalities in Accra, Ghana

John R. Weeks[1]
Department of Geography
San Diego State University

Allan G. Hill
Harvard School of Public Health
Harvard University

Douglas A. Stow
Department of Geography
San Diego State University

Arthur Getis
Department of Geography
San Diego State University

Debbie Fugate
Department of Geography
San Diego State University

Prepared for the Annual Meeting of the Population Association of America
Los Angeles, California
March 2006

Acknowledgments: This research was supported by grant number R21 HD046612-01 from the National Institute of Child Health and Human Development.

[1] Correspondence concerning this article should be addressed to John R. Weeks, International Population Center, Department of Geography, San Diego State University, San Diego, CA 92182-4493; telephone: 619-594-8040; fax: 619-594-4938; e-mail: john.weeks@sdsu.edu

The Impact of Neighborhood Structure on Health Inequalities in Accra, Ghana

John R. Weeks, Allan G. Hill, Douglas Stow, Arthur Getis, and Debbie Fugate

Abstract

The literature on health inequalities in Africa and other developing regions of the world has overwhelmingly focused on urban-rural differentials, thus ignoring the tremendous variability (inequality) that almost certainly exists within cities of developing nations. We hypothesize that intra-urban variability is impacted by individual risk factors and by the structure of the neighborhood in which an individual lives. That structure includes the demographic composition of the neighborhood and the environmental context within which people live. We use data from the Women's Health Survey of Accra in 2003 to provide individual-level data on health, in order to assess its spatial variability and the individual-level predictors of health differences. We then employ data from the Ghana census of population and housing in 2000 to provide neighborhood demographic composition and contextual data, and data from a high-resolution satellite image acquired in 2002 to add another component of contextual data, and then test models to evaluate the impact of neighborhood structure on health inequalities in Accra, net of individual-level risk factors. Our results indicate that the spatial variability of health levels in Accra and the predictors of that variability are considerably more complex than expected.

Background

There is increasing evidence that tremendous disparities in health exist within urban areas and at least part of the problem is the environment within which people live (Montgomery and Hewett 2005; Montgomery et al. 2003). This is an important issue because projections from the United Nations Population Division suggest that as the world grows from 6.5 billion currently to more than 9 billion by the middle of this century, most of the increase will show up in cities of developing nations (United Nations Population Division 2004). Cities in Africa, in particular, already have birth rates that are consistently above replacement level, and the city populations are increasing as well due to migration from rural areas and from the spread of cities into previously rural areas. This suggests that the classic concern about urban-rural differences in health (and other demographic outcomes) needs to be supplemented, if not replaced, by a concern about what is happening within those cities. The Millennium Development Goals, for example, specifically focus on slum areas of developing cities as Target 11 within Goal 7. UN-Habitat defines slums as places that lack one or more of the following: access to potable water, access to piped sewerage, housing of adequate space and durability, and security of tenure (Carolini 2004). But, while slums may be the worst parts of a city, they are not necessarily the only places that experience poverty and poor health. Indeed, as we show in this paper, they are not necessarily the places with worst health outcomes.

Our objective in this paper is to contribute knowledge about urban inequalities in health by exploiting a relatively rich set of data that we have for the city of Accra, Ghana. The importance of studying a sub-Saharan African city lies in the fact that UN-Habitat estimates that 72 percent of the urban population of sub-Saharan Africa is living in a slum area—the highest proportion in the world (UN-Habitat 2003).

Slums as a Neighborhood Context

Within cities, important aspects of life are organized around neighborhoods, but the literature shows that there are wide divergences in the way in which neighborhoods are defined. Because our research relates to the identification and analysis of urban inequalities, we focus our attention on slum neighborhoods. Millennium Development Goal 7, for example, specifically targets slum areas of developing cities and UN-Habitat defines slums as places that lack one or more of the following five characteristics: (1) access to potable water, (2) access to piped sewerage, (3) housing of adequate space, (4) housing of adequate durability, and (5) security of tenure. Nearly one in six human beings is estimated by the UN to be living in a slum, so it is not inconsequential to understand what exactly a slum is and how it might affect the health and life of urban residents.

The UN-Habitat definition of a slum refers to a "place" but of course every place is composed of individual housing units, some of which may conform more or less closely to the average of its neighbors. We can thus anticipate that every neighborhood will exhibit some variability with respect to its "slumness" and that "slum" is a continuum, rather than a dichotomy. To be sure, we may have to create a threshold along this continuum in order to artificially divide an urban area into slum and not-slum, but the arbitrariness of such a threshold should be apparent.

Neighborhood Effects on Health

We posit that variability in health within urban places, just as between urban and rural places, is importantly a function of the characteristics of place, not just of the people themselves. The medical model of health has, since the 19th century introduction of the germ theory, emphasized the risk of disease experienced by individuals, regardless of context, whereas a purely ecological approach would emphasize the importance of contextual environmental factors (Meade and Earickson 2000). A more holistic, human ecological approach places dual emphases on people and place. Characteristics of place include the provision of potable water, adequate sewerage and disposal of waste, accessibility (geographic and financial) to health clinics and personnel, as well as the adequacy of housing (protection from heat, cold, and water intrusion), the overall quality of the built environment in protecting people from pests and environmental hazards, and the institutional structure that exists to service the needs of the population (Hardoy et al. 2001). Personal characteristics such as education, income, and occupation clearly play a role, of course, in determining access to an adequate diet, personal hygiene, disease avoidance, access to health care professionals, and adherence to medical regimens.

Differences in mortality by social status are among the most pervasive inequalities in modern society, and they are most noticeable in cities (Weeks 2005). So, if one is part of a family of low socioeconomic status, this may put him or her at greater risk of death. Data from nearly all places in the world suggest that the higher one's position in society, the longer he or she is likely to live (Weeks 2005). These same personal characteristics may also influence the level of advocacy that will lead to demands for access to communal infrastructure (e.g., water, sewerage, solid waste disposal) that can improve health levels. Thus, to understand health levels we must understand the characteristics of people themselves, and also the characteristics of their environment. Mitchell, Dorling and Shaw (2002:15) capture the idea this way: "The first explanation, commonly referred to as 'compositional', suggests that area level mortality or morbidity rates reflect the risks of ill health which the resident individuals carry with them. The relationships between individual level factors such as social class and employment status, and the risk of mortality or morbidity, are well documented, powerful, and very robust. The composition thesis thus argues that places with apparently high levels of sickness or death rates are those in which a higher proportion of the residents are at higher risk of sickness or death. The second explanation, commonly referred to as 'contextual', suggests that the nature of day-to-day life in an area can exert an influence on the mortality risk of the resident population, over and above their individual characteristics. The influences might, for example, stem from the social or physical environment. Somehow, life in an area raises or lowers the risk of ill health for the resident individuals so that they experience different risk of illness from that which they might experience living somewhere else."

An important conceptual issue is whether or not the neighborhood effects are endogenous to the compositional characteristics of those neighborhoods, and thus essentially indistinguishable from the compositional effects (Kaufman 2006). Researchers such as Stjärne et al. (2006), in their study of neighborhood impacts on myocardial infarction in Stockholm, have concluded that they are, in fact, distinguishable. In our research, however, the neighborhood context is measured not just from aggregations of individual characteristics, but more specifically from the physical context that defines a neighborhood.

We recognize that in a geographically mobile world, place can be a problematic concept. People may work in a different place than they live, and they may traverse through other environments between home and work, and they may travel to different places for personal and/or economic reasons. This is the classic problem of the epidemiologist in trying to detect the various places where an infected/affected individual was exposed to a health risk. In developing countries, adult males tend to be more mobile than women or children, and so it may be that the health of women and children will be more closely allied with the place of residence than will the health of males. This may help us to understand the finding that in Ghana, for example, urban poverty is a stronger predictor of poor health for women and children than it is for men (Taylor et al. 2002). Nonetheless, residence is almost uniformly the place to which people are attributed when it comes to the measurement of morbidity (the incidence and prevalence of disease) and mortality. If we had details about the relative exposure of people to different places, then that information could theoretically be incorporated into an analysis of intra-urban variability, but we do not yet have that kind of information for any sizeable population on earth, and so we must be content to assume that the place of residence has the single most important impact on the health of most residents.

Data on the 'compositional' or personal characteristics of people living in an area are typically drawn from a combination of censuses, surveys, and vital statistics. From these data we can calculate rates of morbidity and mortality by age, sex, as well education, occupation and other socio-demographic characteristics according to their availability from the questions asked on the census, survey, or vital statistics records. It is much more difficult to obtain data about the environmental context in which people live. Housing data from censuses can often be aggregated to yield overall measures of the economic well-being of a neighborhood with, for example, indicators of the average connection of housing units to the utility infrastructure. Similar data are often provided in surveys. But, there is no consistency in the availability of such data and in all events they do not provide global measures of the overall built environment and its relationship to the natural environment within a neighborhood. Yet, because the neighborhood ecology is potentially a major contributor to the variability in health levels, it is crucial that we measure it if we are to understand intra-urban variability in health. This is where remotely-sensed imagery enters the scene, and where opportunities exist to close the large gaps that currently exist in our knowledge of the relationship between the urban environment and health.

In order to appreciate the value of remotely sensed imagery for analysis of urban places, it is important to understand what information can be extracted from such images. The image itself is composed of a two-dimensional array of pixels from which radiant energy has been captured for an area on the ground that is equal to the spatial resolution of the image. The information recorded for each image depends upon the particular sensor, but the brightness within a given band is assigned a digital number. The combination of digital numbers representing relative reflectance across the different bands of light yields the spectral signature of that pixel. Particular types of land cover (e.g., vegetation, soil, water, impervious surface) tend to have unique spectral signatures. The more bands that a sensor has the more detailed can be the land cover classification. If there are only a few bands it is possible to differentiate vegetation from non-vegetation, but with more bands it may be possible to differentiate a field of corn from a field of wheat or, within the urban area it may be possible to differentiate a tin roof from a tile roof. The typical tradeoff in imagery is that lower spatial resolution imagery will tend to have more bands (i.e., higher spectral resolution), as well as greater spatial coverage, than higher spatial resolution imagery. Our team's experience working with imagery for urban places suggests that higher spatial resolution is more important in characterizing an urban place than is the number of bands available for analysis (Rashed and Weeks 2003; Rashed *et al.* 2001; Rashed *et al.* 2003; Weeks 2004b; Weeks *et al.* 2005). This is because the built environment is configured differently, and normally less homogeneously, than the natural environment. Also, the two most useful ways that we have found of quantifying urban places from imagery are in terms of (1) the proportional abundance or <u>composition</u> of fundamental land cover classes (as just discussed); and (2) the spatial <u>configuration</u> of the pixels identified with each land cover class. The latter can be measured by a set of measures known as landscape metrics. These algorithms quantify the spatial configuration of the pixels of specific land cover classes (known as "patches") in a given area (such as a census tract) (McGarigal 2002). They were developed originally for applications in landscape ecology, but have been shown to have considerable potential value for describing the urban environment (Herold *et al.* 2002; Weeks *et al.* 2005). In describing their use in landscape ecology, McGarigal notes that "the habitats in which organisms live, for example, are spatially structured at a number of scales, and these patterns interact with organism perception and behavior to drive the higher level processes of population dynamics and community structure" (McGarigal 2002:1).

As we measure and classify the information from the imagery, we have two purposes to which the data are to be put. The first is to allow us to differentiate the characteristics of one neighborhood from another, so that we can quantify aspects of the neighborhood context and incorporate those as variables into our predictive models. In this use, we define a neighborhood from sources other than the imagery, and we use the imagery to create variables for each neighborhood that are not available from any other source. The second use is to define neighborhoods from the imagery itself—to find patterns of similarities and differences in the imagery that permit us to create an independent definition of a neighborhood which will then be validated from other sources of information, including field work on the ground. As we discuss later in the Research Design section, one of our goals is to evaluate the extent to which these two uses of the imagery lead to similar conclusions about the environmental and spatial contexts within Accra.

Within a city the social context will vary from place to place, in a pattern that might be called intra-urban ecology. This idea is also captured by the concept of environmental context, which suggests that the community within which you live will influence your behavior because we are social creatures who respond to the behavioral cues of people around us. Gladwell has called this the "Power of Context," which powerfully shapes our lives: "...the streets we walk down, the people we encounter—play a huge role in shaping who we are and how we act" (Gladwell 2000:167). As Weeks (2004a) has pointed out, neighborhood context is one of the theoretically more robust ways in which spatial analysis is beginning to enter social science (and potentially health science) theory as an updated version of human ecology. This implies that population size and characteristics interact with social organization, and with the environment and technology, to produce the behavior that constitutes human society. In turn, human behavior influences population, organization, the environment, and technology and for this reason the concept is that of a system, a human ecosystem (Micklin and Sly 1998; Namboodiri 1988).

Social scientists have tended to focus on the population and social organizational parts of this system, and are often vague, if not dismissive, of the built environment--of the buildings, parks, roads, bridges, and the associated infrastructure that humans create out of the natural environment and which become the places where everyday life takes place. Micklin and Sly (1998) put the built environment under technology, representing one set of "tools" available to human society. Yet, the built environment is more than that--it is the actual environment in which a large fraction of humans spend their entire lives. The natural environment is so transformed by urbanization that the majority of urban residents in wealthy countries spend little time touching soil and interacting with flora and fauna. Even more importantly, the built environment is not just a product of human activity; it is also a very important element of what Namboodiri (1988) has called the goal of human ecology, which is "to identify the linkage between the dynamics of human interdependence and the pursuit of the art of living." Local context is emerging as an important way of conceptualizing inequalities in the social world (Tickamyer 2000), and this approach is exemplified by the work of Gatrell (2003) and Sampson (2003), and especially Chapter 2 in Montgomery et al. (2003).

Neighborhood context thus provides a conceptual framework to aid in our categorization of data from remotely sensed imagery. It suggests that different kinds of built environments may well be associated with different kinds of human behavior. Among these behaviors are almost certainly aspects of life that influence health levels.

Data and Methods

We first discuss our definition of a slum, drawing upon data from the 2000 Census of Ghana, and we illustrate our methods of using those data to create new neighborhoods that are similar with respect to slumness. Then we use data from the 2003 Women's Health Survey in Accra (WHS) to estimate the extent to which health measures vary spatially within Accra. We look at data aggregated by slum neighborhood, and then analyze data at the individual level to measure the impact of slum (and other) neighborhood characteristics on individual-level indicators of health, net of personal risk factors.

Creating a Slum Index to Define Neighborhoods

A major innovation in our paper is the definition of a neighborhood, which has been problematic within the literature (see Montgomery and Hewett 2005 for a review). We have access to a ten-percent anonymized random sample of individual-level census data for the year 2000 for all 1,724 enumeration areas (EAs) in the city of Accra, the capital and primate city of Ghana. Since the average population per EA is less than 1,000, an EA is closer in concept to a US Census Block than it is to more standard unit of a census tract, which typically contains numerous blocks. The EA may thus be too small to represent the neighbhorhood in which a person lives in Accra because the small size and arbitrary boundaries do not necessarily conform to local perceptions of neighborhoods. We do not have a measure of such local perceptions, but we do have the ability to create quantitative indices that summarize each EA so that we can examine neighboring EAs and see if they are similar or not to the reference EA. In other words, we want to find "edges"—places that offer a disjuncture in characteristics, suggesting that we have crossed from one type of neighborhood into another. Note that a practical advantage in combining EAs into larger areal units to define a neighborhood is that it affords us a larger sample size that facilitates the our statistical analysis by increasing the power of our estimates.

The process of creating a slum index begins by operationalizing the UN-Habitat definition of a slum. We are able to do this because the 2000 Census of Population and Housing in Ghana asked questions that relate specifically to the UN-Habitat definition of slums. Thus, each housing unit in our ten-percent anonymized sample was scored as follows:

If the housing unit does not have piped water, then slum1 = 1 (else 0);

If there is no toilet and no sewage connection, slum2 = 1 (else 0);

If the resident is not the owner, slum3 = 1; (else 0);

If the building material is less durable, slum4 = 1 (else 0);

If the number of persons per room is greater than 2, slum5 = 1 (else 0)

Slum index for each housing unit (S_h)= Σ (slum1…slum5)

Table 1 shows the distribution of housing units in Accra by each of these characteristics. The majority of homes in Accra do not have piped water, they do not have a toilet that is connected to the sewer, and the majority of units are not owned by a resident. Nearly half have 3 or more persons per room, but only a handful of the housing units had what we defined as a non-durable roof and outer walls. Indeed, the vast majority of housing units in Accra are shown in the census as having outer walls of cement or concrete and roofs of slate, asbestos, or corrugated metal. An asbestos roof may have unintended health consequences, but it is generally considered to represent a durable roofing material.

TABLE 1 ABOUT HERE

Having calculated the slum index for each housing unit, the slum index for each EA was then calculated as the mean value for all housing units in that EA:

$$S_{EA} = \frac{\sum_{h=1}^{n} S_h}{n}$$

For all housing units in Accra, the mean slum index was 2.43, with a standard deviation of 1.1. The minimum was zero—no slum characteristic—and only 6.5 percent of homes in Accra had that score. The maximum of five was shared by 0.7 percent. The median was 3 of the slum characteristics per housing unit, with those three most often being lack of piped water, no toilet connected to the sewer, and three or more people per room. From paper maps and EA descriptions provided by the Ghana Statististical Services, we have created a digital boundary map (a shapefile) of the 1,724 EAs in metropolitan Accra.. Figure 1 is a map of the EAs in Accra according to the average slum index per EA. Slums are nearly ubiquitous in Accra, as in most sub-Saharan African cities, but there is a spatial pattern, as evidenced by the Moran's I of .33, which is statistically significant well beyond the .001 level. The white spots or "holes" in the map are places for which there are no census data, and include a huge roundabout near the airport on the northeast side, a military base on the east side, and salt flats on the west side.

FIGURE 1 ABOUT HERE

Redefining Neighborhoods into "Analytical Regions"

Although Moran's I tells us that there is a spatial patterning to the "slumness" within Accra, the map shown in Figure 1 reflects the seeming scatter-shot nature of development within the city (Pellow 2002). To define areas that may closer approximate the city's neighborhoods, we used a method of areal aggregation developed by Duque Cardona (2004) to regroup the 1,724 enumeration areas into a smaller set of 214 homogeneous and spatially contiguous neighborhoods, which we call "analytical regions" (ARs).

The problem of aggregation of spatial data is conceptualized as a special case of clustering in which the geographical contiguity between the elements to be grouped should be considered. This particular case of clustering methods is usually known as contiguity-constrained clustering or simply the regionalization problem. Previous approaches include Openshaw's Automated Zoning Procedure (AZP) (Openshaw and Rao 1995) and the SAGE system developed by Haining and his associates (Wise *et al.* 2001). Duque's approach involves linear optimization to implement a decision rule determining the "edge effect"--whether a neighboring EA has a slum index score that is similar enough to attach it to and thus enlarge the current neighborhood or whether it is sufficiently dissimilar to suggest that it is part of another neighborhood.

Figure 2 shows maps the average slum index by analytical region. It can be seen that the aggregation process reduced Moran's I to a value that is no longer statistically significant, indicating that, as we had hoped, we have now accounted for the spatial patterning in the neighborhoods. This means that we have been able to discern from the data the pattern that is obvious within the city—slum areas are often cheek-by-jowl with wealthy areas. Slumness is not a spatially continuous phenomenon. This is illustrated in Figure 3, which maps the top twenty ARs according to the slum index (the most slum like) and the bottom 20 (the least slum like). There are several of these extremes of neighborhoods that are not only physically quite close to one another, but in some cases actually adjacent to one another.

FIGURE 2 ABOUT HERE

FIGURE 3 ABOUT HERE

Using the Slum Index to Create Predictors of Health

We now have three measures of slumness that can be attached to each individual person whose health has been measured: (1) the slum index associated with the housing unit in which that person lives; (2) the slum index for the EA (near neighborhood) in which the person lives; and (3) the slum index for the AR (entire neighborhood) in which the person lives. This provides us with opportunity to measure (1) the relationship between health and a person's housing characteristics, and then (2) the relationship between health and the relative similarity of each person's housing unit to the closer and broader neighborhood.

Measures of Health

We use data from the 2003 Women's Health Survey in Accra (WHS) to derive indicators of health. The WHS contains data from in-person interviews, a clinical examination and laboratory work as well as data on the household's facilities using questions similar to the census of 2000. Data were collected from nearly 3,200 women aged 18 and older in a multi-stage cluster probability sample of 200 EAs in Accra (for details, see Duda et al. 2005). The depth and breadth of the WHS provide a wide range of possible measures of morbidity, but with the disadvantage that the data are available for women in only 200 of the 1,724 EAs. These 200 EAs are incorporated into 122 of the 214 ARs. However, when we aggregated data for ARs, we used only those 46 ARs that had at least 25 women.

The health measures we use are drawn from the SF-36 questions that measure eight different components of health, including four indices of self-reported physical health and four indices of mental health (Ware 2006). We will focus on the index of general health (GH)—an overall assessment of health. The principal risk factor associated with any measure of health is age, and Figure 4 shows the distinct age pattern for three of the SF-36 health measures, including

GH—our focus in this analysis, along with physical function (PF), and health transition (HT) which are shown for comparative purposes. Physical functioning and general health both decline with age, and the transition from better to worse health compared to a year ago increases with age. Thus, in order to compare one area to another with aggregated data, it is necessary to calculate age-standardized health measures. We did this by applying the age-specific health rates for each AR to a standard population (P_a) defined as the age structure of all women in the WHS. Thus, the age-standardized health rate for each AR (h_{ar}) is found as:

$$h_{AR} = \frac{\sum h_a P_a}{P} \times 1000$$

where

$$h_a = \frac{hlth_a}{p_a}$$

= the age-specific health rate in the given AR.

Finally, the measure that we use is a relative index (Rel_h_{AR}, the ratio of h_{AR} to the average for the entire standard population (H):

$$\mathrm{Re}l\_h_{AR} = \frac{h_{AR}}{H}.$$

FIGURE 4 ABOUT HERE

Results

Ecological Analysis

We begin with an ecological analysis, comparing age-standardized prevalence rates for each of the health measures across the 46ARs in which there are at least 25 women on which to base a rate. Since the original EA sample sizes in the WHS were chosen with probabilities proportional to size, the more populous areas are therefore likely also to be generally representative of the population. The purpose of this analysis is to evaluate the extent to which there is spatial inequality in health outcomes and, if so, if that variability is associated in particular with the slum characteristics of neighborhoods.

The results shown in Figure 5 indicate that there is, indeed variability in health levels among the 46 analytical regions for which we were able to calculate age-standardized relative indices of the general health index (GH). Higher scores indicate better than average self-reported health, while lower scores indicate where poor than average health predominates. The pattern is not intuitively obvious, however, since in some instances the well above average places are contiguous to the well below average places.

FIGURE 5 ABOUT HERE

This same spatial "confusion" was exhibited by the neighborhoods in terms of their slumness, so it is reasonable to ask whether the health levels are statistically correlated with the slum levels. With respect to the General Health index, the answer is no, with a correlation coefficient that is not statistically significantly different from zero. However, visualizing the data in Figure 6 offers a more nuanced perspective. It can be seen that it in the eastern side of the side, there is a close fit in North Teshie between the slum index and poorer than average health. There is also a similar close fit on the western side of the city in the Abossey Okai. Of some interest is that both of these areas are relatively industrial in nature. In the north center of the city, Nima has historically been the city's worst slum, but perhaps even because of that and the attention the area has received, it is not one of the areas with the poorest health. However, just to the southwest of Nima, the area of New Town (a traditional magnet for migrants) does have below average levels of health, although it is not one of the worst slums. To the northwest the areas of Kaneshie and Bubashie have poor health, but are not high on the slum index. The same is true of Osu, an older area near the beach to the east of the city center. Closer to the city center, the areas of Old Fadami and Adabraka score high with respect to being slums, but they do not exhibit the poorest levels of health. In general, the ecological analysis suggests that the relationship between slumness and health is more complicatedly place-specific than might be expected within an urban area.

FIGURE 6 ABOUT HERE

Individual-Level Analysis

Turning to the individual-level analysis we are able to utilize data for all women, not just those who live in the ARs that were more populous and which thus permitted the ecological analysis. Initially, we will ignore the location of each woman and ask if health levels vary by the typical set of risk factors such as education, possession of household goods (index of economic well-being), income, labor force status, marital status, food security and slum characteristics of the housing unit in which they live, and of course age. We again rely on the GH index as the health outcome of interest, and we focus on women of reproductive ages, 18-49, in order to minimize the age effect.

The results of the ordinary-least squares regression are shown in Table 2. Even when controlling for age there are several variables that are statistically significant predictors of general health. The first of these is food security, measured as a dummy variable where '1' indicates that the person always has enough food and the kind of food that they want to eat. This is positively associated with better health. The household goods index is a count of the number of six different items (such as radio, TV, refrigerator, etc.) possessed by the household, and is recognized as a good index of economic well-being. The variable is, as expected, positively associated with good health. Unemployment is a dummy variable where '1' indicates that the woman was unemployed at the time of the interview. Being unemployed is negatively associated with good health. Being a renter is a measure of the insecurity of the housing, but in these data being a renter rather than an owner is positively associated with good health. The final variable, besides age, is whether or not the woman grew up before age 12 in a city. Being a city dweller is positively associated with good health, as might be expected. Variables that did not wind up being statistically significant include education, marital status, income, lack of a toilet, and the slum index for the neighborhood. Note that this latter variable is a contextual variable, but if it does not show up as significant in an OLS, it will not be significant in a more properly specified multi-level model, so its lack of significance in this model suggested that the multi-level was not necessary to understand the impact of living in a slum, because that was not directly, at least, a significant predictor of health levels.

TABLE 2 ABOUT HERE

Most disappointing about the results in Table 2 is the fact that these variables, including age, were able to explain only 8 percent of the variability in the index of general health. Although not shown here, the result was the same with other measures of health. Thus, at the individual-level, the same "confusion" of predictors is present as was shown above for the ecological analysis. The standardized residuals from this analysis were not spatially autocorrelated, so there is no evidence of spatial clustering, but the spatial "confusion" that we noted above is not necessarily confusion per se, but rather may be indicative of spatial non-stationarity—the existence of different relationships among variables at different places throughout the city.

We tested for spatial non-stationarity using the Geographically Weighted Regression software (GWR) (Fotheringham et al. 2002). Using data for 2,215 women aged 18-49, we employed the General Health index as the dependent variable, predicted by those variables that had emerged as being statistically significant in the OLS (see Table 2): age, food security, household goods index, unemployment, and having grown up in a city. Each woman was georeferenced to the centroid of the enumeration area in which she lived, and the model was optimized at an 800km band around each point in the calculations involving a moving window around all points in Accra. The research group that created GWR offer a rule of thumb for deciding if spatial non-stationarity exists in a dataset (Charlton et al. 2003). They suggest comparing the standard error for the global regression coefficient for each predictor variable with the interquartile range of the spatially varying coefficients for that variable. An interquartile range of local parameters greater than two times the standard error of the global estimate provides evidence of the existence of spatial nonstationarity in that predictor variable. Each of the five variables that we used in the GWR model followed this pattern, as shown in Table 3. What is remarkable about these findings is that even age has a different impact on health depending upon where you live within the city.

TABLE 3 ABOUT HERE

These results can be visualized by mapping the coefficients produced by the geographically weighted regression models. Figure 7 illustrates this by mapping the spatial variability in food security as a predictor of general health among women of reproductive age in Accra. Not only does the coefficient vary spatially, but there are some places where food security is negatively associated with health, even though in most places it is more predictably associated with better health. It is some interest to note that the highest coefficients for this variable are located in Teshie, where it had been previously been noted at the ecological level that there is a close overlap between slum conditions and the average level of health among women.

FIGURE 7 ABOUT HERE

Conclusion

We began with a relatively simple model of intra-urban health patterns in Accra, hypothesizing that there was spatial variability in health within Accra, and that this would be explained at least partly by community contextual factors, even after accounting for individual level risk factors. Following the still sparse literature on urban context within cities of developing countries, we hypothesized that slum areas would, in particular, be sites of lower than average levels of health.

Our results suggest that our original hypotheses were not wrong, per se, but that the health situation in Accra is vastly more complex than the literature and thus our simpler models would suggest. Most puzzling is the relative inability of any of the usual risk factors at the individual level to explain intra-individual variability in health levels. Answers to that puzzle may lie within the neighborhoods themselves, as suggested by the results of the geographically weighted regression. That analysis confirmed at the individual level what was shown at the ecological level: Not only do health levels vary by where you are in Accra, the predictors of health levels also vary according to where you are. In particular, it is not clear whether slums are overrated or underrated with respect to their impact on health, but our analysis—the first of its kind as nearly as we can tell from the literature—indicates that slums are far from being all alike with respect to health levels. Some of the worst slums in Accra also have some of the poorest health levels, but some do not. Furthermore, poor health is evident in some places that are not considered to be slums, and some slum areas have reasonably good levels of health. There is clearly much more to be learned.

References:

Carolini, Gabriella. 2004. "Interim Report of the Task Force 8 on Improving the Lives of Slum Dwellers." www.unmillenniumproject.orgh (accessed

Charlton, Martin, A. Stewart Fotheringham, and Chris Brunsdon. 2003. *GRW3: Software for Geographically Weighted Regression*. Newcastle, England: University of Newcastle.

Duda, Rosemary, Rudolph Darko, Richard Adanu, Joseph Seffah, John Anarfi, Shiva Gautam, and Allan G. Hill. 2005. "HIV Prevalence and Risk Factors in Women of Accra, Ghana: Results from the Women's Health Study of Accra." *American Journal of Tropical Medicine and Hygiene* 73:63-66.

Duque Cardona, Juan Carlos. 2004. "Design of Homogeneous Territorial Units: A Methodological proposal and applications." PhD Dissertation, Departamento de Econometria Estadistica y Economica Espanola, University of Barcelona, Barcelona.

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Chichester, England: John Wiley & Sons.

Gatrell, Anthony C. and Janette E. Rigby. 2003. "Spatial Perspectives in Public Health." in *Spatially Integrated Social Science*, edited by M. F. Goodchild and D. G. Janelle. New York: Oxford University Press.

Gladwell, Malcom. 2000. *Tipping Point*. London: Little, Brown & Company.

Hardoy, Jorge E., Diana Mitlin, and David Satterthwaite. 2001. *Environmental Problems in an Urbanizing World*. London: Earthscan Publications.

Herold, Martin, Joseph Scepan, and Keith C. Clarke. 2002. "The use of remote sensing and landscape metrics to describe structures and changes in urban land uses." *Environment and Planning A* 34:1443-1458.

Kaufman, Jay S. 2006. "Socioeconomic Context." *Epidemiology* 17:4.

McGarigal, K. 2002. "FRAGSTATS Documentation, Background Material." http://www.umass.edu/landeco/research/fragstats/documents/fragstats_documents.html (accessed

Meade, Melinda S. and Robert J. Earickson. 2000. *Medical Geography, Second Edition*. New York: The Guilford Press.

Micklin, Michael and David F. Sly. 1998. "The Ecological Complex: A Conceptual Elaboration." Pp. 51-84 in *Continuities in Human Ecology*, edited by M. Micklin and D. L. Poston. New York: Plenum Press.

Mitchell, Richard, Danny Dorling, and Mary Shaw. 2002. "Population Production and Modelling Mortality--An Application of Geographic Information Systems in Health Inequalities Research." *Health & Place* 8:15-24.

Montgomery, Mark and Paul C. Hewett. 2005. "Urban Poverty and Health in Developing Countries: Household and Neighborhood Effects." *Demography* 42:397-425.

Montgomery, Mark R., Richard Stren, Barney Cohen, and Holly Reed. 2003. "Cities Transformed: Demographic Change and Its Implications in the Developing World." Washington, DC: National Academies Press.

Namboodiri, Krishnan. 1988. "Ecological demography: its place in sociology." *American Sociological Review* 53:619-633.

Openshaw, S. and L. Rao. 1995. "Algorithms for reengineering 1991 Census geography." *Environment and Planning A* 27:425-446.

Pellow, Deborah. 2002. *Landlords and Lodgers: Spatial Organization in an Accra Community*. Westport, CT: Praeger Publishers.

Rashed, Tarek and John R. Weeks. 2003. "Assessing Vulnerability to Earthquake Hazards Through Spatial Multicriteria Analysis of Urban Areas." *International Journal of Geographical Information Science* 17:549-578.

Rashed, Tarek, John R. Weeks, M. Saad Gadalla, and Allan G. Hill. 2001. "Revealing the Anatomy of Cities Through Spectral Mixture Analysis of Multispectral Imagery: A Case Study of the Greater Cairo Region, Egypt." *Geocarto International* 16:5-16.

Rashed, Tarek, John R. Weeks, Dar A. Roberts, John Rogan, and Rebecca Powell. 2003. "Measuring the Physical Composition of Urban Morphology using Multiple Endmember Spectral Mixture Analysis." *Photogrammetric Engineering and Remote Sensing* 69:1111-1120.

Sampson, Robert J. and Jeffrey D. Morenoff. 2003. "Spatial (Dis)Advantage and Homicide in Chicago Neighborhoods." in *Spatially Integrated Social Science*, edited by M. F. Goodchild and D. G. Janelle. New York: Oxford University Press.

Stjärne, Maria K., Johan Fritzell, Antonio Ponce De Leon, and Johan Hallqvist. 2006. "Neighborhood Socioeconomic Context, Individual Income and Myocardial Infarction." *Epidemiology* 17:14-23.

Taylor, Patricia, Carla Rull Bousson, Joan Awunyo-Akaba, and John Nelson. 2002. *Ghana: Urban Health Assessment*. Washington, DC: Environmental Health Project, U.S. Agency for International Development.

Tickamyer, Ann R. 2000. "Space Matters! Spatial Inequality in Future Sociology." *Contemporary Sociology* 29:805-812.

UN-Habitat. 2003. *Guide to Monitoring Target 11: Improving the Lives of 100 Million Slum Dwellers*. Nairobi: United Nations Human Settlements Programme (UN-Habitat).

United Nations Population Division. 2004. *World Urbanization Prospects: The 2003 Revision*. New York: United Nations.

Ware, John E., Jr. 2006. "SF-36® Health Survey Update." http://www.sf-36.org/tools/sf36.shtml (accessed 2006).

Weeks, John R. 2004a. "The Role of Spatial Analysis in Demographic Research." in *Spatially Integrated Social Science: Examples in Best Practice*, edited by M. F. Goodchild and D. G. Janelle. New York: Oxford University Press.

—. 2004b. "Using Remote Sensing and Geographic Information Systems to Identify the Underlying Properties of Urban Environments." in *New Forms of Urbanization: Conceptualizing and Measuring Human Settlement in the Twenty-first Century*, edited by A. G. Champion and G. Hugo. London: Ashgate Publishing Limited.

—. 2005. *Population: An Introduction to Concepts and Issues, 9th Edition*. Belmont, CA: Wadsworth Thomson Learning.

Weeks, John R., Dennis Larson, and Debbie Fugate. 2005. "Patterns of Urban Land Use as Assessed by Satellite Imagery: An Application to Cairo, Egypt." Pp. 265-286 in *Population, Land Use, and Environment: Research Directions*, edited by B. Entwisle and P. C. Stern. Washington, DC: National Academies Press.

Wise, S., R. Haining, and J. Ma. 2001. "Providing Spatial Statistical Data Analysis Functionality for the GIS User: The SAGE Project." *International Journal of Geographical Information Science* 15:239-254.

Table 1. Characteristics of Housing Units According to Slum Criteria, Accra, 2000

Housing Characteristic	Percent of housing units
No piped water in house	56.3
House does not have a toilet connected to a sewer	73.9
Residents are not the owners	61.6
Roof and siding are not of durable material	0.9
3+ persons per room	47.8
Number of housing units	366,540

Figure 1. Map of Slum Index by EA in Accra, 2000

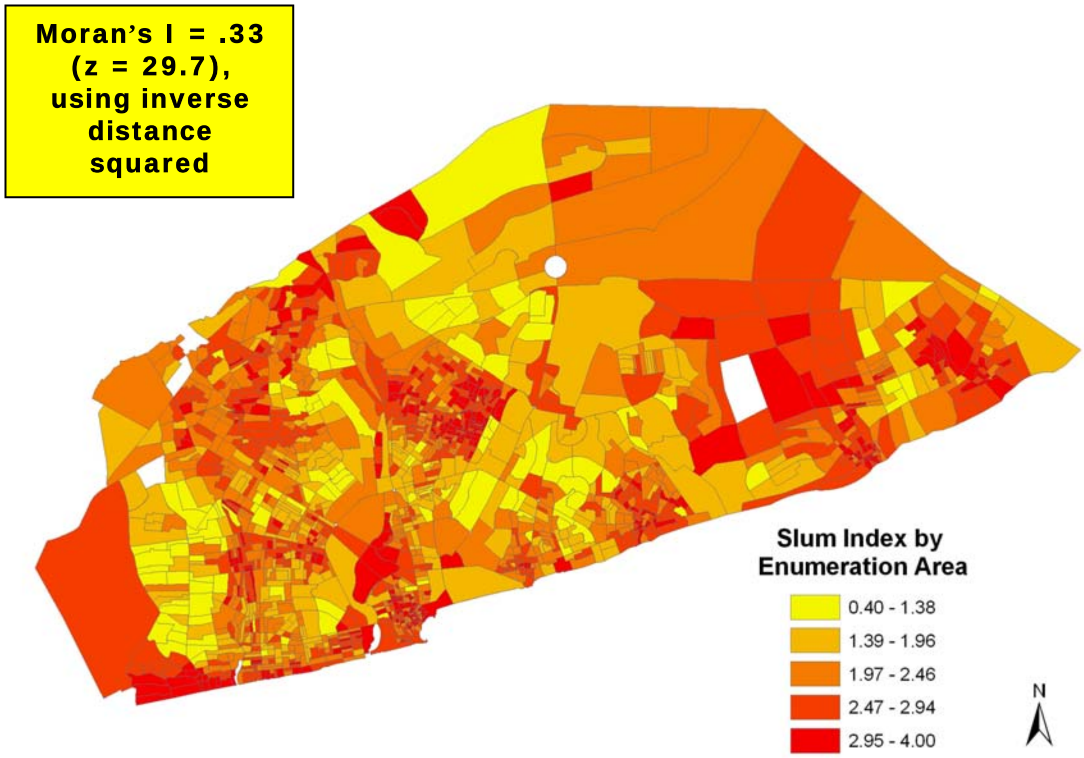

Figure 2. Map of Slum Index by Analytical Regions, Accra, 2000

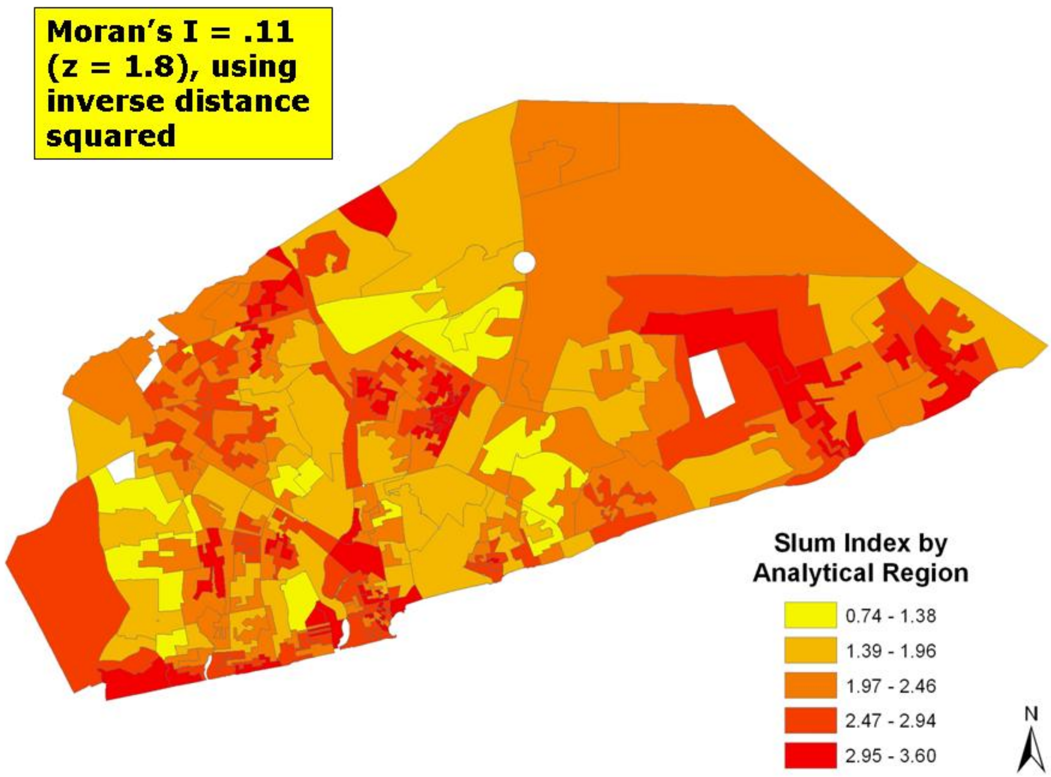

Figure 3. The top twenty best and worst ARs by Slum Index

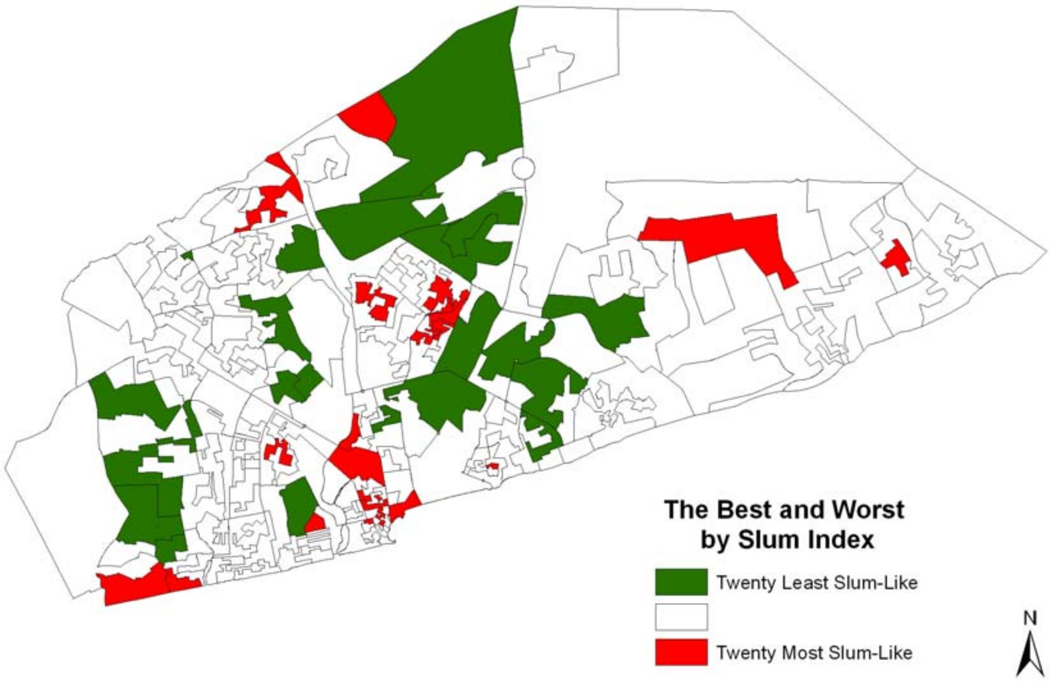

Figure 4. Health Measures by Age

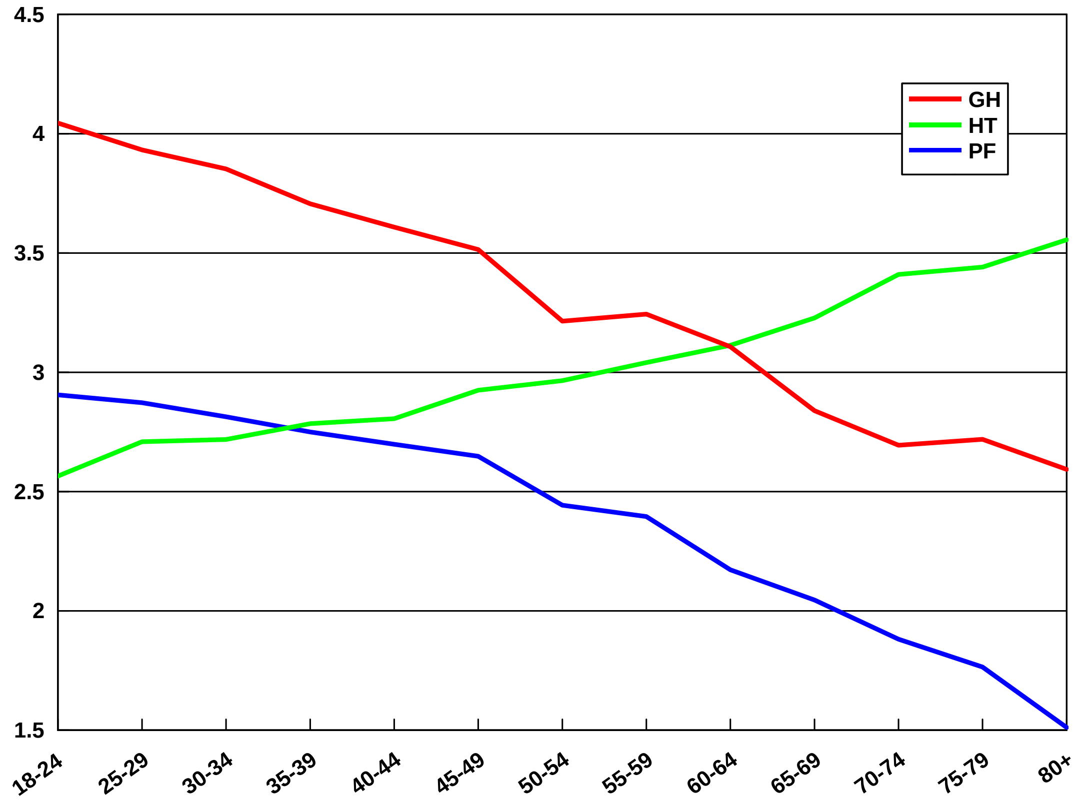

Figure 5. Age-Standardized Relative General Health Index by Analytical Region, Accra, 2003

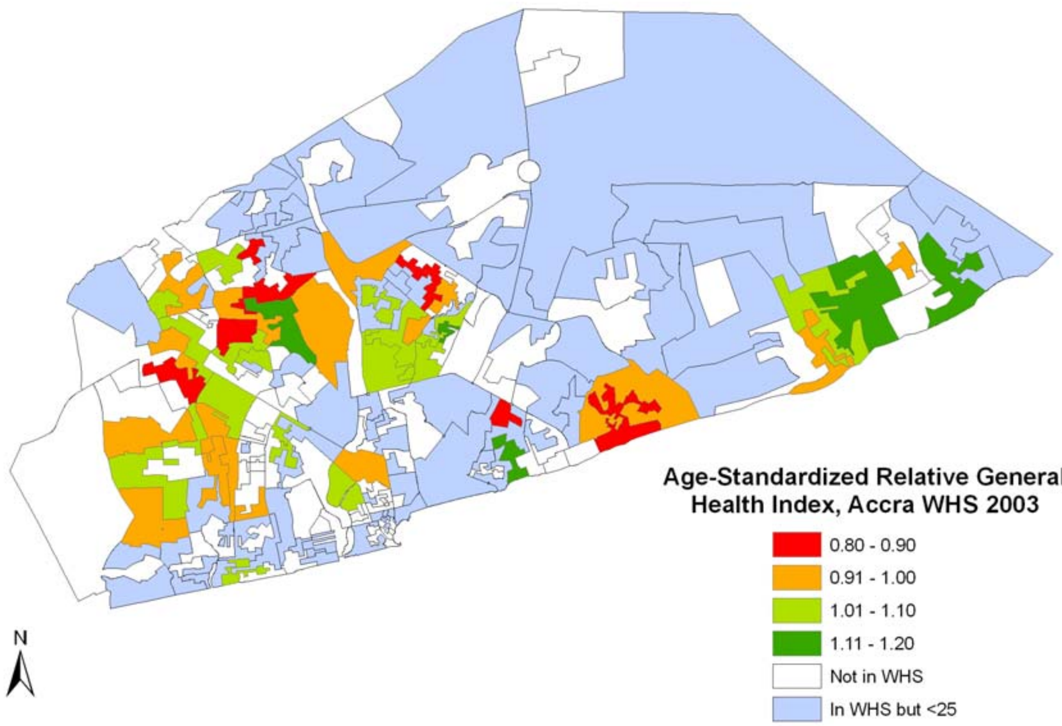

Figure 6. The top ten ARs within the WHS in terms of poorest health, and most slum-like

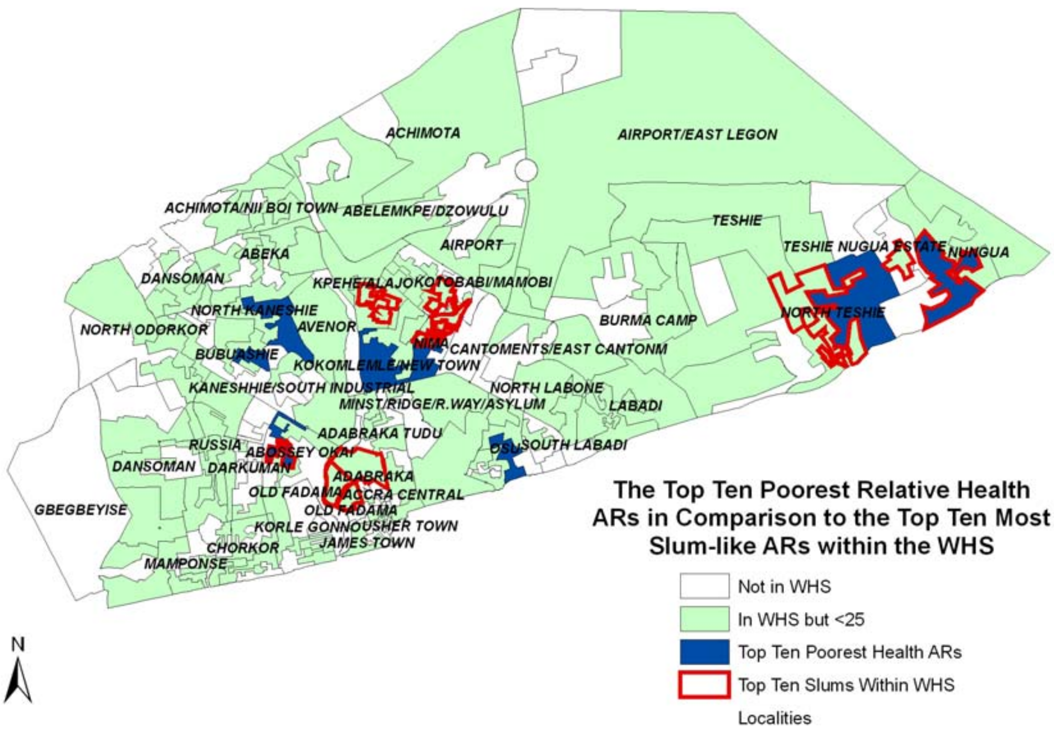

Table 2. Predictors of Individual-Level General Health Index, Accra, 2003

Variable	**Standardized Beta Coefficient**	**t-score**
Food security	.149	7.113
Household goods index	.093	4.147
Unemployed	-.079	-3.818
Not the owner of housing unit	.057	2.764
Grew up in the city, not a village	.056	2.695
Age	-2.00	-7.875
Not statistically significant:		
Education		
Marital status		
Income		
Persons per room		
No toilet		
Dependent variable = General Health Index		
R2 = .08		
N = 2199 women aged 18-49		

Table 3. Spatial Nonstationarity Test for Predictors of Individual-Level General Health Index, Accra, 2003

Variable	**Standard Error (SE) of Global Coefficient**	**2 times SE**	**Interquartile Range (IQR) of Local Coefficient**	**Ratio of IQR to 2 x SE**
Food security	.140	.280	.983	3.51
Household goods index	.034	.068	.333	4.90
Unemployed	.193	.386	1.320	3.42
Grew up in the city, not a village	.139	.278	.713	2.56
Age	.008	.016	.068	4.25

Figure 7. Spatially Varying Coefficient of Food Security as a Predictor of General Health, Women 18-49, Accra, 2003