Intra-urban Differentials in Poverty and Health in Accra, Ghana

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ABSTRACT

INTRODUCTION

Throughout most of human history, until approximately the beginning of the twentieth century, cities were less healthy places in which to live than were rural areas. However, increasing human control over disease benefited city dwellers far more than the rural population for most of the twentieth century. Yet, early in the twenty-first century there is concern that rapid population growth in the cities especially of developing countries has resulted in a new set of health inequalities. There is increasing evidence of growing disparities in morbidity and mortality within city populations. The urban elite may still have superior health levels relative to others in a country, but many urban residents probably live in less healthy environments than people in the countryside. This intra-urban variability in health has important implications not just from a human rights perspective, but from an economic perspective as well. Sustainable economic growth is a cornerstone of global policy to reduce levels of poverty worldwide and simultaneously increase the well-being of populations and reduce the pressure on the natural environment that poverty tends to produce. It is urban economies that almost always lead the way in development, and it is in the urban areas of developing nations where the highest rates of population growth are being experienced. The United Nations projects that the majority of the population in developing countries will be living in cities by the middle of this century, and the health of that population is a key ingredient in the sustainability of economies. To the extent that an understanding of the patterns of intra-urban health can lead to policy directed to mitigate and ameliorate inequalities, it will increase the chance that urban residents and the urban economy will be healthier in the future.

One of the biggest obstacles facing researchers studying intra-urban health levels is the general lack of a database that can provide the kinds of information necessary to understand the interlinkages between health and the places where people are living in cities. In the first place, most research uses data aggregated for categories such as slum/not slum or central city/suburbs without reference to where those places are located, and thus without an ability to specify the nature of intra-urban differences. For this, we need data at the neighborhood level. Data collected on the ground from sources such as censuses, vital statistics, and surveys can provide some of the basic information on health levels by neighborhood or region within a city only when they are all geocoded and combined into a single geographic information system (GIS). But even that set of data is not sufficient to describe the character of the built and natural environments that comprise the physical properties of a neighborhood—properties that are potentially closely related to levels of morbidity and mortality. In this paper we assess the value of using data derived from remotely sensed imagery to describe and differentiate the built and natural environments in ways that can be linked up to, and potentially serve as proxy indicators for, health levels within an urban setting. Thus, in this paper we explore and develop the use of remotely sensed imagery and geographic information systems as tools for improving and advancing our understanding of intra-urban levels of health.

BACKGROUND

For the past several decades it has been taken largely for granted that urban populations have lower levels of morbidity and mortality than do rural populations. While this urban superiority is not challenged in general terms, there is ample evidence that significant health disparities and inequalities exist within cities of more developed countries (see, for example, Mitchell *et al.* 2002; Rytkonen *et al.* 2001), and there is increasing evidence that residents in city slums in developing nations may well have health levels that are worse than those experienced by people living in rural areas of the same nation (Fry, Cousins, and Olivola 2002; Haddad, Ruel, and Garrett 1999; Menon, Ruel, and Morris 2000; Timaeus and Lush 1995). Gould (1998) has in fact argued that in sub-Saharan Africa the narrowing of the rural-urban health gap is partly a result of the deterioration of health levels in cities. In sub-Saharan African countries, with the fastest national rates of population growth in the world, we are finding the fastest growth rates to be in urban places. According to data from the United Nations Population Division (2004), the urban populations of this region grew at a rate of 5.8% per year between 1990 and 2000, doubling the urban population every 12 years. Sub-Saharan Africa is still viewed as a predominantly rural region but with such growth rates, very soon the majority of the region's people will live in urban places, many of them in mega cities like Lagos, Ibadan and Kinshasa, or large metropolitan areas such as Accra, the capital of Ghana. This growth is not evenly spread within the urban areas, however. In some instances it is concentrated in slum areas within the older city limits while in other cases it is distributed around the expanding periphery. Either way, the rates of local population growth far outstrip the capacity of city or local governments to keep pace with the provision of education, housing, water, sanitation and other social services. International pressures, under the rubric of structural adjustment or neo-liberal economic policies, have exacerbated the situation for the urban poor where responsibilities for the provision of education and health facilities have been devolved to local levels of governments with slender budgets and weak technical capacities to respond. In addition, many services, especially health services, are now offered on a "cash and carry" basis with some statutory allowances for fee exemptions by the poor. These allowances are in practice often unpaid. The net effect is that urban poverty is almost certainly deepening, both in older slums and in newly settled areas with rapid population growth, resulting in large urban health disparities in the city. Thus, it is likely that it is now in cities and not in the rural areas where we can observe the starkest contrast in health.

With poor water and sanitation, the urban environment is degrading quickly as people make what adaptations they can to these new challenges. In Accra as in Sao Paolo (Brazil), the subjects of recent analyses, it is estimated that the ultimate result of inadequate sanitation leaves a situation in which poor children in slum and poorer neighborhoods are nearly three times as likely to have diarrhea, cholera, and other enteric diseases, as are children of wealthy families with better sanitation services (Songsore and McGranahan 1998; Timaeus and Lush 1995). Further, when electricity is unavailable, households resort to charcoal for cooking with all the attendant risks of using this fuel in crowded quarters. These risks include not only the risk of fire, but also the more pervasively long-term risk of poor health from the effects of the locally created air pollution as a consequence of local concentrations of particulates and toxic oxides of heavy metals in crowded household environments. In Accra in 2000, 58% of households cooked with charcoal. Without electricity, the monthly costs of lighting for the poor, whether candles, oil lamps or domestic generators, are several times that of household connected to electricity lines. Disposal of solid waste is haphazard, polluting waterways and public roads, leading to invasion of rodents and other vermin. Altogether, the combination of rapid population growth and resource-poor, dense urban environments provides a new challenge for the understanding and then the resolution of the problems faced not just by urban Africans, but by urban dwellers throughout the developing world.

Sustainable development in Africa, as elsewhere in the world, requires that future population growth be absorbed by cities because only in or near cities are increasing numbers of people likely to find the kind of employment opportunities that will permit them to rise above and stay above the poverty level. At the same time, sustainable development requires a healthy population, because only a healthy population can improve levels of economic productivity necessary to lift an economy out of widespread poverty. The conjunction of these two propositions means that sustainable development in the context of continued population growth demands an urban environment that promotes improved levels of health services as well as of health equity among its residents. Because of the very limited resources available to most nations of sub-Saharan Africa, urban health promotion in the future will demand ever more efficient, parsimonious use of scarce resources. It is thus important to identify the minimum threshold requirements of adequate levels of health in the urban environment, so that resources can be devoted to bringing every neighborhood up to at least that level. Since the world's population is becoming increasingly urban, urban inequalities in health pose a significant threat to the well-being of a growing number of people globally. If we are to mitigate these disparities, we must substantially improve our understanding of health within cities—of intra-urban variability in 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 <u>place</u>, 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 of waste, accessibility 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, Mitlin, and Satterthwaite 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 clearly suggest that the higher one's position in society, the longer he or she is likely to live. 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, electricity) that can improve health levels. Overall, then, 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."

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 sociodemographic 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 the remotely-sensed imagery enters the scene, and where we propose to explore the large gaps that currently exist in our knowledge of the relationship between the urban environment and health.

In the past several years there has been at least a minor explosion in the literature on the use of remotely sensed imagery in the public health field. This is perhaps best exemplified by the volume on "Remote Sensing and Geographical Information Systems in Epidemiology (Hay, Randolph, and Rogers 2000), by a special issue of the journal Acta Tropica in 2001, and by a special issue of the journal Photogrammetric Engineering and Remote Sensing in 2002. Without exception, however, these studies have examined only the natural environment in terms of habitat for infectious disease vectors, or in terms of pollutants as potential carcinogens. These are important studies, without any question, but not a single one of them addresses the issue of variability in human health in urban places.

In the past several years there has also been an increasing literature on the use of remotely sensed imagery to characterize the habitat of humans. Among the more influential of these have been the volume on People and Pixels: Linking Remote Sensing and Social Sciences (Liverman *et al.* 1998), and the volume on Remote Sensing and Urban Analysis (Donnay, Barnsley, and Longley 2001). We have also made contributions to that literature (Rashed and Weeks 2003; Rashed *et al.* 2003; Rashed *et al.* 2005; Weeks 2004; Weeks *et al.* 2000; Weeks *et* *al.* 2004; Weeks, Larson, and Fugate forthcoming)}. None of these studies, however, has attempted to link the characteristics of place, as derived from the imagery, to the levels of morbidity and mortality that are experienced by the people in those places.

RESEARCH QUESTIONS

In this paper we focus our attention on an ecological analysis at the neighborhood level, defining neighborhoods rather broadly as localities. Since income inequalities are shown in the literature to be among the strongest predictors of inequalities in health, we examine here the spatial relationship between poverty and health. Specifically, we seek to answer the following questions: (1) Is there a spatial pattern of disparities in health levels in Accra? (2) Is there a spatial pattern of poverty in Accra? (3) If spatial disparities in health exist, and patterns of poverty exist, are the latter predictive of the former? (4) And, if these patterns exist, can they be estimated using data from satellite imagery?

STUDY SITE

The study site is Accra, the capital of Ghana, which is located on the coast of the country, facing the Gulf of Guinea (see Figure 1), which is contiguous to the Atlantic Ocean. The specific area chosen for this study is the administrative unit known as the Accra Metropolitan Area. Responsibility for the health, welfare and governance of this population rests with the Accra Metropolitan Assembly (AMA). The metropolitan area comprises 1.7 million people and 365,550 households according to the March 2000 census. Anticipating possible interventions after the study has been completed, it was decided that it would be advantageous to work within one administrative district--the Accra Metropolitan Area governed by the Accra Metropolitan Assembly--rather than the larger 3-district area known as Greater Accra. There is considerable socio-economic and cultural diversity within this area as work by Songsore and others have demonstrated (Songsore and Goldstein 1995; Songsore and McGranahan 1998; Songsore and McGranahan 1993).

FIGURE 1 ABOUT HERE

Ghana provides an ideal site for this research for two reasons. First, the researchers from Ghana with whom we are associated in this project have already conducted preliminary studies suggesting that there are important inequalities in urban health in Ghana in general and in Accra more specifically (Songsore and McGranahan 1998; Stephens *et al.* 1994; Taylor *et al.* 2002). The plight of poor households in Accra has been the subject of some important previous work. An analysis of existing health data and a household survey by Songsore and Goldstein (1995) revealed the stark contrasts between the better off neighborhoods and the slum areas of the city. This work began the description of the urban ecology of the city. Some new historical work has revealed the distinctiveness of the city's structure, owing more to the continuing urban tradition of Greater Accra than to any imposition of a new layout in colonial times as was the case with other major cities in East Africa. More recently, there have been several studies of urban planning attempting to find ways to improve the provision of basic services to the poorer areas of the city. Meanwhile, population growth has continued unhindered, with Greater Accra growing by nearly 4% per year between the 1984 and the 2000 censuses.

DATA AND METHODS

Women's Health Survey Data

We draw first and most importantly from the Women's Health in Accra survey of 2003 (WHS), a sample of 3,200 women aged 18 and over living in the Accra Metropolitan Area. Data were collected by one of the co-authors between April and July 2003 and provide self-report health data, data from a clinical examination and laboratory work as well as data on the household's facilities matched to the census of 2000. Data were collected from a multi-stage probability cluster sample of 200 of the 1,724 EAs in Accra, and data for this analysis have been aggregated to the locality level, since all 43 localities were incorporated into the WHS.

Census Data

We also draw upon a 10 percent sample of households from the 2000 Census of Population and Housing of Ghana created for us by Ghana Statistical Service for the Greater Accra Metropolitan Area. Variables that are available to us from the census are shown in Table 1. An examination of the variables shows the concern that the government has about local-level determinants of health, because there are several questions about housing type, connection to water and sewerage, bathroom facilities, and kitchen type/cooking methods, all of which are suspected of having health correlates.

TABLE 1 ABOUT HERE

With the assistance of boundary descriptions from the Ghana Statistical Service and a high resolution Quickbird satellite image from Digital Globe, we were able to produce a digital map (shapefile) of all of Accra's enumeration areas. However, as noted above, because of the sampling strategy employed for the WHS, we have aggregated the data up to the locality level, which represents clusters of enumeration areas, as defined by Ghana Statistical Services. There are 43 localities within Accra and our analysis will focus on them because, unfortunately, there are no administrative units between the 1,724 enumeration areas and the 43 localities, each of which contains an average of 40 enumeration areas.

Remotely Sensed Data

Remotely sensed data represent images taken from a distance. Typically they are acquired from some kind of aircraft, especially orbiting satellite spacecraft. A basic premise of remote sensing is that the earth's features and landscapes can be discriminated, categorized, and mapped according to their spectral characteristics. The nuclear reactions of the sun produce electromagnetic energy which is propagated by electromagnetic radiation at the speed of light through space and reaches the earth practically unchanged. As it passes through the atmosphere, part of it is absorbed and the other part is reradiated as thermal energy. 'Passive' remote sensing systems operate by measuring the energy which is reradiated or reflected from the object of interest back to the remote sensor (Lillesand and Kiefer 2000). Images are generally characterized according to resolution and bandwidth. Resolution refers to the size of the image captured by the smallest pixel (picture element) in the image. Thus, a 1-meter image means that the smallest pixel in the image is 1 meter by 1 meter in size on the ground. One meter images tend to be the highest resolution data available from commercial satellites. More detailed imagery typically requires the use of aerial photography. Images also vary according to the bandwidth of energy captured by the image, ranging from panchromatic (gray scale) to multi-spectral (visible red, green, blue, and near-infrared bands, as well as shorter-wave infrared bands that are not visible to the naked eye), and thermal bands that detect surface temperature rather than brightness.

In order to appreciate the value of remotely sensed imagery for analysis of urban places, it is crucial to understand exactly what it is that can be extracted from such images. The image itself is composed of a mosaic of individual pixels from which information has been captured for an area on the ground that is equal to the resolution of the image. The information recorded for each image depends upon the particular sensor, but typically the brightness within a given band is assigned a digital number. The combination of digital numbers of reflectance across the different bands of light represents the spectral signature of that pixel. Each spectral signature is associated with a particular type of land cover (e.g, vegetation, soil, water, impervious surface). The more bands there are in a sensor the more detailed the land cover classification can be. 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 resolution imagery will have more bands than higher resolution imagery. Our team's experience working with imagery for urban places suggests thus far that higher 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.* 2003; Weeks, Larson, and Fugate forthcoming). This is because the built environment is, obviously, configured differently than the natural environment and 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; and (2) the spatial <u>configuration</u> of the pixels identified with each land cover class.

The first task in using the data recorded for each pixel is thus to determine what type of land cover is represented by that pixel. Does it represent vegetation (and perhaps a specific type of vegetation), or bare soil, water, shade, or an impervious surface (such as the roofing material of a building or the asphalt or cement of roads)? These are the basic building blocks of the natural and built environment and each type of land cover is associated with a particular spectral signature. The higher the resolution (i.e., the smaller the pixel size) the more accurately we are able to classify a pixel because it is more likely that the pixel will include only one type of land cover. On the other hand, for lower resolution images, the more likely it is that the pixel will represent a mixture of different land covers, forcing us to make decisions about how appropriately to classify the image. Once we have classified the image according to land cover (the physical property as seen from the air), we are in a position to use information from other sources to make inferences about the way in which the land is being used (which is a socially derived category). From this process we are able to create variables describing the environmental context of a specific place. Thus, when we aggregate the land cover data for all pixels in an area (such as a census tract) we have a measure of the area's land cover <u>composition.</u>

In classifying the data by land cover class, we have previously employed Ridd's (1995) V-I-S (vegetation, impervious surface, soil) model to guide a spectral mixture analysis of medium-to-high resolution multi-spectral images for Cairo for 1986 and 1996, in a manner similar to methods used by Phinn and his colleagues for Brisbane, Australia (Phinn *et al.* 2002), and by Wu and Murray (2003) for Columbus, Ohio. The V-I-S model views the urban scene as being composed of combinations of three distinct land cover classes. An area that is composed entirely of bare soil would be characteristic of desert wilderness, whereas an area composed entirely of vegetation would be dense forest, lawn, or intensive fields of crops. At the top of the pyramid is impervious surface, an abundance of which is characteristic of central business districts, which are conceptualized as the most urban of the built environments.

Methods

Our overall methodology is as follows: (1) summarize data on health levels from the WHS at the locality level; (2) summarize data on poverty from the census at the locality level; (3) summarize data from the imagery at the locality level; (4) run regression models to assess the extent to which measures of poverty can predict health levels in each locality; (5) assess data from the imagery for their ability to approximate levels of poverty in each locality; and (6) use data from the imagery as proxies for poverty to assess their ability to predict health levels at the locality level.

RESULTS

Spatial inequalities in health

The Women's Health Survey focused on women of reproductive age, but oversampled older women. In order not to bias the results by locality in terms of potential large differences in age structure, we restrict our analysis to women aged 18-54. We examined a wide range of potential health indicators, exploring the distributions of each in order to find those that exhibited sufficient variable to be indicative of inequalities. The final list of candidate variables included the following: (1) self-reported overall level of health, standardized through the use of vignettes based on the WHO model; (2) self-reported limitations on vigorous activity during the four weeks prior to the survey, dichotomized into those with at least some limitations and those with no limitations; (3) self-reported bodily pain, dichotomized into those with mild to very severe pain and those with no pain; (4) self-report of every having been diagnosed as having malaria; and (5) the number of other self-reported diagnoses besides malaria.

The overall values for these measures are summarized in Table 2. On a five-point scale from one (best health) to 5 (worst health), the average is 2.5, 42.3 percent of women reported some limitations to vigorous activity, 38.1 percent reported mild to very severe bodily pain, 50.1 percent of women There are, of course, significant correlations among these variables, and we assessed the relative importance of them as a group through the use of principal components analysis. As shown in Table 2, the variables produced two factors with eigenvalues greater than

0.9, together explaining 72 percent of the overall variance among the variables. The most important of the variables, clustering together, are mean self-reported health and limits to vigorous activity. The existence of bodily pain is an important second dimension, and the malaria diagnosis is linked a little more closely to that than to the first component, although it is not clearly in either component. Similarly, the number of diagnoses other than malaria are split in their association with the two components.

TABLE 2 ABOUT HERE

Figures 2 through 6 show that there clear, but differing, spatial patterns with respect to health levels in Accra. Figure 2 reveals the pattern for self-reported health. Moran's I, which measures the extent of spatial autocorrelation (non-randomness in the average level of self-reported health by locality) is statistically significant beyond the .05 level. The percentage of women by locality with some limits to vigorous activity show a similar spatial pattern, which is also statistically significant non-random. In both cases the poorest levels of health are found in the historically oldest sections of the downtown area. The spatial pattern with respect to bodily pain is slightly different. The percent of women diagnosed with malaria shows yet a different pattern in that it is highest in the center section, regardless of proximity to the coast, and lower on the east and west peripheries. This suggests a geographic pattern that may be indicative of water patterns for mosquito habitat. The pattern for all other diagnoses seems to suggest that proximity to Korle Bu Teaching Hospital increases the likelihood of being diagnosed with disease.

FIGURES 2 THROUGH 6 ABOUT HERE

Spatial Inequalities in Poverty

We used data from the census, rather than from the WHS, to measure poverty, but we restricted the analysis to data for women aged 18-54 in order to be consistent with the population for which we had measured health levels. After doing exploratory statistical analysis on a wide range of potential predictors of levels of poverty in each locality, we narrowed the choice to the following variables: (1) percent of the population with less than a secondary education (highly correlated with all measures of education, which is correlated generally with income); (2) percent of economically active women of reproductive age who are working in the informal sector; (3) the mean number of rooms per household dwelling; (4) percent of homes without their own water closet; and (5) percent of households in which charcoal is the fuel for cooking. As can be seen in Table 3, these variables all combined into a single factor when we applied principal components analysis. Given the large size of all factor coefficients, we used the factor score as a measure of poverty/socioeconomic status of each locality.

TABLE 3 ABOUT HERE

The spatial pattern of poverty by locality can be seen in Figure 7. While in general the older sections of Jamestown and Ushertown have the highest poverty (and the worst health levels), the spatial pattern of poverty is not exactly the same as any of the health indicators. Nonetheless, there is a clear spatial pattern, as evidenced quantitatively by the high and statistically significant Moran's I.

FIGURE 7 ABOUT HERE

Does poverty predict health at this spatial scale of aggregation?

Although there are significant spatial patterns to health indicators, and significant spatial patterns to poverty, the latter is not generally predictive of the former, as can be seen in Table 4.

The highest ordinary least-squares regression of poverty was found with respect to the self-reported score on overall health. The data in Table 4 show, however, that variability in poverty from locality to locality was able to explain only 11% of the variation in health levels from locality to locality. Although this was statistically significant, it is obviously not as high a level as we would have expected. Also, we found that there was no evidence of spatial autocorrelation in the residuals, indicating that there was no underlying spatial pattern that was not captured by the regression model.

What is the spatial pattern of data from the satellite imagery?

In this paper we report only the analysis of proportional abundance of land cover classes drawn from our classification of the multispectral Quickbird image of Accra. Note that the image does not cover all of the study area, so our analysis is confined to 39 of the 43 localities (and for some of the eastern localities, the imagery covers only part of the area, but we summarized those data nonetheless). In contrast to work done in arid climates such as Egypt, tropical areas such as Accra have significant vegetative canopies that hide the underlying land cover on the ground. In particular, it is not obvious in many areas how much land area might be devoted to impervious surface or bare soil underneath the canopy. However, we also found that there is considerable and reasonable variability in vegetation that may serve as a useful proxy for what is happening on the ground. We used two measures of vegetation—the proportional abundance of land area within each locality for which the land cover class was identified as vegetation, and then a more nuanced measure of vegetation known as the normalized difference vegetation index (NDVI). The spatial patterns of both are quite similar and are shown in Figures 8 and 9.

FIGURES 8 AND 9 ABOUT HERE

Can the Imagery Variables Be Used as Proxies for Poverty and/or Health?

The data in Table 5 show that both measures of vegetation are highly but inversely correlated with poverty—the less vegetation in an area, the higher is the poverty level. Or, put another way, it is in the wealthier areas that there is the greatest amount of vegetation per area. The proportional abundance of vegetation and the NDVI both explain nearly two-thirds of the variability from locality to locality in the poverty index.

TABLE 5 ABOUT HERE

However, we have already seen that poverty is not as good a predictor of health indicators as we had anticipated, so a proxy measure of poverty is unlikely to be a good proxy measure of health indicators. This is born out by the regression results shown in Table 6, where it can be seen that neither measure of vegetation is a statistically significant predictor of self-reported health (or any of the other health indicators—data not shown).

TABLE 6 ABOUT HERE

DISCUSSION AND CONCLUSIONS

We have shown that there are very discernible spatial patterns of health inequalities in Accra, and similarly there are very clear spatial pattern to poverty. However, contrary to our expectation, at this ecological level of analysis, poverty was not very highly predictive of health. We also found that using data from the satellite imagery showed that a lack of vegetation is associated with poverty, but since poverty levels at the locality level are only weakly associated with health, the lack of vegetation is similarly not very predictive of poor health.

Our next step is to see if the context of poverty at the EA level (rather than the larger locality unit level) helps to explain variability in health at the individual level, based on a multi-level (hierarchical) model.

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Figure 1. Study Site of Accra, Ghana

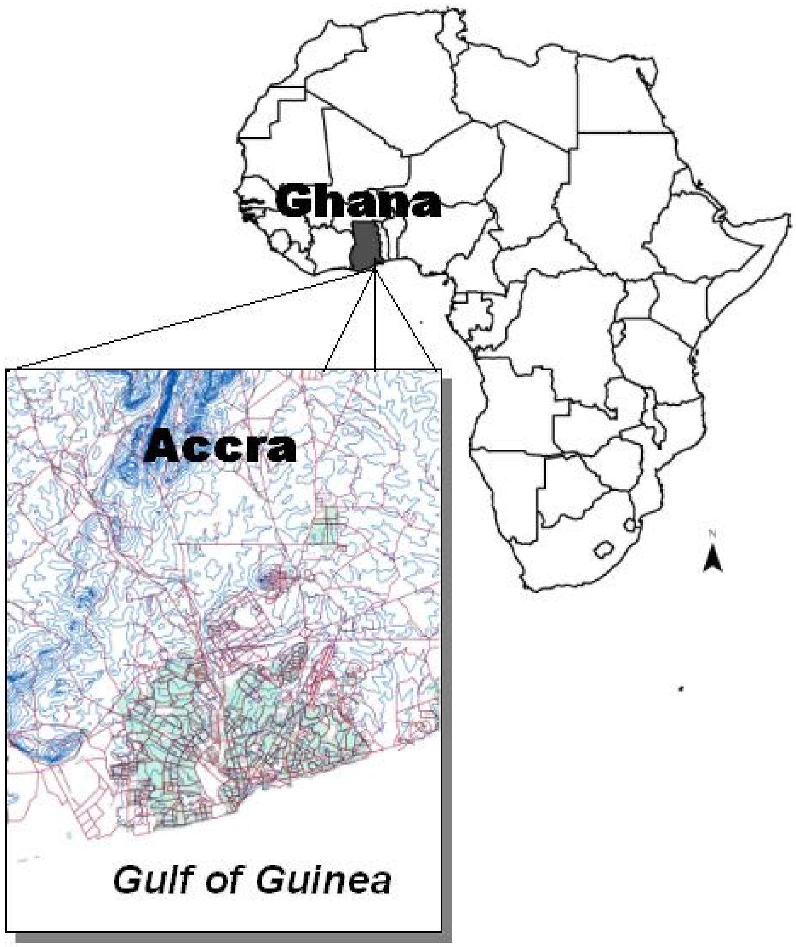

Table 1.- Variables Available from the 2000 Census in Ghana

Type of Residence
Relationship to Head
Sex
Age
Nationality (Ghana/other ECOWAS/African not ECOWAS/not African)
Ethnicity (see Table 2 for detail)
Birthplace (born here/born elsewhere)
Birthplace, if outside of Accra
Usual Residence
Residence in 1995
Religion
Marital Status
Literacy
Ever Attended School
Highest Level of Schooling
Highest Grade (in years of schooling)
Labor Force Status
Days worked
Hours worked
Occupation
Industry
Employment Status
Employment Sector
Male Children Ever Born
Female Children Ever Born
Male Children Surviving
Female Children Surviving
Children Born Last 12 Months
Total Children Ever Born
Dwelling type
Outer wall material
Floor material
Roof material
Tenure
Owner
Rooms
Bedrooms
Lighting source
Water source
Toilet Facilities
Ownership of Toilet
Cooking source
Kitchen type
Bathing type
Solid waste disposal method
Waste water removal method

Table 2. Health Levels Among Women Aged 18-54 in Accra, Ghana

Variable	Overall average:	Overall Standard Deviation	Factor 1 Score	Factor 2 Score
Mean self-reported Health	2.5	0.34	.867	.093
Limits to vigorous activity	42.3%	15.9	.881	.165
Mild to very severe bodily pain	38.1%	14.6	.047	.934
Malaria diagonosis	50.1%	19.6	.516	.608
Mean n of diagnoses	0.3		.585	.452


Mean Self-Reported Health (5 is worst; 1 is best) by Locality
Moran's I= .40; Z(I)=2.14 at 1500m

Figure 2

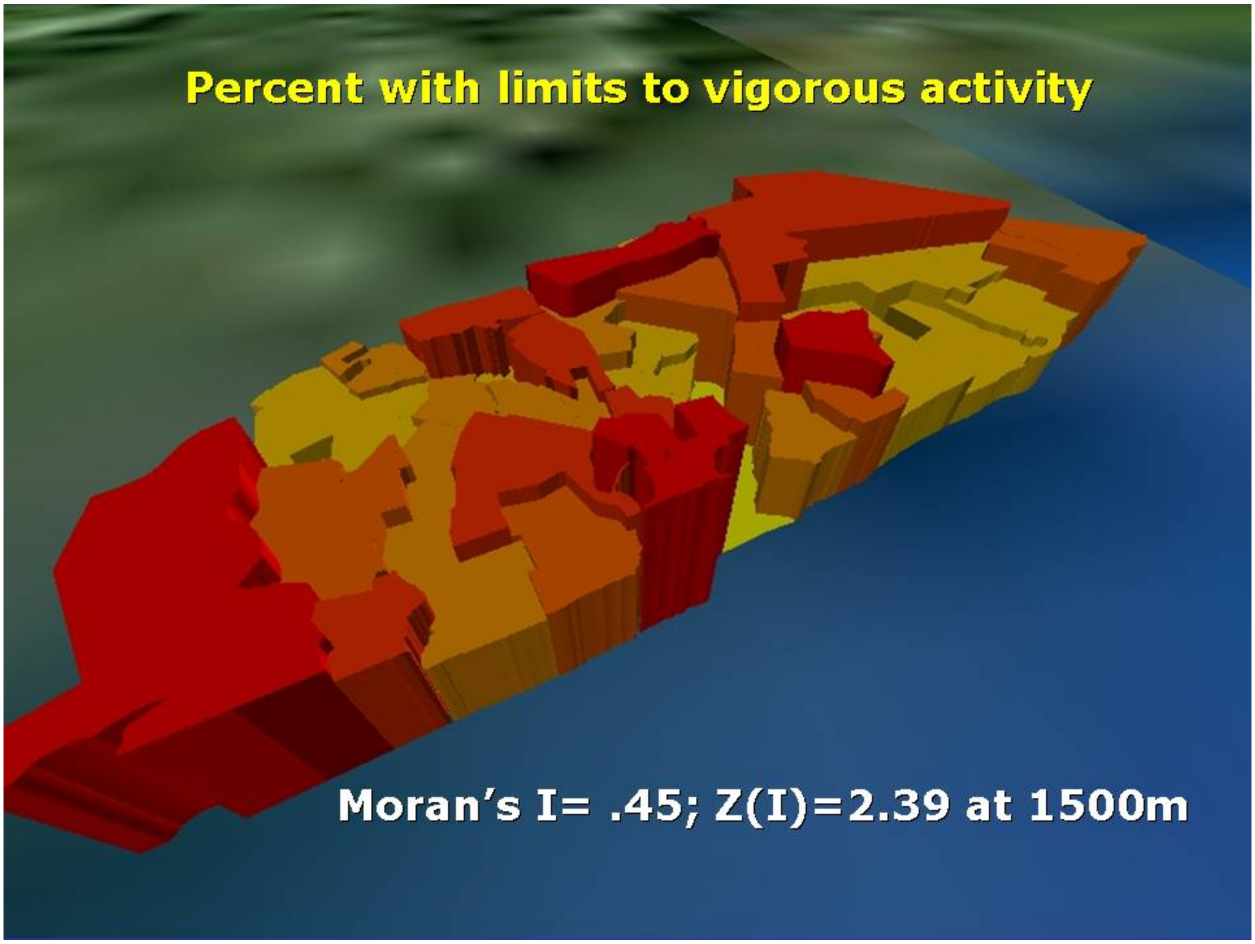
Percent with limits to vigorous activity
Moran's I= .45; Z(I)=2.39 at 1500m

Figure 3

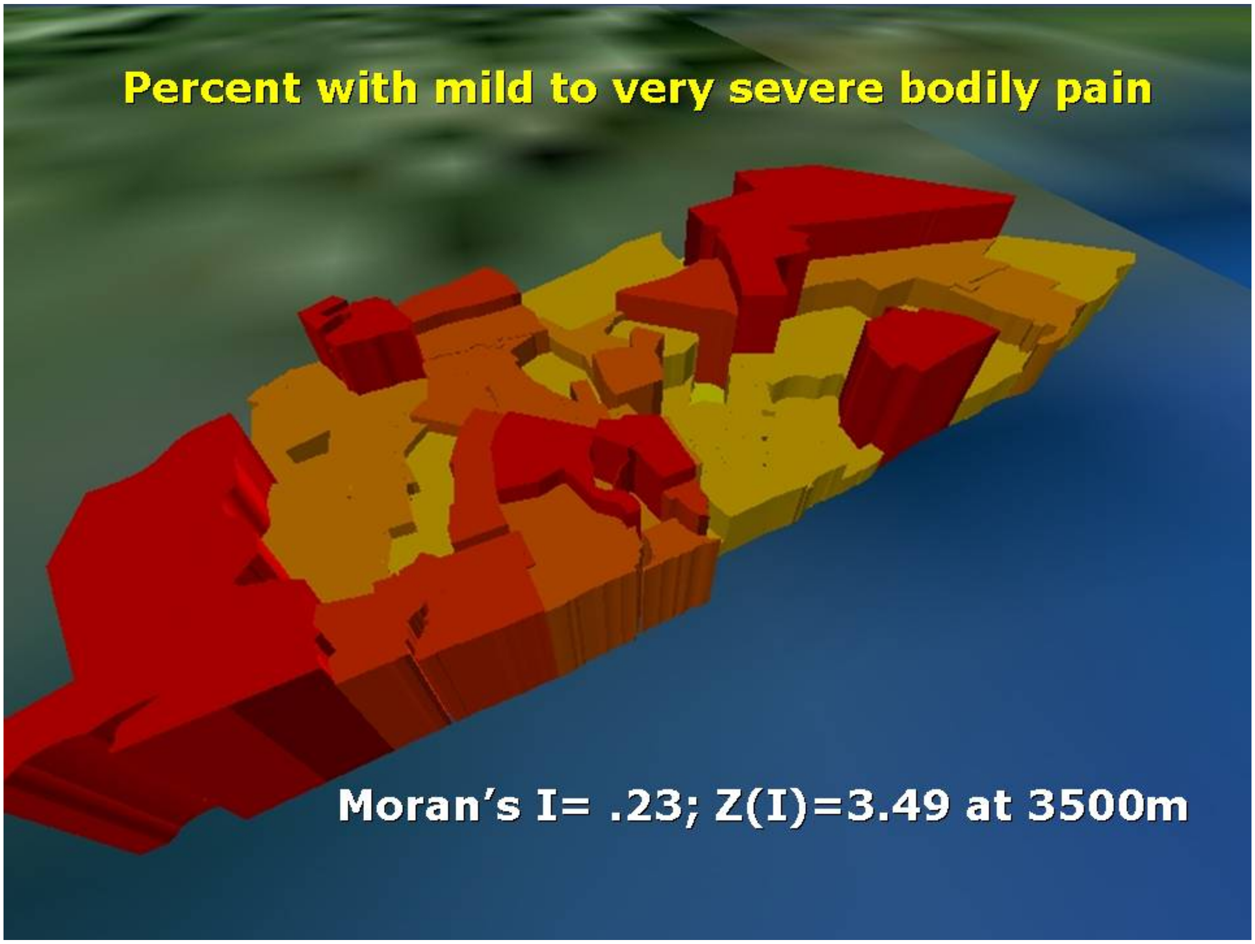
Percent with mild to very severe bodily pain
Moran’s I= .23; Z(I)=3.49 at 3500m

Figure 4

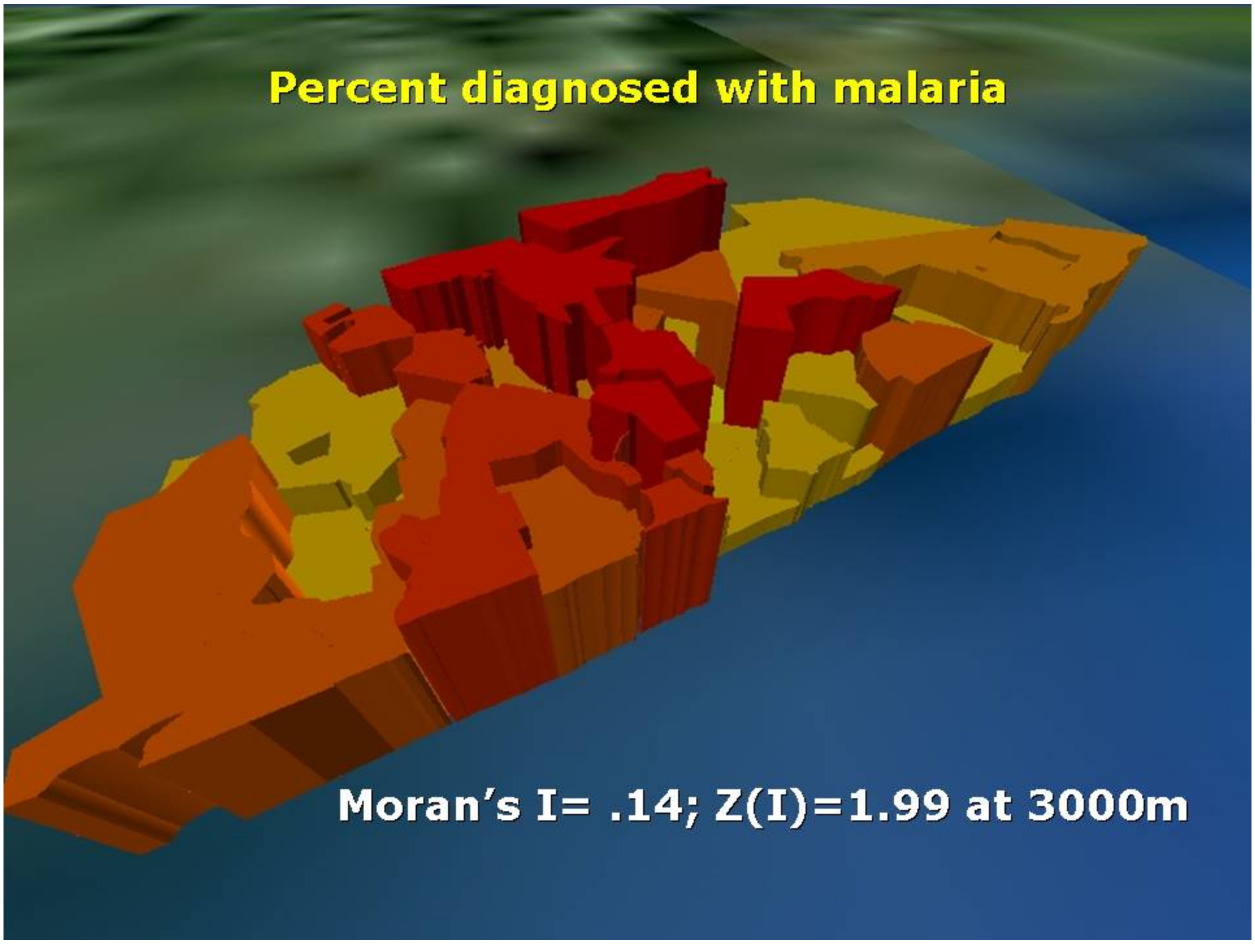

Figure 5

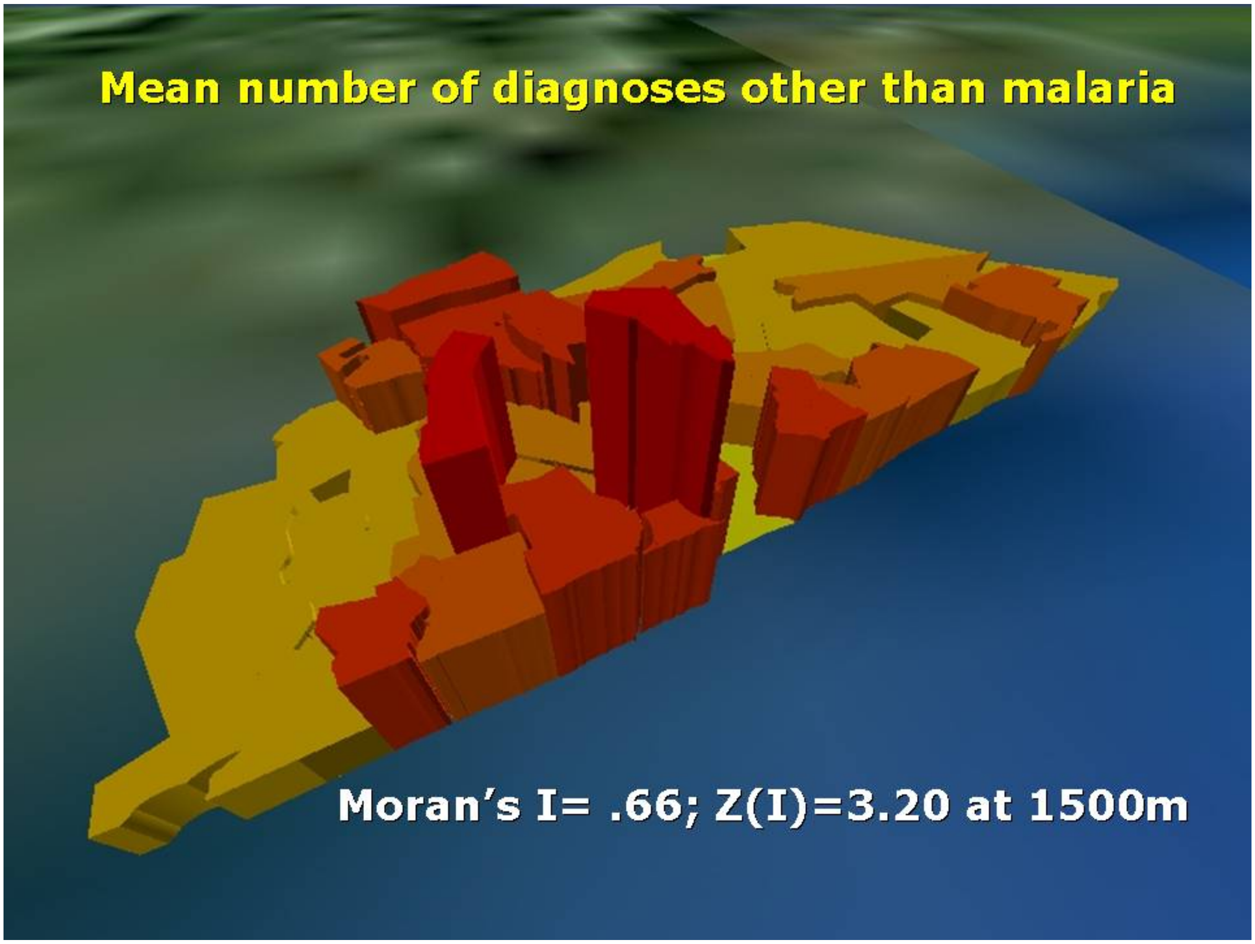
Mean number of diagnoses other than malaria
Moran's I= .66; Z(I)=3.20 at 1500m

Figure 6

Table 3. Measures of poverty by locality, Accra, Ghana

Variable	Overall average:	Overall standard deviaton	Factor 1 Score= poverty/SES
Pct with less than secondary educ	27.8	9.6	.858
Pct working in informal sector	64.8	8.7	.838
Mean N of rooms	2.5	0.52	-.879
Pct w/o WC	69.6	19.8	.938
Pct cook w/charcoal	60.0	15.3	.961

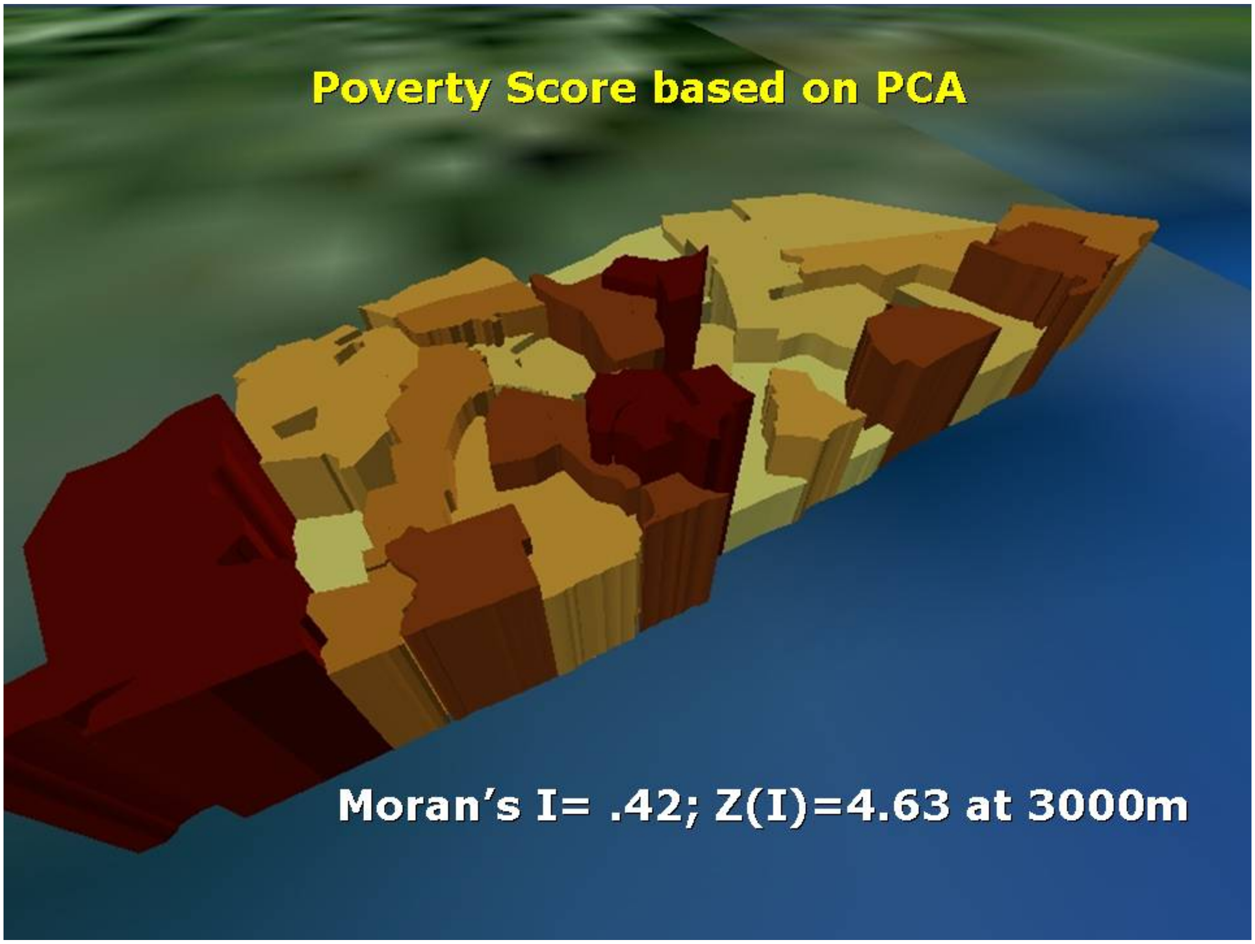

Figure 7

Table 4. Regression of Poverty on Health Indicators

Variable	Standardized Beta Coefficient	t-score
Poverty Score	.361	-2.42

Dependent variable is self-reported health score

R = .361

Adjusted R2 = .108

No outliers; little evidence of heteroscedasticity; Moran's I for residuals = .33; Z(I) = 1.69 at 1500m

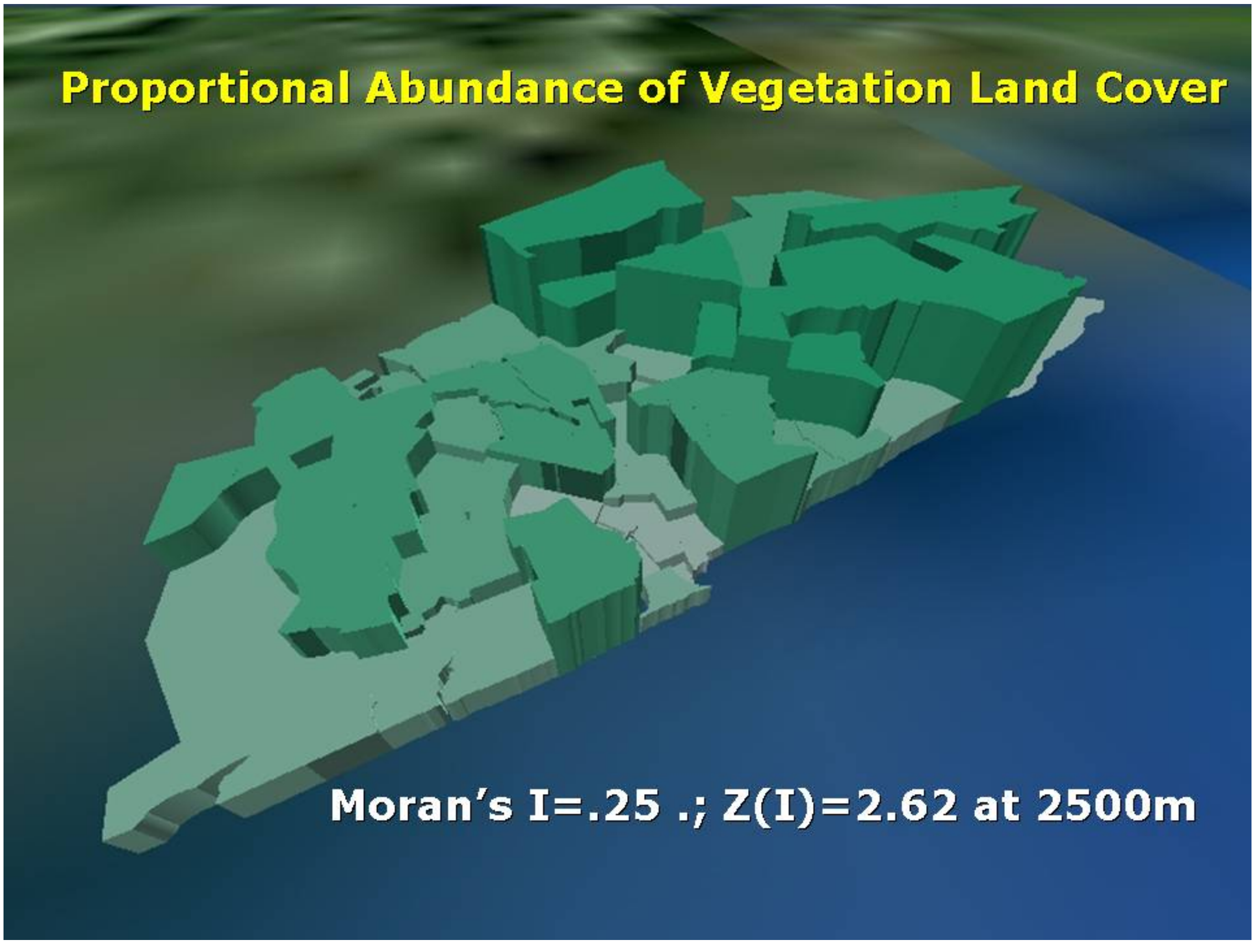
Proportional Abundance of Vegetation Land Cover
Moran's I=.25 .; Z(I)=2.62 at 2500m

Figure 8

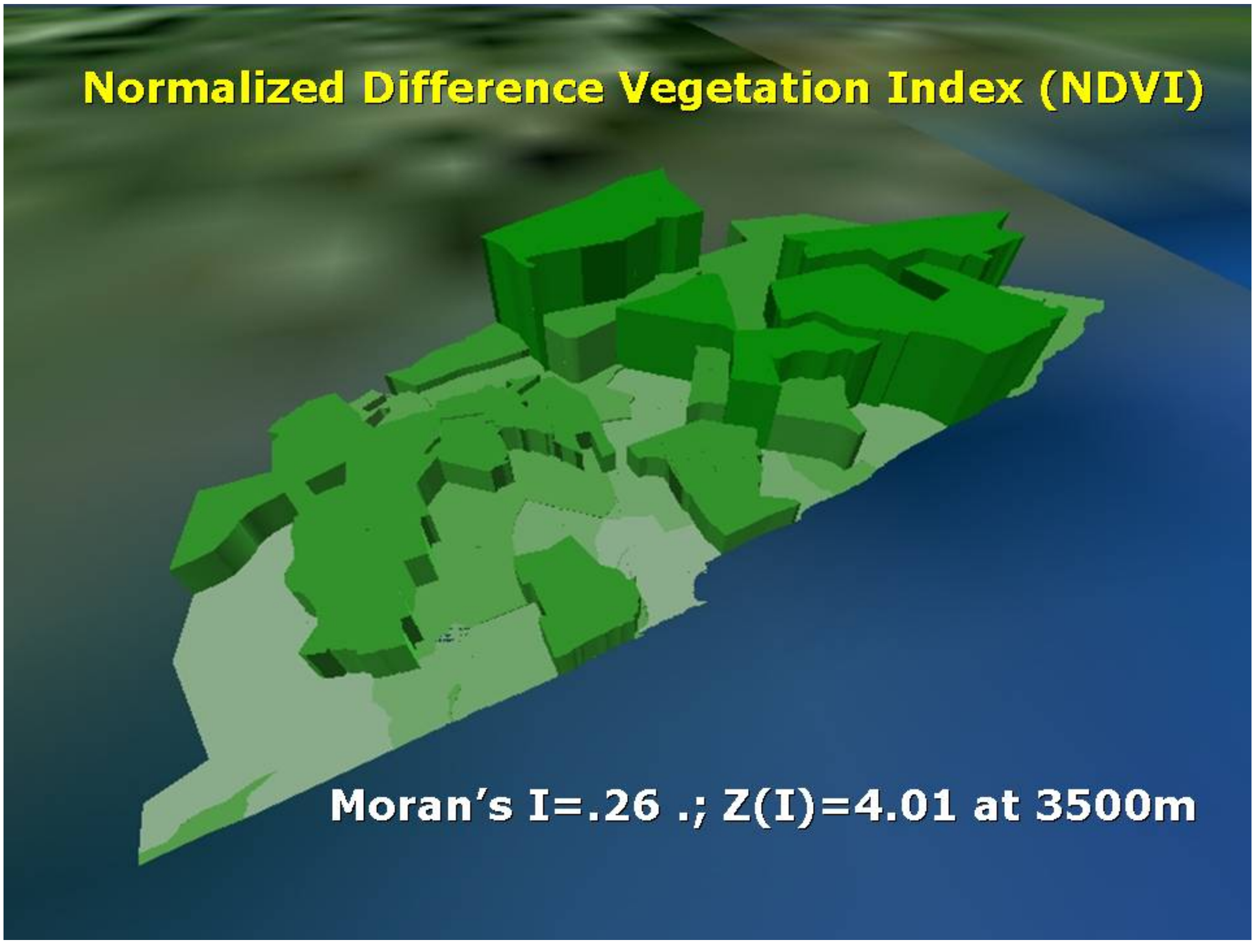
Normalized Difference Vegetation Index (NDVI)
Moran's I=.26 .; Z(I)=4.01 at 3500m

Figure 9

Table 5. Vegetation as a Predictor of Poverty Levels by Locality

Variable	Standardized Beta Coefficient	t-score
Pct Vegetation	-.793	-7.92

Dependent variable is poverty score for locality

Adjusted R2 = .62

No outliers; evidence of heteroscedasticity;
Moran's I for residuals=.43, Z(I)=2.26 at 1500m

Variable	Standardized Beta Coefficient	t-score
NDVI	-.798	-8.04

Dependent variable is poverty score for locality

Adjusted R2 = .63

No outliers; little evidence of heteroscedasticity; Moran's I for residuals = .21, Z(I)=1.83 at 2000m

Table 6. Vegetation as a Predictor of Health Levels by Locality

Variable	Standardized Beta Coefficient	t-score
Pct Vegetation	-.283	-1.77

Dependent variable is self-reported health score aggregated at the locality level

Adjusted R2 = .05

Two outliers; some evidence of hetero-scedasticity; Moran's I for residuals = .44; Z(I)= 2.24 at 1500m.

Variable	Standardized Beta Coefficient	t-score
NDVI	-.295	-1.85

Dependent variable is self-reported health score aggregated at the locality level

Adjusted R2 = .06

One outlier; some evidence of heteroscedasticity; Moran's I for residuals = .38; Z(I)= 1.92 at 1500m.