Can we spot a neighborhood from the air? Defining neighborhood structure in Accra, Ghana

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Abstract

Slums are home to a large fraction of urban residents in cities of developing nations, but little attempt has been made to go beyond a simple slum/non-slum dichotomy, nor to identify slums more quantitatively than through local reputation. We use census data from Accra, Ghana, to create an index that applies the UN-Habitat criteria for a place to be a slum. We use this index to identify neighborhoods on a continuum of slum characteristics and on that basis are able to locate the worst slums in Accra. These do include the areas with a local reputation for being slums, lending qualitative validation to the index. We show that slums also have footprints that can be identified from data classified from satellite imagery. However, variability among slums in Accra is also associated with some variability in the land cover characteristics of slums.

Keywords

Slums; Accra; Ghana; Remote sensing; GIS

Introduction

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 2006a). 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 implies 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 (Weeks et al. 2004).

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. Martin (2003, p. 362) argues that this is because "[t]he neighborhoods that we define through research or social exchange are always subject to redefinition and contention; they are not self-evident." Neighborhoods are spatially and socially constituted, but their salience to human behavior depends importantly on the way in which people, both within and outside of the neighborhood, "imagine" or mentally conceptualize the place. Furthermore, some places may be more identifiable as neighborhoods than others, either because of distinct physical boundaries (a river, a highway, a hillside, etc.) or because of a distinct set of social and environmental characteristics (such as an ethnic enclave). Because neighborhoods are places they should be

identifiable on a map. However, if we accept the contingency of neighborhood definition, we must also accept the possibility of fuzzy boundaries of neighborhoods—the edges of places that are not clearly in one neighborhood or another. Furthermore, we must recognize the possibility that these boundaries may change over time, just as the characteristics of the neighborhood are apt to change.

Recognizing the spatial and social fuzziness of neighborhoods does not make them any less important to study. Rather, it imposes upon us the obligation to think carefully about how we implement a definition in our own research, to understand the limitations of any single definition, and to interpret our results in the light of our particular definition. Our own definition of a neighborhood will be constrained immediately by the data that we are able to assemble. Most research is based upon data collected at a spatial scale determined by someone other than the researcher. It is for this reason that the most common concept of a neighborhood in the literature on cities in the United States is based on the census tract (Diez Roux 1998, 2001). The work in Chicago by Sampson and his associates (Sampson 2003; Sampson and Laub 1990; Sampson and Morenoff 2003) has attempted to go beyond the somewhat arbitrary census-based boundaries and, as discussed below, we attempt to go beyond the census-tract equivalent in Accra, Ghana.

There can be little question that one of the most important reasons why social scientists are interested in intra-urban variability in neighborhoods is because of an interest in inequality: Why are some neighborhoods more dangerous and less healthy than other neighborhoods? Why are some neighborhoods composed of predominantly less-advantaged persons, and how does that impact the well being of all residents? In richer countries the inequalities among city neighborhoods may be obvious, but in cities of developing nations they tend to be stark; so stark that almost the only differentiation that is routinely made among neighborhoods is whether or not they are slums (UN Habitat 2006). In its State of the World's Cities 2006/7 the UN-Habitat devoted a great deal of attention to exploring the nature of slums, giving some depth to its criteria for classifying a place as a slum, which we discuss below. This is a useful step forward from the widespread practice throughout the literature of identifying slums almost entirely on the basis of local reputation (see, e.g., Neuwirth 2005; Roy and Alsayyad 2004).

Because our research relates to urban inequalities in a city of a less developed nation, we too focus our attention on the identification of slum neighborhoods. Slum neighborhoods are defined largely by their physical and infrastructural environment, rather than by the demographic characteristics of residents, although we can be certain the residents have some influence themselves on the physical environment. Nonetheless, the important aspect of a slum is that it is a characteristic of place, not specifically of the people residing there. For this reason, we believe that it may be possible to identify such places from satellite imagery, thus improving our analytical capabilities in parts of the world where detailed census data at the local level are typically not available.

Our objectives, then, are twofold: (1) to define slum areas by exploiting a relatively rich set of data that we have for the city of Accra, Ghana, and then (2) to assess whether these neighborhoods can be identified through an automated classification of remotely sensed high-resolution imagery.

The study site

Accra is the capital of Ghana, and is located in the south on the coast of the country, facing the Gulf of Guinea. The specific area chosen for this study is the administrative unit known as the Accra Metropolitan Area (AMA). The metropolitan area comprised 1.6 million people and 365,550 households according to the March 2000 census, and it is estimated to have reached

2 million as of 2006 (United Nations Population Division 2006b). There are known to be 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). An analysis of existing health data and a household survey in the 1990s by Songsore and Goldstein (1995) revealed stark contrasts between the better off neighborhoods and the slum areas of the city. Agyei-Mensah (forthcoming) notes that these studies helped lead to the development of the recently enacted (2003) Ghana Poverty Reduction Strategy.

The urban structure of Accra seems quite typical of the coastal cities of West Africa which all bear the marks of the more important European colonizers—in the case of Accra, Christiansborg Castle built by the Danes, Ushertown where the Dutch had presided, and Jamestown, which served as the British seat of power. Twenty-first century Greater Accra is a sprawling urban area and the neighborhoods reflect multiple strands of history, including (1) race-based town planning until 1923; (2) the development of elite areas populated largely by Europeans, including the military cantonments; (3) older villages dominated by different ethnic groups and which are now incorporated into the larger city; (4) parts of the city such as "New Town" that have been reception areas for migrants into the metropolis; and (5) an incompletely implemented urban plan, leading to wide disparities in neighborhood formality and infrastructure. These are features shared by many West African coastal cities, thus increasing the possibilities of generalization from Accra to other cities.

The uneven pattern of infrastructure is a consequence of weak planning controls in the era since independence during which Accra has increased dramatically in population. A Master Plan of Accra was produced in 1958, but it was not fully implemented. Schemes were prepared for pockets of land, resulting in a series of disconnected plans which fragmented the orderly development of the city. Accra has no coherent, consistent spatial development strategy (Yankson et al., forthcoming, p. 8). In this type of environment it can be expected that a large proportion of the city will be characterized as being a slum, consistent with the estimate by UN Habitat (2006) that 66% of urban Ghanaians live in a slum neighborhood.

Defining a slum

UN-Habitat defines slums as places that lack one or more of the following: (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.

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 acquired from Ghana Statistical Services a 10% anonymized random sample of individual-level census data for the year 2000 for all 1,724 enumeration areas (EAs) in Accra. Since the average population per EA is <1,000, an EA is closer in concept to a US Census Block Group than it is to the more standard unit of a census tract, because census tracts average 4,000 inhabitants, whereas they may be divided into as many as four block groups. The EA may thus

be too small to represent the neighborhood 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 per area that facilitates the 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 at least the first four of the UN-Habitat's five slum criteria. The fifth, which refers to the legal of security of tenure, is more difficult to infer from census data. Each housing unit in our 10% anonymized sample was scored as follows:

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

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

3. If the number of persons per room is >2, slum3 = 1 (else 0);

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

5. If the resident is not the owner, slum5 = 1 (else 0);

6. 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 three 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.

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% of homes in Accra had that score. The maximum of five was shared by 0.7%. The median was three 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 Statistical Services, overlaid on a high-resolution DigitalGlobe Quickbird image (discussed in more detail below), we have created a digital boundary map (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,

evidenced by a Moran's *I* of 0.33, which is statistically significant well beyond the 0.001 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.

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 Fig. 1 reflects the seeming scatter-shot nature of development within the city (Pellow 2002). Furthermore, EAs are generally quite small in geographic area and thus may represent portions of neighborhoods, rather than a full neighborhoods. At this geographic scale there is a also a fair amount of variability from EA to EA in the slum index, as the inset of Fig. 1 demonstrates.

To define areas that may more closely approximate the city's neighborhoods, we used a method of areal aggregation developed by Duque Cardona (2004) to regroup the 1,724 EAs 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.

An advantage of this approach is that it provides a way of dealing with the modifiable areal unit problem (MAUP) as outlined by Openshaw (1984). The issue is that when we aggregate data for geographic areas, we may find that the results differ according to how we draw the boundaries of those areas. If we modify the area, we may modify the results. There is no way to eliminate this problem in the real world, but the more intelligently we define an area, the higher the probability is that each area will appropriately account for the spatial differences that we are seeking to observe. Although we are forced to start with arbitrarily defined census boundaries, the areal aggregation procedure attempts to group contiguous areas based on the intelligence that we have about their housing characteristics. In this way, we are able to generate what appear at least initially to be the "best" solutions for the areal definitions of neighborhoods, at a given point in time. We emphasize the latter point because, consistent with Martin's view discussed above, that neighborhood's are temporally contingent (Martin 2003), the MAUP emphasizes the spatial contingency of a neighborhood: (a) boundaries of neighborhoods can shift as the built environment and the social structure change over time, and (b) we may or not be successful in identifying those boundaries. Thus, we must always be cognizant of the fact that we are trying to capture a potentially nebulous and moving target.

With these caveats in mind, Fig. 2 maps the average slum index by analytical region. 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 that existed at the EA level. 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 Fig. 3, which maps the top ten ARs according to the slum index (the most slum like) and the bottom ten (the least slum like). There are extremes of neighborhoods that are not only physically quite close to one another, but in some cases actually adjacent to one another.

What characteristics of a slum can be derived from imagery?

We employ Ridd's vegetation, impervious surface, bare soil (V-I-S) model of the urban scene as the basis of our classification system for inferring land use from the land cover data derived from satellite imagery (Ridd 1995). Ridd's work relies on the concept that the dominant "building blocks" or materials of urban areas are vegetation, impervious surface, and soil. By extracting the proportional abundance of each of these types of surface materials, it is possible to characterize the different types of land-*use* occurring within a city. High levels of impervious surface (streets, parking lots, and roofs) will be indicative of dense, especially commercial, center-city areas, while high levels of vegetation would be indicative of city parks if located within the inner perimeter of the city, or low-density residential and agricultural uses if located on the periphery. Bare soil may be associated with industrial areas and with low-income residential areas.

It is the latter, in particular, in which we have an interest, because we expect that slums will have a combination of impervious surface (largely from roofs) and bare soil (especially streets and walkways) that would indicate residential areas in a sub-Saharan city, but relatively little vegetation, at least in comparison to other residential areas. Accra is in a moist tropical zone in which vegetation flourishes naturally, but the crowdedness of slums, in combination with the need to use wood for cooking, building homes, and creating furniture, among other things, is hypothesized to lead to denuded neighborhoods.

An additional metric is a measure of texture. This index is created by passing a moving window over adjacent pixels to measure the variability in brightness from one window to the next. High variability in the pattern of brightness is evidence of texture—A diversity of land cover on the ground—Whereas low-variability indicates little texture. Slum areas are often very densely settled with little variability of land cover due to the similarity of building materials and the lack of planned areas that might include lawns, parks, roadways, parking areas, commercial buildings, and so forth.

In analyzing satellite imagery for urban places, our experience 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, 2003; Weeks 2004; Weeks et al. 2005). This is because the built environment is configured differently, and normally less homogeneously, than the natural environment. For this reason, we use data from a DigitalGlobe Quickbird image that has a spatial resolution of 0.6 m in the panchromatic range, and 2.4 m in the multi-spectral bands. This resolution allows us to summarize data within each of the EAs and within each AR. The only limitation is that the only high-resolution satellite imagery available at a time period reasonably close to the census does not cover the entire AMA. Accra is characterized by a regular cloud cover (and experiences occasional dust storms), and so there was very limited availability to us of cloud-free imagery.

Results

Characteristics of the slum areas

We have already shown in Figs. 1 and 2 that there is considerable spatial variability in neighborhoods with respect to slumness. The slum index is a composite of five different criteria, but the five ingredients do not contribute equally to its overall construction. For the ARs created by the slum index, the bivariate correlation coefficient between the AR slum index and the proportion of housing units in the AR without piped water was 0.87, followed by a coefficient of 0.81 with the proportion of housing units with no toilet and sewer connection. The other high correlation is with the proportion of housing units with three or more people per room ($r = 0.74$). The other two slum components—durability and security of tenure—were

less well correlated with the overall slum index ($r = 0.21$ and 0.43, respectively). So, the implication is that the slum index that we have created is especially focused on crowded homes and lack of infrastructure.

The slum index was created from housing variables and is conceptualized as a set of characteristics of place, rather than the people living there. However, we are naturally interested in the extent to which people living in slums are different from people living elsewhere. Table 2 summarizes the results of a multiple regression analysis in which we have evaluated the role of socioeconomic variables as predictors of the slum index. The most important predictor is low-educational status. As the percentage of neighborhood residents with less than a secondary education goes up, the slum index also rises. The next most important predictor was occupational status. As the percentage of people in the lower occupational strata goes up, so does the slum index. The ethnic variables capture another element of socioeconomic status because the Akan (largely the Ashanti) tend to be the more politically and economically influential groups in Ghana and as their proportion increases in a neighborhood the slum index goes down. Non-Africans tend to be better off economically and educationally than the Ghanaian population and as the non-African proportion increases in a neighborhood its slum index goes down. Other variables in the model were not statistically significant, but were in the expected direction. Higher proportions of Muslims in a neighborhood were associated with a higher slum index, and slum neighborhoods also have a higher proportion of young children.

Overall, it can be seen that 53% of the variability in the slum index can be explained by the combination of these socioeconomic and ethnic factors. This is a very good statistical fit, albeit less than perfect. Can we use these characteristics of residents to pinpoint geographically where the slums are? From the above regression analysis, we have calculated the predicted slum index for each analytical region in Accra and then we have compared the top ten slums derived in this way with the top ten slums derived from the slum index. If we require exact prediction, then only two of the top slum ARs are among the top ten as predicted by the socioeconomic characteristics, although those are in fact the two worst slums according to our index—Nima and Ussher Town.

Although predicting only two of the top ten does not sound like a close fit, the geographic fit shown in Fig. 4 tells a different story. We have drawn a 500-m buffer around each of the predicted ten worst slums and within those buffered areas are found six of the top ten slums. Thus, the socioeconomic characteristics of residents put us very close to, even if not necessarily exactly on top of, the worst slum areas. This close relationship between slum housing and lower socioeconomic status of residents is not surprising, but rather confirms that using two different sets of data from the census can help us to identify the geographic location of the worst slums in Accra. We turn now to the question of whether the imagery can predict those locations.

Overall predictability of slums from the imagery

Can the variability in a neighborhood's slum index be predicted by data from the remotely sensed image? The answer from the data in Table 3 is a qualified yes. The R^2 for the overall slum index is 0.38, with the proportional abundance of vegetation in the analytical region being the most important predictor, with a small amount of predictive power added by the texture measure. Both factors are in the expected directions: A slum is associated with less vegetation and less variability in the land cover. However, the residuals are spatially autocorrelated, with a z-normalized Moran's I value of 3.67. This indicates that there is an underlying spatial component that is not accounted for in the original regression model. From the standpoint of classical statistics, this is a problem because it suggests a violation of one of the underlying assumption of regression analysis which is that the data are randomly distributed. On the other hand, Tobler's "First Law of Geography" (Tobler 1970,2004) suggests that while all things

are related to one another, near things are more related. Put another way, spatial autocorrelation should be expected and should be accounted for, rather than being seen as a problem.

Diagnostics within GeoDa software indicated that the spatial autocorrelation in the data could be accounted for by utilizing a spatial error model which incorporates a spatial weights matrix as one of the inputs to the regression calculations. The calculations for such a model are built into the GeoDa software (Anselin 2003), and the results of the revised model produced a pseudo-R^2 of 0.42, after taking spatial autocorrelation into account. This suggests a slight improvement over the original R^2 of 0.38, but given the differences in the way the two values are calculated, we should not place too great a weight on the difference. Rather, we interpret this to mean that the corrected model is not materially different from the original model, but that the fit is improved a bit when we take the spatial component into account.

Looking at the individual components of the slum index, we find that the R^2 for the proportion of homes in a neighborhood with no piped water was 0.30 when predicted by a combination of vegetation and texture. Again, the diagnostics suggested the use of a spatial error model, which then produced a pseudo-R^2 of 0.37, suggesting that the spatially corrected model provides a better fit to the data. If we use the proportion of homes with no toilet and sewer as the slum index, the R^2 increases to 0.67, with no spatial autocorrelation in the residuals. Once again, the amount of vegetation was the most important predictor, accompanied by the texture measure. The only other component of the slum index that has a reasonable fit with the imagery is the proportion of homes in which there are two or more people per room. The original R^2 is 0.16, as can be seen in Table 3, but that is 0.25 when taking spatial autocorrelation into account in the spatial error model. Vegetation is the most important predictor in this instance, but it is closely followed by the proportional abundance of bare soil. In this case, the less bare soil, the higher is the proportion of homes that are crowded. This probably reflects the very crowded circumstances in which closely spaced buildings leave little room for either vegetation or bare soil.

From a global perspective, then, we can conclude that the land cover data do differentiate neighborhoods in a reasonably predictable fashion. Are the imagery variables able to locate the worst slums? If we looking for an exact match, the answer is the same as with the SES predictors. Among the top ten slums as predicted by the imagery are only two of the top slums according to our slum index. The imagery was able to pinpoint the second worst slum (Ussher Town) but not the worst (Nima).

As was true with the prediction of slum areas from the socioeconomic status of residents, the land cover data from the imagery also comes very close geographically to the worst slum neighborhoods, even if not necessarily in the exact place. This is shown in Fig. 5 where it can be seen that a 500-m buffer drawn around the ARs predicted by the imagery to be the ten worst slums captures six of the ten worst slum areas according to our index. Clearly, then, the low level of vegetation and the low level of texture within neighborhoods of Accra is symptomatic of slum areas. This could well be thought of as exemplifying the MAUP. If we treat the neighborhoods narrowly, we get less meaningful results than if we define them geographically more broadly.

Of some interest is the fact that the six ARs predicted as slums by the imagery are the same six predicted by the socioeconomic characteristics of the residents. Or, to turn that around, there are four slum areas that neither set of indicators was able to predict. These four are the neighborhoods of Adabraka, Korle, Mpoase, and Mampose, and for some reason are outliers with respect to their predictability as slums. What is different about these places? To answer this question we grouped the ten worst slums into three categories: (1) Nima and Maamobi; (2) Usshertown/Accra Central/Osu; and (3) the "Outliers." We then compared each group

according to the set of socioeconomic and cultural characteristics that are available from the census, as well as the data derived from the imagery. The results are shown in Table 4.

The only difference with respect to the components of the housing-based slum index is that a higher proportion of homes in Nima/Maamobi are built of less durable material than is true in the other areas. This may help to account for the clear public perception of this area as a major slum in Accra. The education and occupational status variables are nearly identical across the three slum groupings, although in terms of illiteracy the outlier slums do have a lower average percentage illiterate. Among the very biggest differences are cultural factors. The Nima/ Maamobi neighborhood is heavily Muslim, whereas the Ussher Town area is heavily Ga, and the "Outliers" have a much higher percentage Akan and Charismatic Christians than the other slums. There are also differences in the land cover as assessed from the satellite imagery. Nima/ Maamobi has a high proportion of impervious surface along with low vegetation, whereas the "Outliers" have less impervious surface, more bare soil, and more texture than do the other areas.

Although the differences can be seen in Table 4, it is not readily apparent how to interpret them. It appears that cultural differences can lead to slums that look different from one another, both in terms of the characteristics of residents and in terms of how the area looks when seen from above. We discuss this in more detail below.

Discussion and conclusion

We have shown that it is possible to use census data and geospatial aggregation techniques to create neighborhoods that can be quantified in terms of their slumness. We have focused our attention on the ten worst slums measured in this way. There is a high correlation between socioeconomic characteristics of neighborhoods and the slum index, and there is also a high correlation between land cover metrics and the slum index. In particular, our analysis has shown that land cover data can identify the parts of the city in Accra where at least six of the ten worst slums are located.

Our analysis was, however, based on predictions of slums informed by the slum index because our predicted values were based on regression models incorporating data from the slum indices. What would the results be if we use "naked" results from the imagery? The data in Table 3 show clearly that low vegetation is the major land cover characteristic of a slum in Accra and in Fig. 6, we show that the top ten ARs in terms of low vegetation are all located within the band of Accra near the coast in which slums are located. However, the low vegetation areas are confined to the grouping in Table 4 shown as "Ussher Town/Accra Central/Osu." Of some importance, however, is that all ten of the lowest vegetation areas in Accra are within this area. Thus, if we used that single criterion to find slums, we would be very close to one group of the worst slums. We would have no false positives, but we would have false negatives in the sense that the low-vegetation variable does not capture all slums. It did not find Nima/Maamobi, nor did it find the "Outliers."

Somewhat serendipitously we discovered that the top ten ARs in terms of the percentage of impervious surface are all located within the area of Nima/Maamobi. Thus, that area of Accra is different in terms of the land cover feature that most characterizes it. Once again, we would have no false positives, but we would have false negatives because having a high proportion of impervious surface does not identify all slums. Once again, we are left without a unique set of identifiers of the "Outliers."

Overall, our results suggest that slums can be identified and quantified, but their characteristics may vary even within the same metropolitan area. Nonetheless, we have shown that a majority of the worst slums can be identified from land cover data classified from a high-resolution

satellite imagery. It is not yet clear why we have not been able to identify all of the worst slums. We are currently employing two different, complementary approaches, to improving our understanding of these linkages: (1) more sophisticated classification schemes from the imagery, using Definiens object-oriented software; and (2) more intensive on-the-ground field work in neighborhoods of Accra.

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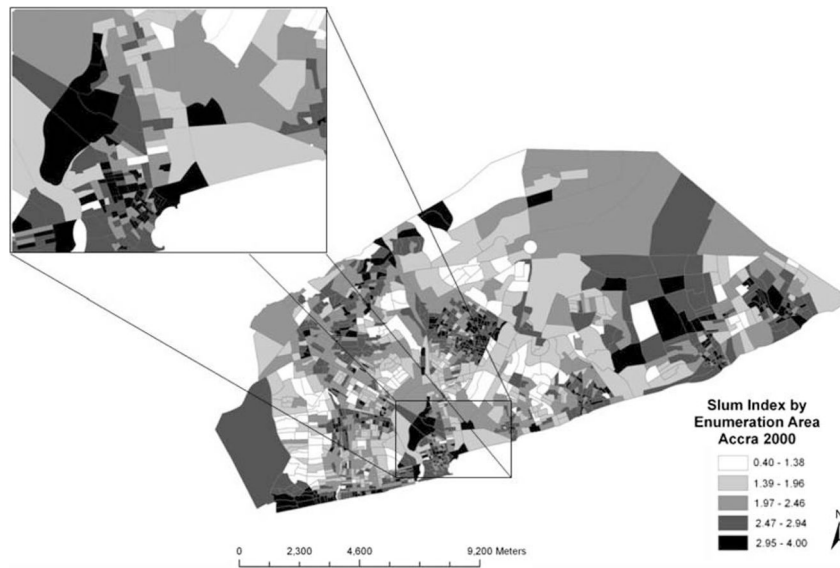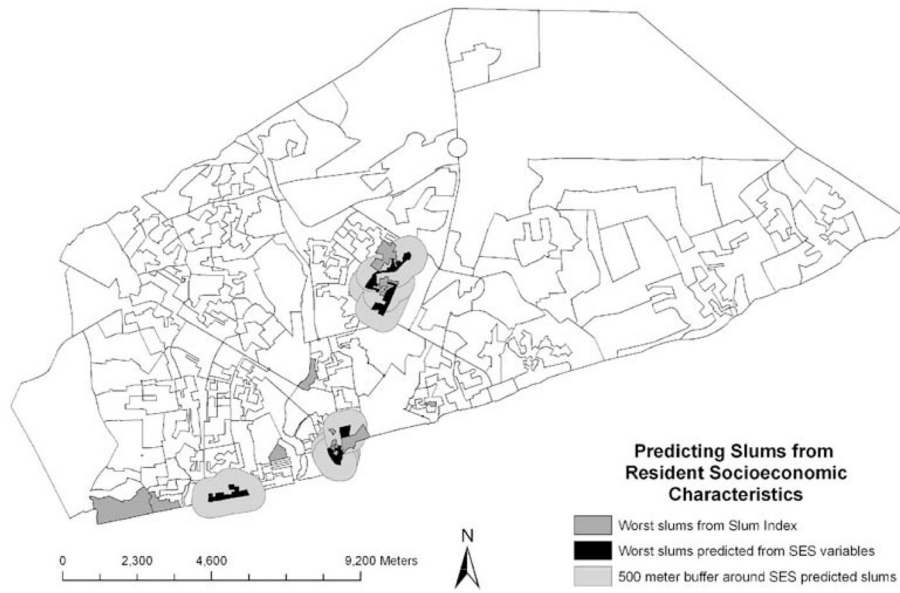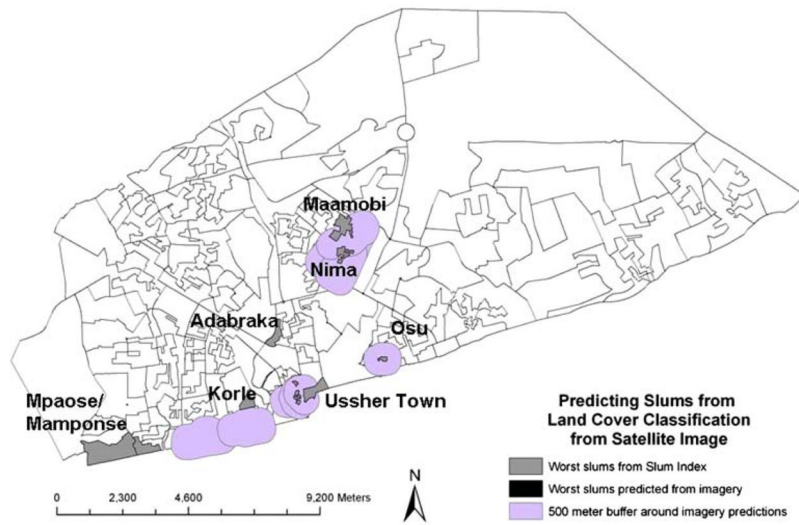
Fig. 1.
Slum index by EA in Accra, 2000

Fig. 2.
Slum index by analytical regions, Accra, 2000
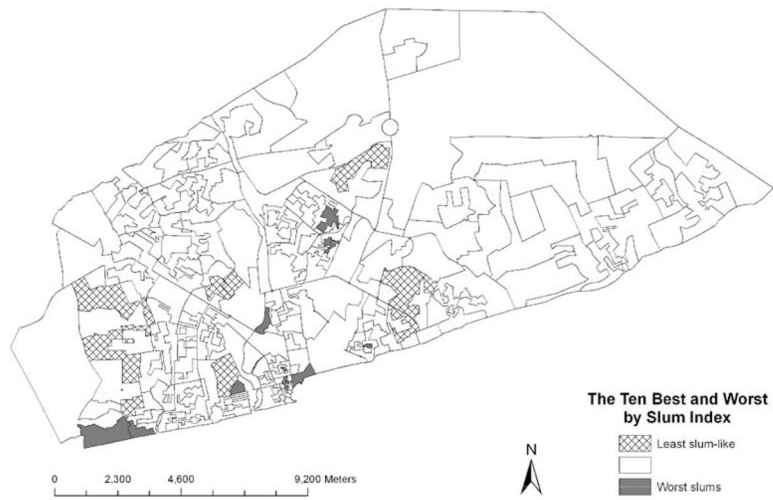
Fig. 3.
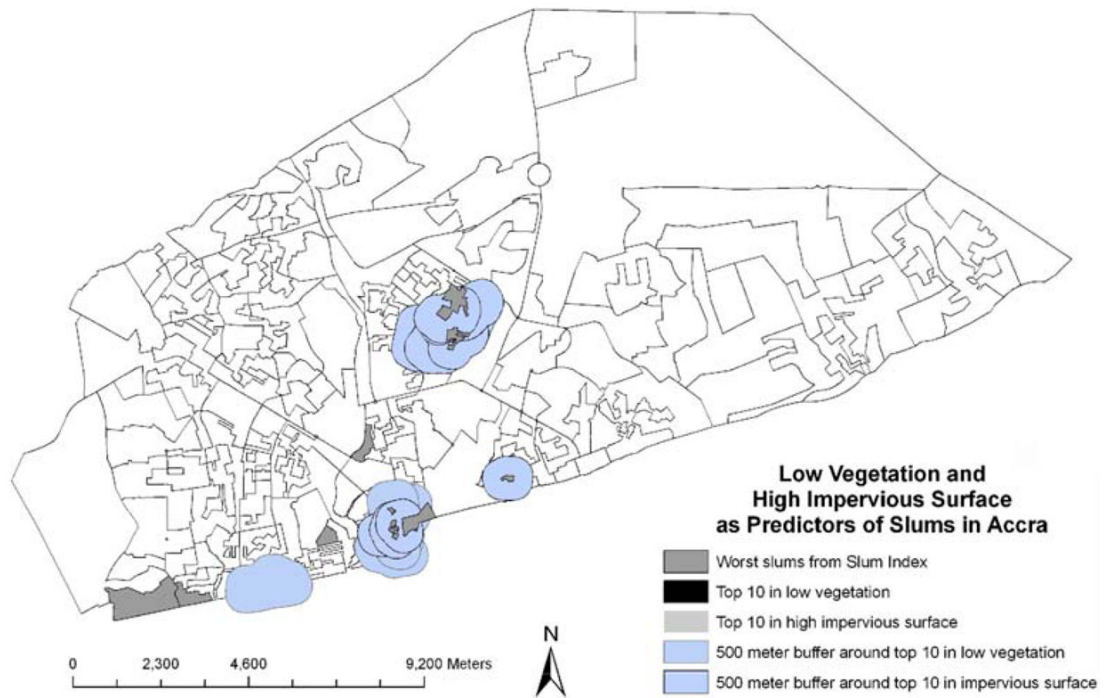The top ten best and worst analytical regions by slum index

Fig. 4.
Proximity of slums to predicted ARs based on socioeconomic status of residents

Fig. 5.
Top ten slums predicted by data from the satellite imagery

Fig. 6.
Predicting slums from imagery without prior knowledge of slum areas

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
3+ persons per room	47.8
Roof and siding are not of durable material	0.9
Residents are not the owners	61.6
Number of housing units	366,540

Table 2

Social variables associated with the slum index

Variable	Beta	T-score
% less than secondary education	0.395	6.296
% lower occupational status	0.298	4.752
% Akan	−0.132	−2.538
% non-African	−0.123	−2.452
% Muslim	0.059	1.113
% under 15	0.045	0.673
Dependent variable = slum index	$R^2 = 0.53$	

Table 3

Satellite-derived land cover classifications as predictors of the slum index and its components, Accra analytical regions

	Overall slum index	Proportion with no piped water	Proportion with no toilet and sewer	Proportion who do not own home	Proportion with less than durable roofing	Proportion with 2+ persons per room	SES-based slum index
Percent vegetation	−0.724 (−9.86)	−0.647 (−8.30)	−0.926 (−17.22)			−0.349 (−5.10)	−0.688 (−11.67)
Texture	−0.198 (−2.70)	−1.82 (−2.33)	−0.197 (−3.66)	−0.157 (−2.20)			0.132 (2.24)
Percent bare soil				−0.154 (−2.15)		−1.44 (−2.10)	
Adjusted R^2	0.38	0.30	0.67	0.04	0.00	0.16	0.61
R^2 spatial error model	0.42	0.37	n/a	n/a	n/a	0.25	0.68

Numbers in parentheses are *T*-scores

Table 4

Comparison of characteristics of groupings of the ten worst slums

	Nima/Maamboi	Ussher Town/Accra central	"Outliers"
Proportion no piped water	0.86	0.77	0.86
Proportion no toilet and sewerage	0.97	0.95	0.96
Proportion not owning home	0.79	0.86	0.79
Proportion with less durable material	**0.14**	0.04	0.03
Proportion with 2+ per room	0.64	0.61	0.56
Percent with less than secondary education	33	31	28
Percent illiterate	24	23	**18**
Percent with lower status occupations	91	90	90
Percent under age 15	32	32	32
Percent 55+	8	**11**	5
Percent Muslim	**51**	15	10
Percent Catholic	12	5	8
Percent Protestant	14	35	19
Percent Charismatic	17	29	**43**
Percent Akan	20	17	**44**
Percent Ga	6	**60**	20
Percent Ewe	13	6	**21**
Proportion vegetation	0.06	0.04	0.05
Proportion impervious surface	**0.84**	0.79	**0.60**
Proportion bare soil	0.10	0.15	**0.24**
Texture	3,337	3,806	**4,658**