Mapping Slums Using Spatial Features in Accra, Ghana

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***Abstract*—In order to map the spatial extent and location of slum settlements multiple methodologies have been devised including remote sensing based methods and field based methods using surveys and census data. In this study we utilize spatial, structural, and contextual features (e.g., PanTex, Histogram of Oriented Gradients, Line Support Regions, Hough transforms and others) calculated at multiple spatial scales from high spatial resolution satellite data to map slum areas and compare these estimates to three field based slum maps: one from the UN Habitat/Accra Metropolitan Assembly (UNAMA) and two census data derived maps based on the UN Habitat definition of a slum, a simple slum/non-slum dichotomy map and a slum index map. When comparing the remotely sensed derived slum areas to the UNAMA slum definition results indicate an overall accuracy of 94.3% and a Kappa of 0.91. When compared to the dichotomous, census derived slum maps the results are not as accurate. This reduced accuracy is due to the substantial over prediction of slums, especially if only one criterion was missing, using the census data. In relation to the slum index, the remote sensing estimates of slums were significantly correlated with an r^2 of 0.45 and when population density was taken into account, the correlation increased to an r^2 of 0.78. Overall, the remote sensing methodology provides a reasonable estimate of slum areas and variations within the city.**

I. Introduction

The lesser developed world is rapidly urbanizing, and much of the urban population in these burgeoning cities lives in slums, or informal settlements. It is currently estimated that 32.7% of global developing regions' urban population lives in slums. In sub-Saharan Africa 61.7% of urban populations live in slums[1]. People living in these slums often experience socioeconomic vulnerabilities including poverty, unemployment and underemployment combined with little education. Furthermore, slums are often located in sites that are disproportionately exposed to environmental hazards such as landslides, flooding, devegetation, open sewers, and industrial waste[1]. Given these vulnerabilities that slum dwellers face, it is a useful endeavor to develop methodologies to identify and map slum locations so that aid, slum upgrading programs, and disaster relief can effectively target these vulnerable communities[2].

According to the United Nations, the official definition of a slum is based on five criteria: housing unit durability, sufficient living area, access to improved water, access to sanitation, and security of tenure[3]. If one of the above criteria is missing then that household is a slum [3]. While these characteristics are a definitive way to determine a slum, this definition requires the use of household surveys and/or census data to compute it. This makes performing slum assessments costly and time consuming because it requires substantial numbers of trained people on the ground to talk to or visually inspect individual dwellings. Consequently slum mapping tends to be either spatially limited when performed by slum mapping teams or temporally limited when derived from census variables that are typically collected once every ten years.

Remotely sensed data are less limited spatially or temporally but, they are limited to only examining the external features of structures. Therefore, it is not directly possible to determine which housing units have sufficient living area, access to improved water, access to sanitation, and security of tenure and thus are slums as characterized by the UN-HABITAT definition. However, slum areas are generally poor, unplanned neighborhoods with little, if any zoning enforcement for dwellings. These types of areas are typically characterized by small buildings, haphazard street and walking path networks, lack of vegetation, and dense building construction[4]. This leads to spatial patterns that allow for the contextual detection of slum areas using high spatial resolution satellite data.

In this study we use spectral information and spatial patterns derived from a number of spatial features (PanTex, Line Support regions, Hough, Histogram Orients of Gradient, Fourier, and Local Binary Patterns) computed at multiple spatial scales from Quickbird multi-spectral imagery to map slum locations in the city of Accra, Ghana. We compare this remote sensing classification of slum settlements to multiple field based slum maps including a slum map created by the U.N. and Accra Metropolitan Assembly (AMA) and two census derived measures.

II. Methods

A. Study Area Description

Accra, the capital city of Ghana, is located along the southern coast of Ghana on the Gulf of Guinea. In 2000 the Ghanaian Census recorded the population of the Accra Metropolitan Assembly (AMA) to be 1.6 million. Accra is a low rise city with few buildings taller than a couple of stories. The city has poor urban planning and few streets have names or addresses. According to a 2007 UN Habitat report 42.8 percent of the people in Ghana live in slums, down from 52.1 percent in 2000[2]. Within the AMA limits it is currently estimated that slum dwellers make up 38.4 percent of the

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population and occupy 15.7 percent of the land[5]. Furthermore, the population density of slums in Accra is 607.8 people per hectare, which is considerably higher than the population density for the city as a whole (250.7 persons per hectare) [5].

B. Field Survey Based Slum Data Sets

Results from two different field based assessments were used to categorize slums. The first field based methodology is based on collaboration between the Accra Metropolitan Assembly and UN Habitat (from here on AMAUN map) which produced a slum/non-slum dichotomy map[5]. The AMAUN map identifies slums within the city boundary of Accra using a combination of aerial photography, the number of persons versus number of dwellings derived from the 2000 Ghanaian Census, income levels based on the City's income classification scheme, and contributions from the City's Assembly members and slum dwellers. The AMAUN map depicts 78 slum settlements and pockets within the city[5]. Using this methodology, the entire city was mapped as either a slum or not a slum. For this study the map was georeferenced via rubber sheeting, and then the mapped slum areas were converted into a slum/not slum binary raster for analyses.

The other two slum maps utilized data from the 2000 Ghanaian census. Census data were used in two different ways to map slums: 1) a dichotomous slum/non slum methodology and 2) derivation of a slum index that creates a continuous value for slums. In the dichotomous slum/non-slum methodology, four maps were created at each level of aggregation. The different maps represent areas where greater than 50% of the households met at least one, two or more, three or more, and four or more of the five criteria UN HABITAT use to classify slums. The map based on a continuous slum variable, the slum index, was created by calculating the number of slum criteria from 0 to 5 met be each housing unit in a given area, and then calculating the mean value for all housing units in that area. This methodology was first described by[6] and provides a range of values for slums for the entire area. Both the ordinal and continuous measures slums were examined, because if a household is suffering more than one deprivation relative to the five indicators they are significantly worse off than households that have no or only one deprivation[6].

The data used to calculate these slum measures were taken from a 10% random sample of the 2000 Census of Housing and Population in Ghana. These slum maps were calculated using housing unit level data and then aggregated to the neighborhood level. The neighborhood units are aggregations of Enumeration Areas (EAs) based on areas with which the residents would commonly identify themselves as belonging to and have been described as vernacular neighborhoods[6]. The vernacular neighborhoods consist of 108 neighborhoods that contain anywhere from 1 to 74 EAs. The neighborhoods range in size from 0.21 km^2 to 21.55 km^2 averaging 2.24 km^2 with a population of 100 to 82,330 people with an average of 15,290 people.

C. Remote Sensing Classification

The remote sensing based classification uses a similar methodology to that outlined by [3]. In this study we use a 2.4 m spatial resolution multi-spectral (Blue, Green, Red, and NIR) Quickbird image acquired on April 12, 2002, which is the nearest available image to the 2000 census date. This classification methodology relies heavily on extracting diverse contextual image information to characterize the spatial and structural patterns of physical infrastructure on the ground. First, we divide the imagery into non-overlapping blocks consisting of 4 x 4 pixels and 8 x 8 pixels (average of approximately 15m). Next, for each block we extract a feature set consisting of: a rotation invariant Grey-Level Co-occurrence Matrix (GLCM) contrast texture termed the built up presence index (PanTex)[8]; a Histogram of Oriented Gradients (HoG) feature that captures the distribution of structure orientations [9]; the normalized difference vegetation index (NDVI) local mean, Line Support Regions (LSR) which characterize lines and their orientation [10]; Local Binary Patterns (LBP) a texture algorithm that examines pixel relationships around a center pixel [11]; Hough transform which examines curves based on a set of given edge points by exploiting point/line duality [12]; Fourier transform which examines the edges in the 2d frequency domain [13]; and the local mean of each of the original bands. To account for the contextual properties these features are extracted at multiple scales using window sizes of 8 m x 8 m, 16 m x 16 m, and 32 m x 32 m. In total there are 144 contextual features created that were used as the predictive variables for a Random Forest (RF) classifier (described below).

There are three classes of interest: 1) slum settlement; 2) non-slum settlement (which also includes commercial, industrial, and institutional) and 3) non-settlement (i.e., water, forest, marsh, barren areas, vacant plots). Our sampling scheme follows these steps: 1) each class is trained using 40-50 one hectare plots per class, which were manually selected based on image interpretation and ancillary data such as AMA UN slum map 2) For each class, 1000 non-overlapping points per are randomly sampled within the one hectare plots. Thus the training set has 3000 samples in total (1000 per class). A RF classifier was trained using the 3000 point training set.

Only the neighborhoods and portions of the AMAUN Habitat slum map that were covered by the imagery were used in the analysis. Within the areas defined as slum and non-slum within the AMAUN map, a one hectare plot sampling method was used for assessment. For each class (slum, non-slum and other), 1,500 non-overlapping points were randomly generated within the 50 one hectare plots, resulting in 4500 samples for assessment.

Additional processing was needed to compare the remotely sensed slum estimates to the slum index map because the slum index is a relative measure versus the discrete values derived from the classification. For each neighborhood unit, the percentage of the built-up area (i.e., slum and formal) was determined (i.e., removing nonsettlement/other), and the amount of slum relative to the amount of total built up area was then calculated for each neighborhood unit. This provides a percent slum for each neighborhood. Then the correlation between the percent slum from the classification results and the slum index can be calculated to determine the agreement between these two slum estimates.

III. Results and Discussion

A. Remote Sensing Classification Map

The output of the remote sensing (RS) classification is an approximately 15 m spatial resolution thematic map with three categories: slum settlements, formal settlements, and non-settlement, (Figure 1). The most accurate RF model commonly used the following variables in its splits: HoG, NDVI, PanTex, Hough, LBPM, and Fourier (some at two different block sizes). Overall within the 128 km^2 study area the RS classification results indicated that 25.0% was covered by slum settlement, 59.5% by formal settlement, and 15.5% by non-settlement (i.e., not built up/other). Therefore, 29.6% of the study's built up area was classified as slums. The majority of the areas classified as slum settlement are located on the western and central portions of the city (Figure 1). Pockets of slum settlement areas can also be found along the coast. On the other hand, areas classified as formal settlement did not exhibit any specific spatial pattern. Areas classified as non-settlement can be found throughout the city.

Using the 4500 sampled points an accuracy (agreement) assessment was performed to see how the RS classification performed at predicting the slum and non-slum areas delineated in the AMAUN Slum Map. The accuracy assessment results indicated that the RS classification had an agreement of 95% in identifying non slum areas, a 92% agreement in identifying slums, and an overall agreement (OA) of 94.3% and a Kappa (K) of 0.91. The RS classification agreed with the general locations of all of the slum areas identified in the AMAUN map (Figure 1). The accuracy assessment indicated the remote sensing based classification performed well in identifying the general locations and spatial extents of slums relative to the AMAUN map.

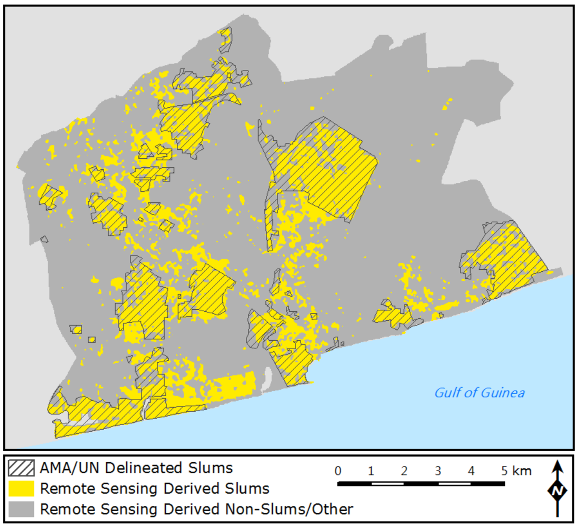

Figure 1. Remote Sensing slum classification overlain with the AMA UN Habitat Slum Map.

B. Relationship between Remotely Sensed and Census Derived Slum Maps

Having assessed the ability the of the remote sensing based classification to predict areas identified as slums by the AMAUN map, the next step is to determine how well the RS classification is able to predict areas identified as slums by the census based measures. The RS classification was compared to four dichotomous maps, one or more slum criteria, two or more slum criteria, three or more slum criteria, four or more slum criteria, and the slum index, all at the neighborhood level. When compared with the three strictest definitions of a slum, greater than one, two or three, slum criteria the RS does correspond well with an OA of 61.5%, K of 0.23, OA 63.5%, K of 0.27, and OA of 61.35% and K of 0.23, respectively. The majority of the city is considered a slum using only one or two criteria, while the RS classification considers the majority of the city as formal settlement. The large portion of the Accra that is represented as slum under the one or two slum criteria maps is a result of greater than 50% of the population not having access to improved water, sufficient living area, and improved sanitation facilities[4]. When the RS classification is compared to the four or greater criteria maps, the overall agreement increases (OA of 74.7% and K of 0.49). This is due to the four plus criteria areas being the most deprived areas that tend to have the spatial patterns of poorly planned developments.

Next the percent of each neighborhood that was RS classified as slum was mapped. It is evident that the worst slums are spatially concentrated in several distinct clusters across the city. This spatial distribution is similar to the AMAUN slum map in terms of the location of the areas with the highest percent slum. To quantify the level of agreement between the remote sensing based classification and the census derived slum index, a simple linear regression model was calculated. This determined the correlation between the percent of a Neighborhood's built up area that was classified as slum to the slum index. The results indicate a moderate correlation ($r = 0.67$, $r^2 = 0.45$, adjusted $r^2 = 0.44$, $p = 0.00$, $n = 81$).

After comparing the slum index and the RS classification results, commercial-institutional neighborhoods are frequently in disagreement. In the RS classification areas that are primarily commercial, industrial, government and institutional are classified as formal. These areas are covered by buildings that are regularly spaced and shaped, which makes them a formal settlement and were classified as such. However, these are locations where few people live and the people who do live in these areas tend to live there informally and cover just a small portion of the neighborhood. Thus these areas have very high slum index values because the census only records the living conditions of the individuals who live in the area and does not account for the density as to which the people are living. Since the remote sensing approach views the area as a whole, and the slum index classification represents only the living conditions of individual households this leads to only a moderate correlation between the two representations of slum distribution.

In order to account for the individual versus areal estimates represented by the two classifications, we examined multiplying the slum index by population density. This limits the impact of sparsely populated spatial units, such as ones with large proportions of nonresidential development, have in the correlation analysis. Additionally, by accounting for population density, the new measure is more representative of an area versus the individual and accounts for people living in very close proximity to one another. When the slum index is multiplied by population density the correlation between the RS classification and the slum index at the neighborhood level increases ($r=0.88$, $r^2 = 0.78$, adj. $r^2 = 0.78$, $p = 0.00$ $n=81$).

IV. Conclusions

Our results indicate that utilizing a spatial feature based classification from Quickbird multispectral image data performed well at mapping the slums as described in the AMAUN map and was a decent predictor of slums according to the census derived slum measures. When the RS classification is compared to the census derived, dichotomous UN Habitat definition of slums, it is apparent that nearly the entire city is considered a slum based on the strictest definition of a slum (area meets at least one of the five slum criteria). Therefore, if we simply had mapped any built up area, as a slum, our RS classification would have done a very good job of predicting this definition of a slum. However, this is not what the people in Accra would consider to be a slum and we did not train the RS classification on this one criteria definition, and therefore the classification results do not depict this strictest definition of a slum well. The RS classification predictions improves as the definition of a slum became more rigorous (i.e., as the number of slum criteria needed to be met increased). In terms of the slum index, the proportion of a neighborhood that is classified as a slum is statistically significantly and positively correlated. This correlation is stronger when the slum index is multiplied by population density which provides more of a spatial context for the slum map versus the individual on which the slum index is based.

One of the overarching limitations of this research is the difficulty in defining what exactly is slum. There is an inherent spatial mismatch when one defines a slum based on the household versus a collection of households and the way in which these households are aggregated in space is important. When limited to census boundaries, it is difficult to map slum areas because many times slum settlements are in areas that contain industrial and/or commercial buildings. In many cases there is some open land that can be settled within these areas which leads to the rise of slums in squatter type settlements that emerge in rapidly growing cities such as Accra. Since census units strive to maintain the same number of persons within each spatial unit, these spatial units contain a mix of land use.

The way in which the UN defines a slum at the household level is a valid approach when determining the number of people who live in slum conditions. However, it becomes difficult to use this methodology to describe slum versus non-slum areas because there is no spatial contiguity requirement for their definition. This is especially difficult to use in areas where there are no inherent or known spatial units. In this study we are fortunate to have very fine-grained census data, a slum map, and a neighborhood map, which allowed us to determine slum values at a high spatial resolution. This is not always possible and the remote sensing classification methodology described here appears to be a valid way to map variability within a city at spatial scales that are smaller than most readily accessible census data. Overall, the remote sensing approach described here could provide a rapidly constructed, excellent first cut for determining where to collect data if one wanted to map slum areas within any city in the developing world.

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References

[1] UN Habitat. (2010/2011). State of the world's cities 2010/2011- Cities for all: bridging the urban divide. United Nations

[2] National Research Council. (2007). Tools and Methods for Estimating Population at Risk from Natural Disasters and Complex Humanitarian Crises. Washington, DC: National Academy of Science.

[3] UN Habitat. (2006/2007). State of the world's cities 2006/2007- The Millennium Development Goals and Urban Sustainability: 30 Years of Shaping the Habitat Agenda. United Nations.

[4] Graesser, J., Cheriyadat, A., Vatsavai, R.R., Chandola, V., Long J., & Bright, E. (2012). Image based characterization of formal and informal neighborhoods in an urban landscape. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(4), 1164–1176..

[5] Accra Metropolitan Assembly (AMA). (2011). Slum Situation Analysis Report Participatory Slum Upgrading and Prevention: Millennium City of Accra, Ghana. UN Habitat.

[6] Weeks, J. R., Hill A., Stow, D., Getis, A., & Fugate D. (2007). Can we spot a neighborhood from the air? Defining neighborhood structure in Accra, Ghana. *GeoJournal*, 69(1-2), 9-22.

[7] Engstrom, R., Ofiesh, C., Rain, D., Jewell, H., & Weeks, J. (2013). Defining neighborhood boundaries for urban health research in developing countries: A case study of Accra, Ghana. *Journal of Maps,* 9 (1), 36-42.

[8] Pesaresi, M., Gerhardinger, A., & Kayitakire, F. (2008). A robust built-up area presence index by anisotropic rotation-invariant textural measure. IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens. (JSTARS), 1(3), 180–192.

[9] Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. *2005 IEEE Computer Society Conference Computer Vision and Pattern Recognition*.

[10] Unsalan, C. (2006). Gradient-magnitude-based support regions in structural land use classification, IEEE Geoscience and Remote Sensing Letters, 3(4), 546-550

[11] Ojala, T., Pietikainen, M., & Maenpaa, T. (2002). Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24 (7), 971-987

[12] Ballard, D. (1981). Generalizing the Hough Transform to Detect Arbitrary Shapes. Pattern Recognition, 13 (2), 111-122

[13] Smith, S. (1997). The Scientist and Engineer's Guide to Digital Signal Processing. San Diego, CA: California Technical Publishing