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Conceptualizing and Measuring Urban Locations: Comparing a satellite view with the Demographic & Health Surveys

Audrey Dorélien[1], Princeton University
Deborah Balk, CUNY
Mark Montgomery, Population Council
Megan Todd, CUNY

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I. ABSTRACT

There is widespread awareness that the world is becoming increasingly urban, both in terms of population (urbanization) and the spatial extent of urban land (urban expansion). However, understanding of these trends is limited by the lack of a globally consistent framework: there is no standard definition of an urban area nor agreed upon spatial boundaries of them. By comparing Demographic and Health Surveys (DHS) data, which uses each country's rural/urban classification system, to Global Rural-Urban Mapping Project (GRUMP) data, which primarily uses nighttime lights as an urban proxy, we are able to better understand what is meant by "urban" in the two data sources and to learn more about how to conceptualize an urban continuum. We do this by analyzing the distribution and characteristics (i.e. household electrification, rural/urban classification, poverty) of DHS clusters falling in and out of GRUMP light extents.

II. OVERVIEW

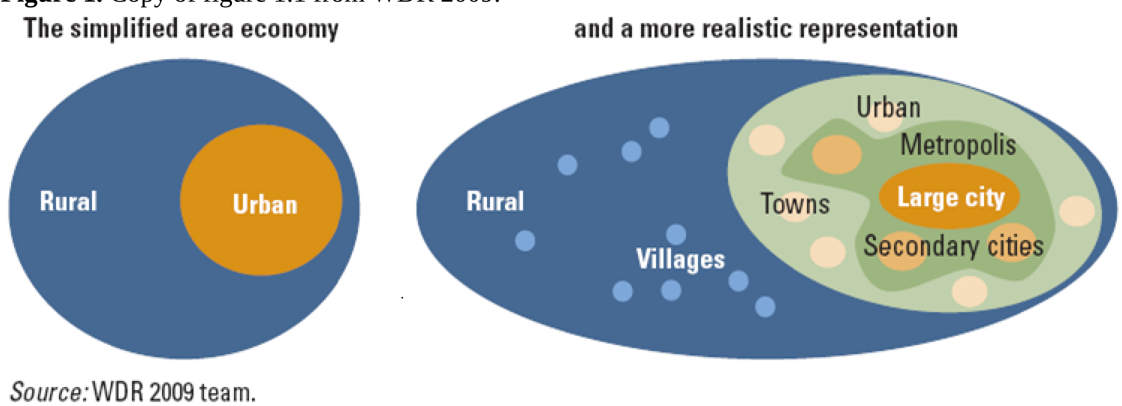
There is widespread awareness that the world is becoming increasingly urban, both in terms of population (urbanization) and the spatial extent of urban land (urban expansion). However, our understanding of these trends is limited by the lack of a consistent framework: there is no standard definition of an urban area (UN, 2008), nor agreed-upon spatial boundaries of urban areas (Balk, 2009). This makes cross-country comparisons and aggregations difficult. Researchers don't know what they are capturing when they include an urban dummy in their analysis. To illustrate this point, Utzinger and Keiser (2006) categorized the national urban definitions used in 228 countries for which the United Nations compiled data in 2005 into ten categories. The most common definitions were based on population size, economic activity, and administrative function or some combination of these. But even within definitional categories, there were differences. For instance, although many countries defined urban areas based on population size, the size threshold varied.

[1] Corresponding Author: Audrey Dorélien, Office of Population Research, Princeton University, email: dorelien@princeton.edu

Some argue that "there is little point in searching for a common definition of urban since what is perceived as an urban area *does* vary between nations so that the effort should be on individual nations arriving at definitions of urban which are most appropriate to the characteristics prevailing in that nation, rather than attempting to arrive at some universal standard criteria for distinguishing urban and rural"(Hugo IUSSP paper 2002). In this paper, we cross-validate two sources of urban definitions—a spatial dataset designed to measure the spread of urban areas and a household survey designed to measure the demographic characteristics of populations.

The simple rural/urban dichotomy is not a realistic description of human settlements—over time rural settlements have acquired many characteristics that in the past were associated mainly with urban settlements (e.g. rural electrification); furthermore new types of settlements such as transition zones have emerged (Wratten 1995; Hugo et al. 2003; WDR 2009). Finally there are different objectives for defining urban areas which partly explains the plethora of available definitions therefore in this paper we are not trying to create a new definition of urban, but to better understand what is meant by urban in these two data sources and to understand the challenges of conceptualizing an urban continuum based on multidimensional terms.

Figure 1. Copy of figure 1.1 from WDR 2009.



Demographic and Health Surveys (DHS) are nationally-representative surveys that collect data on household and individual characteristics throughout the developing world. As of 2009, the survey program has collected spatial data (geocodes) for 67 DHS in 36 countries (MEASURE DHS website, 2009a). For surveys with spatial information, the DHS provides geographic coordinates for the sampling clusters, consisting of approximately 15-30 households, as well as the rural/ urban classification of the clusters as defined by the country's national statistical office. The geo-referenced DHS data can now be linked spatially to data from Columbia University's Center for International Earth Science Information Network's Global Rural Urban Mapping Project (GRUMP) database, which estimates the spatial extent of urban areas from satellite data of nighttime lights (CIESIN et al., 2004). Whereas the DHS uses each country's urban/rural classification, which often varies from country to country, GRUMP's definition is based on a systematic and globally consistent measure.

We focus here on cross-validating the two data sources, by analyzing the distribution and characteristics (i.e. household electrification, rural/urban classification, poverty) of DHS clusters falling in and out of GRUMP light extents. We do this by addressing the following questions: Do GRUMP light extents indicate urban places – that is, are the lights a good proxy for urban areas? To help answer this question, we first ask whether: GRUMP light extents adequately capture electrified places? Because the GRUMP database depends on the use of nighttime lights imagery to identify urban areas, and because lights are emitted only by electrified areas, having additional geo-referenced measures of electrification from the DHS gives a sense of what kinds of settlements are missed by the nighttime lights imagery.[2] We find that GRUMP light extents do identify the majority of highly electrified localities but as we show below the measurement is imperfect. Further we find only moderate agreement between the urban classification used by GRUMP and DHS: while we find that GRUMP light extents identify most of the locations defined as urban we also find that GRUMP light extents identify many locations identified as rural. Upon closer inspection, these locations are peri-urban and possess many functional urban characterisitics. As a result, we argue that when used in combination the GRUMP light extents and DHS urban classification produce a finer grain continuum of urbaness than is available from either data set alone.

Our study also brings to light shortcomings in the DHS geo-referenced data – particularly earlier survey rounds – that have not been previously mentioned and which may serve as reminder to others DHS data users that care in use and interpretation is warranted.

Prior Research

The majority of the literature validating the quality of global urban maps has compared the satellite-derived global urban maps to a high resolution remotely sensed standard at a country or city level. Tatem et al. (2005) compared five satellite derived global urban maps including GRUMP to a medium–resolution Kenya settlement map. Schneider et al. (2009) compared the accuracy of six global urban maps including GRUMP against 140 medium-resolution city maps generated by Landsat imagery. Potere et al.'s (2009) analysis takes a two tiered approach. They compared eight global urban maps with 140 medium resolution city maps and with 10,000 high-resolution Google Earth validation sites. All of these studies found that most pixels classified as urban by the high resolution maps fell within GRUMP light extents, but a large number of pixels classified as rural also fell within GRUMP light extents. The comparisons in these papers are important as the different remote sensing data and techniques are evaluated; but to an important degree, which database is best depends on one's intended objective or use of the data. Our paper is the first systematic analysis of its kind: we compare a global urban map, GRUMP, with geo-referenced household data, rather than another remotely-sensed database.[3] This allows us to compare the global urban map to the country-specific

[2] That is once gas flares and other light sources have been purged from the processed imagery.
[3] Fugate's dissertation (2008) also used both remote sensing data and DHS but she was not performing a cross validation. She estimated the population size and population age structure of sub-national regions by linking remote sensing, census, and DHS data.

definitions and learn more about the characteristics of the localities categorized by the global map.

III. DATA AND STUDY DESIGN

In this study, we pool the 20 DHS surveys from 1990-2000 so that they correspond at the mid-point (1995) with the GRUMP extent data to ask how these two different approaches to understanding urbanization compare. The temporal restriction arises because GRUMP extents, which are based on 1994/95 imagery, are not able to capture newly electrified localities.[4] The temporal constraints impact the quality of our data but this is discussed further in the data quality section. For countries with multiple DHS surveys, we use the DHS survey that is closest to the 1994/1995 time period. All but one (Bangladesh) of the twenty geocoded DHS surveys in this period are in Africa (see Appendix), and of these all but two (Chad and Egypt) represent countries in Sub-Saharan Africa. The restriction of our analysis to Africa and Bangladesh arises because the early geocoding efforts were concentrated there.

The GRUMP light extent dataset is a spatial database that indicates the extent or "footprint" of urban areas, along with information such as place name, population and area. To detect urban extents, GRUMP primarily uses the 1994/95 stable city lights dataset from the National Oceanic and Atmospheric Administration's nighttime lights satellite data, which measures permanent light (Elvidge et al., 1997). For the attributes, names and population associated with human settlement are compiled from national statistics offices and external sources and spatially linked to the extents. Population for an GRUMP extent is calculated by summing the population of the settlement points and cross-validating them with population values for the administrative areas in which each extent overlaps; because population data for administrative units and settlement locations often vary considerably the final assignment of a population value to the GRUMP mask is an iterative process (Balk et al., 2005). Some known small cities or towns are not detected in the night-time lights satellite data; in these cases, urban extents are estimated as circles, the size of which is predicted from a country- or region-specific regression of urban extent size on population (see Balk et al., 2005 for additional details). In our analysis, we will distinguish these imputed extents from the light extents (see the Figure 3). A third source of GRUMP extents are Digital Chart of the World (DCW) footprints. In the development of GRUMP, it was concluded that the DCW footprints were outdated and unrealistically small and these were eventually replaced with imputed extents (circles) (Balk personal communication).We use DCW in this analysis to see if they capture small poorly electrified towns.

A DHS survey cluster, the primary sampling unit for DHS, comprises a group of households. The boundaries of a cluster may or may not coincide with a census enumeration unit. The geographic data (latitude and longitude) attributed to the clusters

[4] The spatial changes of urbanization may be happening so rapidly that the lights of 1995 substantially misrepresent the situation even 10 years later. In our preliminary analysis there was a clear temporal trend with GRUMPs ability to capture electrified areas—GRUMP's ability to capture highly electrified areas significantly declined after 2000.

are presumed to be the geographic centroid of the group of households (Balk et al., 2004; CITE DHS geocoding techniques). In rural areas, clusters may contain households from more than one village and may represent a geographically large area; in contrast, in urban areas clusters tend to represent geographically small areas (Balk et al., 2004). We compute cluster level variables. The primary variables of interest are cluster electrification (calculated as the proportion of households in the cluster that have electricity) and urban/rural classification. Because we are also interested in functional definitions of urbanization, we also looked at indicators often used to measure poverty and urban-ness, such as the proportion of households in the cluster that had access to improved drinking water and toilet facilities as well as durable flooring, and adequate living area. With the exception of adequate living area, which we anticipate that on average there is likely to be less living space per person in cities than in rural villages, we expect that these indicators will measure access to urban amenities.

Access to improved water and sanitation were defined based on guidelines from the WHO Joint Monitoring Program for Water Supply and Sanitation (WHO/UNICEF JMP website 2010). A household is coded as having access to improved drinking water if the water is piped into the dwelling or yard/plot; water was from public tap/standpipe, tube well, well with a pump, or borehole, protected well, protected spring, or rainwater (having access to bottled water was included as protected although the WHO/UNICEF JMP website highlights some problems with this).. Therefore in this paper, improved water refers to the source and not necessarily the quality of the water (which may decline with urbanization if the infrastructure is inadequate). Improved sanitation includes flush toilets regardless of whether excreta go into sewer or septic tank, and pit latrines that are ventilated or are covered with a slab. Durable flooring includes finished flooring such as cement, tiles, linoleum, parquet, etc. Durable flooring doesn't include earth floors or wood planks (UN-Habitat 2006). Many surveys lacked the "sleeping room" variable, nonetheless where appropriate, adequate living area was defined as having no more than three people sleep in the same room.

Adjusted Weights

Our analysis pools together clusters from all 20 surveys. For our descriptive work, we, create a weighting scheme for the clusters, so as to take account of the large differences in country populations and sample sizes among these surveys. Furthermore the number of clusters in each survey is not proportional to the country's population size (see appendix). When analyzing the clusters in a pooled sample, we must adjust for these two types of differences between places. Therefore, the survey's sample weights in the pooled dataset are rescaled in order to represent the twenty countries in proportion to their populations. "An expansion weight was calculated for each country and then multiplied by the original sample weight. The weights were then renormalized to average to one across the pooled sample" (Balk et al. 2004). We will present both the weighted and un-weighted descriptive statistics in this paper; weights will not be used in any of the regressions. The weighted statistics give a more representative picture of the urban universe in Africa and Bangladesh.

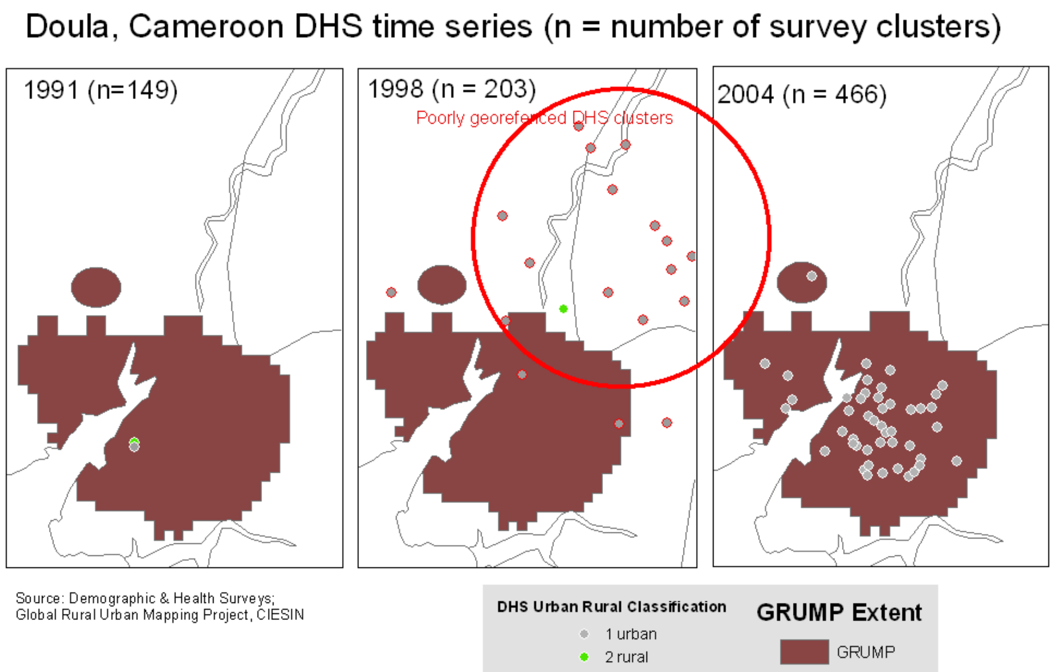
Data Quality

GRUMP's approach has some known shortcomings. The main problem is that nighttime lights exhibit overglow, whereby lights recorded by the satellite sense extend beyond the geographic limits of the on-the-ground light source. Hence, the measured light extents are thought to be larger than urban extents measured in other ways, such as impervious surface measurements (Elvidge et al., 2004; Tatem et al. 2005; Potere and Schneider 2007). Furthermore, in less-developed regions, such as in Africa, GRUMP may leave some small and poorly electrified urban areas undetected, despite the impuation efforts described above (recall imputed extents, i.e. circles) (Balk et al., 2005).

DHS's geocoding procedures have also been subject to errors, especially in the early stages of this effort in the 1990s. In at least one country, Cameroon, it appears that there are geo-coded clusters that should be located within urban areas, but they are not (Figure 2). The detection of this problem was made possible by comparing three years of data, and by overlaying it with the GRUMP light extents. Both are clues to inconsistencies – over time and place – in the geocoding: Because the sample for the 1991 survey was much smaller than either of the two subsequent ones, without the spatial information from GRUMP, one might assume that the 1998 cluster locations for the 1998 survey were other neighborhoods in Doula. The 2004 survey conforms to the urban extent, and the limited 1991 sample, further suggesting that something is amiss with the coordinates for 1998. (In this analysis, data from the 1991 Cameroon survey is used instead of the 1998 one.) In some countries, many clusters (sometimes both rural and urban) share the same point location (as in the 1991 panel of Figure 2). Chad 1996-1997 DHS, where 247 clusters share just 45 point locations, provides the most obvious example of this. Shortcomings in the data collection in the early rounds of the geocoding may be to blame. Another common problem is that depending on the administrative layer used, cluster points may be located outside of the respective country's administrative boundaries. Apart from this last problem, which arises from not having a standard set of DHS boundaries, the DHS has instituted procedures to ensure that these early problems have not been repeated in more recent rounds.[5] Although not a problem in our data sample, in recent DHS surveys that report HIV status, random error is deliberately introduced to geographic coordinates; DHS limits to error to 2 km or less in urban areas and up to 5 km in rural areas (Measure DHS website, 2009b).

Figure 2. This figure shows for Doula, Cameroon, GRUMP light extents and DHS clusters in 1991, 1996, and 2004. A large number of clusters classified as urban by the DHS in 1998 were located north of the GRUMP light extents. We also used Google Maps to verify that the location of these clusters do not appear to be in urban areas.

[5] Upon request author can provide a more detailed list of DHS geocoding errors.



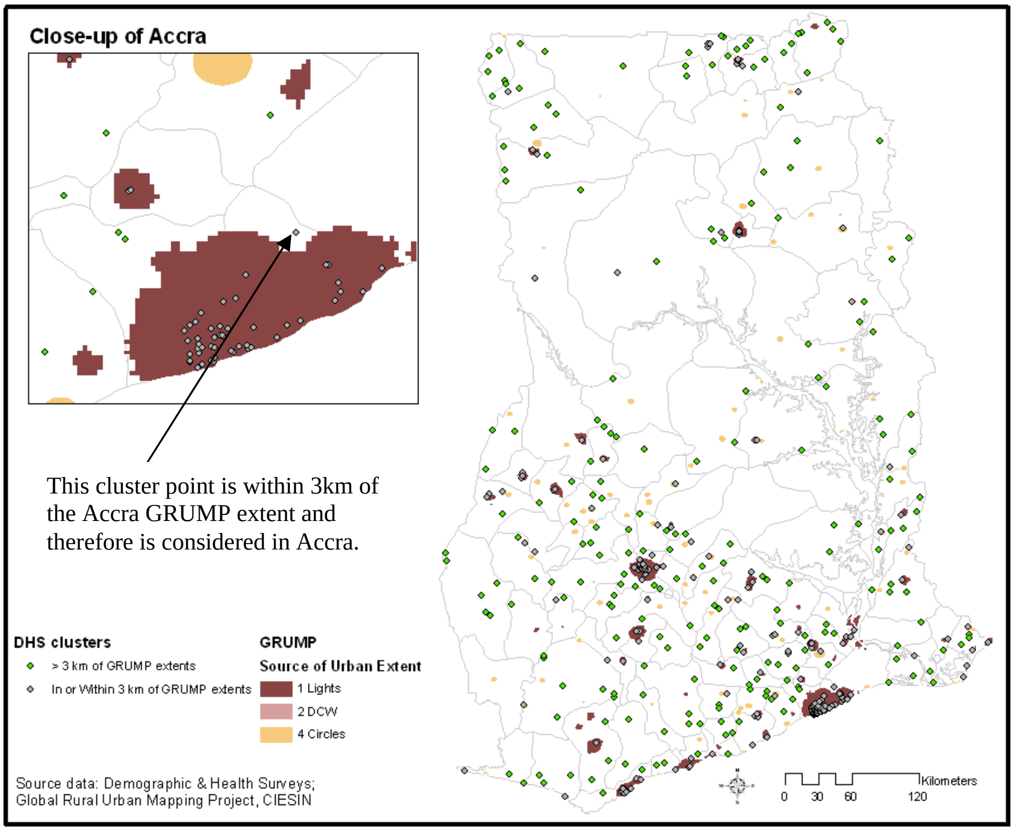
Methods

We integrated the DHS data with the GRUMP light extent data using programming tools in ArcMap 9.3 and Python 2.5. Any DHS cluster point contained within or within 3 km of the boundary of GRUMP light extent was merged. There are two reasons for associating cluster points within 3 km buffer to a GRUMP light extent: first, the nighttime lights are accurate within 3 km (Elvidge, 1997)[6] and in DHS countries with HIV reporting the DHS cluster points have up to 2 km of deliberate error introduced in urban areas for confidentiality purposes. In what follows, we will describe these clusters as being within a GRUMP light extent. Overall, more than half (n = 3,343 percent= 55.26%) of all DHS clusters were spatially matched with a GRUMP extent.

To better understand the nature of these data, consider the case of Ghana. Figure 3 contains a map with DHS cluster points as well as GRUMP extents.

Figure 3. This map illustrates the different sources of GRUMP light extents and illustrates which clusters were joined with a GRUMP extents and which were not. Grey clusters falling outside of GRUMP extents are within 3km and are therefore joined to the nearest GRUMP extents.

[6] That is, the positional accuracy of the sensor responsible for the night-lights detection is accurate within 3 km. The true edge of the night-lights is somewhere between where we render it and an additional 3 km beyond. For this reason, DHS clusters located up to 3 km beyond the edge are considered to belong to the nearest light.



This paper's analysis primarily consists of descriptive statistics, ordinary least squares regressions, and spatial statistics, as well as descriptive maps, each of which is described in turn below.

IV. ANALYSIS

Do the GRUMP light extents capture electrified places?

As discussed above, the GRUMP extents are primarily based on remote-sensing of nighttime lights, supplemented by imputed extents ("circles") for smaller cities that were known not to have been detected by the light sensor. In this section, we use the DHS clusters to quantify GRUMP's ability to identify electrified localities. Specifically we compare the distribution of cluster electrification (the proportion of a cluster's households with electricity) within GRUMP light extents and outside of GRUMP extents. We also analyze the likelihood that clusters with a certain proportion of electrified households are spatially matched to a GRUMP extent.

On average, clusters located inside GRUMP light extents are more highly electrified than clusters outside these extents. Forty-four percent of the DHS clusters inside GRUMP extents had more than 75 % of households electrified, compared with less than four percent of DHS clusters outside of GRUMP extents. Still, 733 clusters inside GRUMP extents are not electrified. Applying the pooled-sample weights increased the proportion of highly electrified clusters, the mean electrification of GRUMP clusters rose to 72.07% and the mean electrification of clusters outside of GRUMP rose to 12.84%. Later in this section we look to see if these clusters were joined with GRUMP's "circles" – the extents based regression estimates rather than on direct nighttime lights – or if these clusters represent poor neighborhoods within GRUMP extents. [In other words, we will try to determine whether this is a socioeconomic feature of cities, that some within-city neighborhoods are not electrified, or a problem of measurement.] Likewise we try to understand why 51 fully electrified DHS clusters were not in GRUMP extents at all (Table 1).

What is the likelihood that clusters with a certain proportion of electrified households are captured by – that is, were spatially matched to – a GRUMP extent? The GRUMP extents contain the overwhelmingly majority of electrified clusters, especially highly electrified ones – close to 94% of clusters with more than 75% of households electrified or clusters which were fully (100%) electrified. But as the proportion of electrified households decreased, so did the ability of GRUMP extents to identify these clusters. Only 25.23% (733) of the non electrified clusters were captured by GRUMP Extents (Table 1). The same pattern was found when the pooled-sample weights were applied.

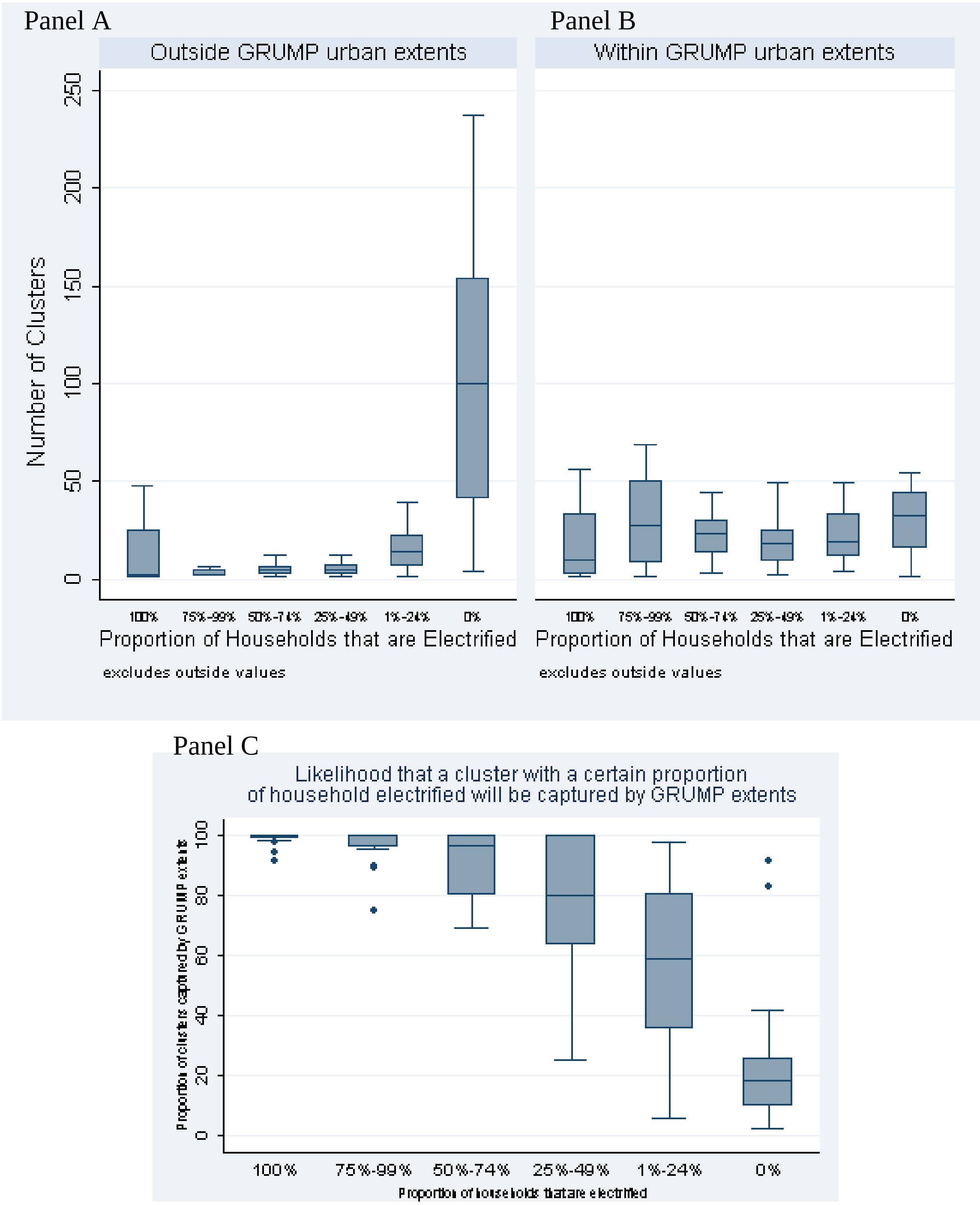
Table 1. Distribution of DHS clusters by Cluster Electrification and GRUMP extents.

Households in each cluster that are electrified:	Clusters in GRUMP extents (urban clusters)			Cluster not in GRUMP extents (rural clusters)			% of clusters captured by GRUMP extents by electrification	
	Number	%	% wgt[c]	Number	%	% wgt[c]		% wgt[c]
100%	760	22.65	40.74	51	1.85	3.77	93.71	92.04
75%-99%	732	21.81	25.00	48	1.74	4.14	93.85	86.06
50-74%	399	11.89	9.14	49	1.78	3.19	89.06	75.37
25- 49%	334	9.95	6.80	88	3.19	5.57	79.15	56.61
1-24%	398	11.86	6.17	349	12.66	14.58	53.28	31.14
0%	733	21.84	12.14	2,172	78.78	68.75	25.23	15.88
Missing [a]	187	-		111	-		-	
Total [b]	**3,356**	**100**		**2,757**	**100**		**54.90**	
Mean Electrification		**54.16%**	**72.07%**		**6.68%**	**12.84%**		

Notes: (a) The Nigeria DHS clusters do not have information on cluster electrification. (b) Total does not include clusters with missing electrification information.(c) based on sample weights.
Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN).

Figure 4 is a box plot of our 20 DHS country frequency distribution of clusters in an out of GRUMP extents by electrification category. Panel A indicates that most clusters outside of GRUMP light extents are not electrified; there are very few well electrified clusters outside of GRUMP extents with the exception of Egypt which contributes 48 of 51 fully electrified clusters. Whereas Panel B, shows that even within GRUMP extents there is wide variation in cluster electrification. Panel C shows that GRUMP tends to capture the highly electrified clusters and that as electrification declines, a cluster is less likely to fall within a GRUMP extent.

Figure 4. Box plots of showing the distribution of DHS clusters by Cluster Electrification and GRUMP extents.



Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN).

<u>Electrification by GRUMP Source</u>

As mentioned in the data and study design section, while the GRUMP extents are primarily based on the nighttime lights, there are two other sources of urban footprints–

circles and DCW footprints. The majority of the DHS clusters within GRUMP extents were captured by lights. Although the majority of the clusters within lights were highly electrified (mean proportion of electrified households = 66%), there were still a substantial number (240) of poorly electrified clusters within lights. On average, clusters that fell within circles and DCW were poorly electrified. More than half of the un-electrified clusters captured by GRUMP fell within circles, which were not based on nighttime lights imagery (Table 2).

Table 2. Distribution of DHS clusters by Cluster Electrification and GRUMP source; and Characteristics of GRUMP extents by cluster electrification. Unless otherwise stated, these are the un-weighted results. Applying the rescaled weights increased the mean electrification, size, and population of the GRUMP extents.

Households in each cluster that are electrified:	Source of GRUMP extents			All GRUMP Extents	
	Lights (no.)	Circles (no.)	DCW (no.)	Avg. Size of GRUMP extents(km^2) (95% Conf. Interval)	Avg. Population of GRUMP extents(1995) (95% Conf. Interval)
100%	754	2	4	2,685 (2,393 – 2,977)	5,097,783 (4,676,955 – 5,518,610)
75%-99%	705	26	1	3,191 (2,825 – 3,557)	4,218,245 (3,818,669 – 4,617,822)
50-74%	354	41	4	1,058 (764 – 1,358)	1,526,305 (1,194,518 – 1,858,092)
25- 49%	279	51	4	277 (148 – 406)	544,153 (378,960 – 709,346)
1-24%	277	108	13	158 (139 – 179)	352,487 (300,978 – 403,997)
0%	240	425	68	65 (57 – 73)	93,617 (74,471 – 112,763)
Mean electrification	**66%**	**10%**	**7%**	**Mean size = 1,436**	**Mean pop. = 2,356,682**
Mean electrification (wgt)	**78.9%**	**22.57%**	**21.98%**	**Mean size (wtg) = 2,016**	**Mean pop. (wtg) = 4,219,936**

Notes: Nigeria doesn't have information on cluster electrification and is therefore excluded from this analysis.
Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN)

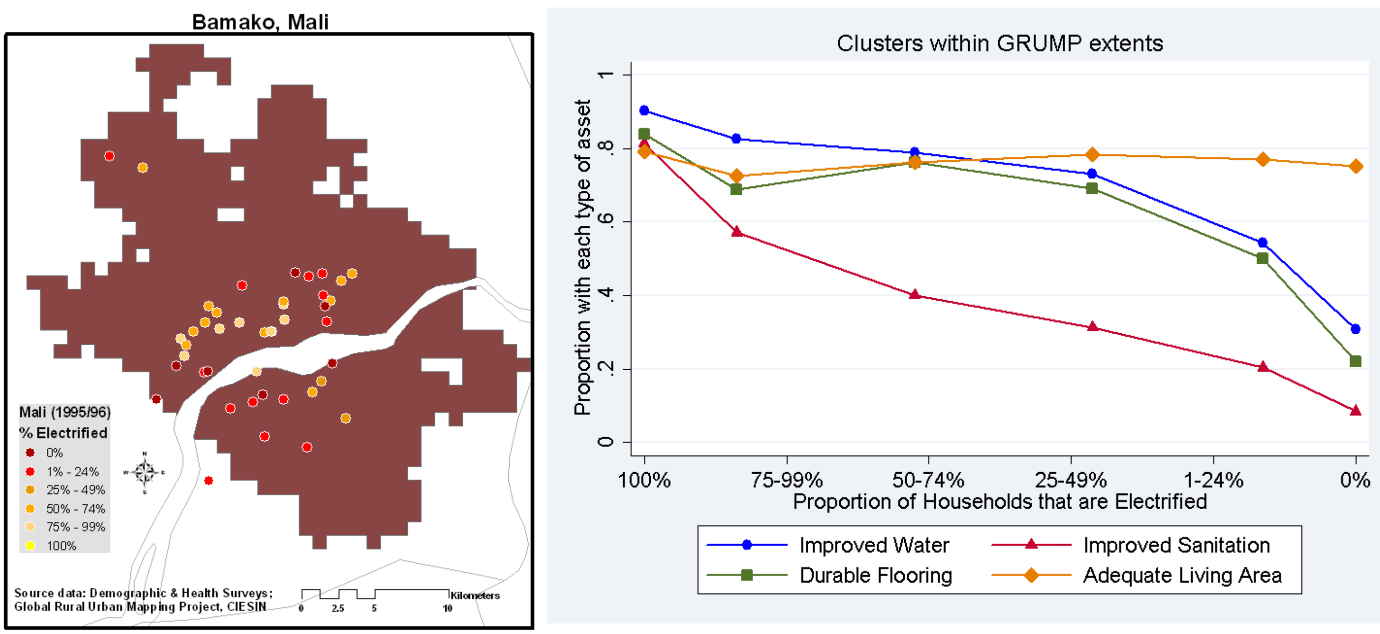
As shown in Table 2, highly electrified clusters are more likely to be located in larger GRUMP extents than are poorly electrified clusters. The mean area of GRUMP extents with non-electrified clusters is 65 square kilometers. In contrast, the mean area of GRUMP extents with fully electrified clusters is 2,685 square kilometers. Likewise, highly electrified clusters are more likely to be found in more populous GRUMP extents. The mean 1995 population extents within which fully (100%) electrified clusters are located in is 5,097,783. In contrast, the mean 1995 population of GRUMP extents within which non-electrified (0%) clusters are located in is 93,617.

It's no surprise that GRUMP extents identify clusters in large electrified localities better than small poorly electrified clusters, and the majority of the poorly electrified smaller localities that were captured fell within "circles" or DCW-based footprints – the footprints intended to capture the smaller localities.

Can poverty explain poorly electrified clusters found within GRUMP extents?

The GRUMP extents inform us that the locality is electrified, but we cannot assume that there is a consistently high degree of electrification throughout the GRUMP extents (see Figure 5a). The DHS clusters can tell us a bit about intra-urban variation. Specifically, we can test the hypothesis that the poorly electrified clusters captured by GRUMP extents represent poor neighborhoods. We used the proportion of households with access to improved water and sanitation, durable flooring, and adequate living area as a proxy for poverty.[7]

Figure 5. (a) Map of Bamako, Mali, GRUMP extents with cluster electrification. It is clear that there is a lot of intra-city variation in electrification. (b) This figure shows the proportion of households in the pooled-sample which each type of assets by cluster electrification categories. Electrification is positively correlated with access to improved water and sanitation as well as durable flooring. Therefore, on average, poorly electrified clusters also had fewer assets.

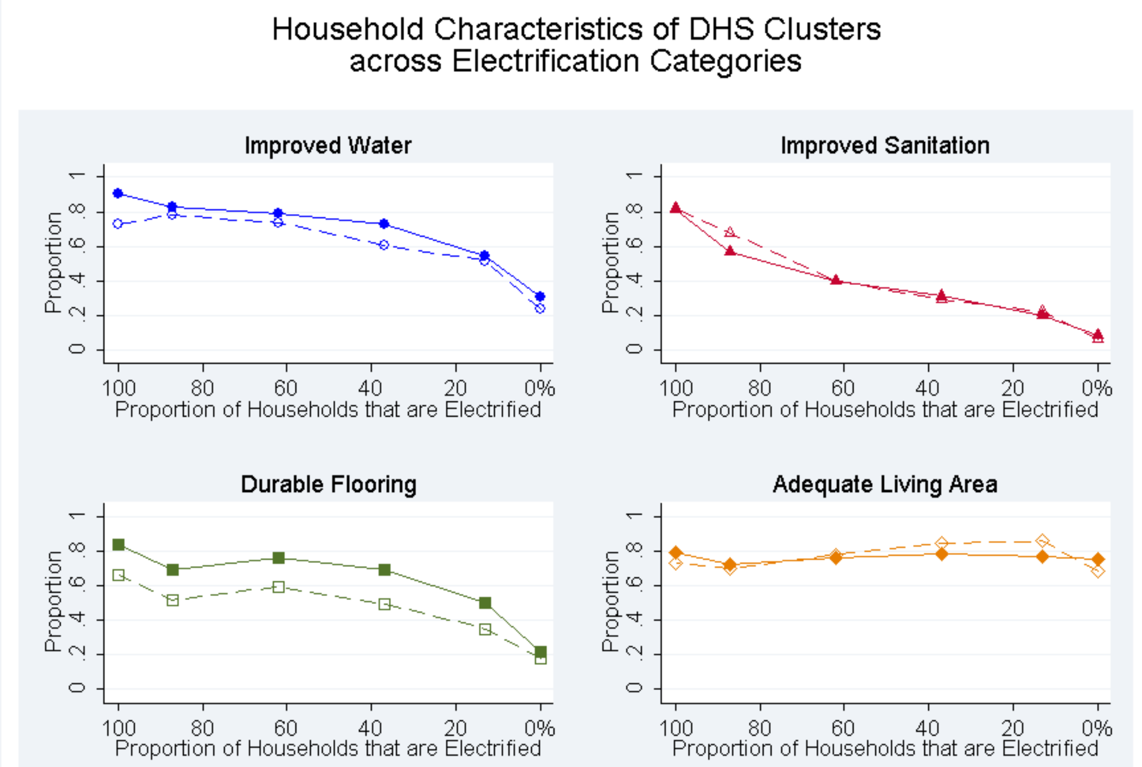


Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN).

Figure 5b shows that clusters with zero electrified households had substantially less access to improved water and sanitation as well as durable flooring than clusters with a larger proportion of electrified households. As electrification diminishes so do these other amenities. Access to sanitation shows the strongest – and most linear – relationship with electrification.

Figure 6. Household characteristics of DHS clusters across electrification categories. Solid lines represent characteristics of DHS clusters within GRUMP light extents. Dashed lines represent characteristics of DHS clusters outside GRUMP light extents (aka defined as rural by GRUMP).

[7] These variables account for many of the variables used to define slums by UN-Habitat.



Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN).

Here we compare DHS clusters that fall within GRUMP extents ("urban") with those located outside of GRUMP extents ("rural"). Electrification is highly correlated with other household characteristics. Both rural and urban DHS clusters with high electrification also have high proportions of households with access to improved water and sanitation as well as durable flooring and vice versa. Nevertheless, *non-electrified* urban clusters had significantly more access to improved water, improved sanitation, and durable flooring than non-electrified rural clusters. Although statistically significant the magnitudes of the differences were relatively small. *Fully-electrified* urban clusters were better off in terms of household characteristics with the exception of access to improved sanitation than highly electrified rural localities.

We find that sanitation varies considerably by the proportion of the cluster electrified with large differences in sanitation between poorly and well electrified clusters. Clusters are alike regardless of whether or not they are located within or outside a GRUMP extent. In other words electrification matters a lot and electrified clusters are more likely to be within GRUMP extents (that is urbanized) but clusters with low levels or electricity regardless or where they are on the urban continuum are less likely to have improved sanitation. It is important to note that our definition of improved sanitation is not limited to facilities connected to a sewer or septic tank.

Rural clusters can have similar characteristics to urban clusters. It's clear that the GRUMP extents captured some poor urban clusters but why didn't the GRUMP extents capture the well lighted rural clusters with high access? All but three of the fully electrified clusters located outside of a GRUMP light extent were in Egypt, a relatively rich country; therefore these highly electrified and well-off clusters were not captured by GRUMP most likely because of their physical size and/or population density.

Next we ran an OLS regression to more formally test the relationship between the proportion of electrified households in a cluster and whether the cluster is in GRUMP light extent, along with these other household poverty proxies (improved water and sanitation, durable flooring, and adequate living area). We also controlled for interaction between falling in GRUMP extents and the other household characteristics. Finally we also included country-specific dummy variables. Eighty-one percent of the variation in cluster electrification could be explained by our model. All of our variables (excluding country-specific dummies) were highly statistically significant. The results of the regression confirm our descriptive statistics. Clusters that fall within GRUMP extents were significantly more electrified than those that were located outside of them. Clusters with no access to improved water, no access to improved sanitation, no durable flooring, and or insufficient living area were significantly less electrified than clusters with access to those assets. We included an interaction term with these assets and GRUMP extents and found the effect of improved water and durable flooring even greater in urban areas. Improved sanitation, however, had a negative interaction: while access to sanitation is a very strong predictor in general of whether or not a cluster is electrified, that effect is dampened in urban areas, presumably because some urban dwellers live in poverty with limited access to this type of infrastructure. Similarly, the interaction of adequate living space – a seemingly invariant characteristic with respect to electrification in general – suggests that living area has a modest positive association in rural areas and an equally negative association in urban ones. Perhaps electrification is more likely in urban areas when housing is compacted such as in high-rise dwellings. In sum, poverty as proxied by these key assets does help explain the poorly electrified clusters that fall within GRUMP light extents. It is interesting, however, that these relationships – especially that of sanitation – are complex.

Table 3. Results of OLS regression.

Proportion of electrified households in a cluster	*Coef.*	*Std. Err*
Within GRUMP Extents	0.147	0.019
Proportion of households with Improved Water	0.036	0.011
Proportion of households with Improved Sanitation	0.353	0.020
Proportion of households with Durable Flooring	0.139	0.015
Proportion of households with Adequate Living Area	0.080	0.020
GRUMP*Improved Water	0.230	0.015
GRUMP*Improved Sanitation	-0.094	0.021
GRUMP*Durable Flooring	0.156	0.017
GRUMP*Adequate Living Area	-0.160	0.025
Country Dummies (hidden)		
Constant	-0.017	0.022
R-squared	.8145	
Number	5994	

Note: All coefficients are significant at the P< .001 level.

Do the GRUMP extents indicate urban areas?

GRUMP extents are often used as a proxy for urbanization (McGranahan et al., 2007; Balk et al., 2004; Tatem et al., 200?), specifically to delineate urban areas. In this part of the paper, we analyze how well the GRUMP extents are able to capture DHS urban localities. We use the urban/rural classification of the clusters within GRUMP extents to analyze whether the GRUMP extents appear to overextend the urban areas that they are intended to proximally represent. Throughout this analysis, it is important to remember that the DHS rural/urban classifications use the definition of urban adopted by the national statistical office, which have undergone very little modification more than 50 years ago (Hugo et al., 2003) and which vary from country to country. Furthermore, the conceptual basis from which these urban-rural dichotomies arose may or may not correspond well to the concentrations of settlement and economic activity that the nighttime lights sensor proximally detects.

Table 4. Contingency Table and Map Agreement Measures: validating GRUMP extents based on DHS urban classification.

		DHS urban classification	
		Urban	**Non Urban**
GRUMP Classification	**Urban**	2,339	1,204
	Non Urban	137	2,731

Sensitivity = Proportion of urban clusters captured by GRUMP	94.47%
Specificity = Proportion of rural clusters not captured by GRUMP	69.40%
Probability that a cluster falling within GRUMP was urban	66.02%
Probability that a cluster falling outside of GRUMP was rural	95.22%

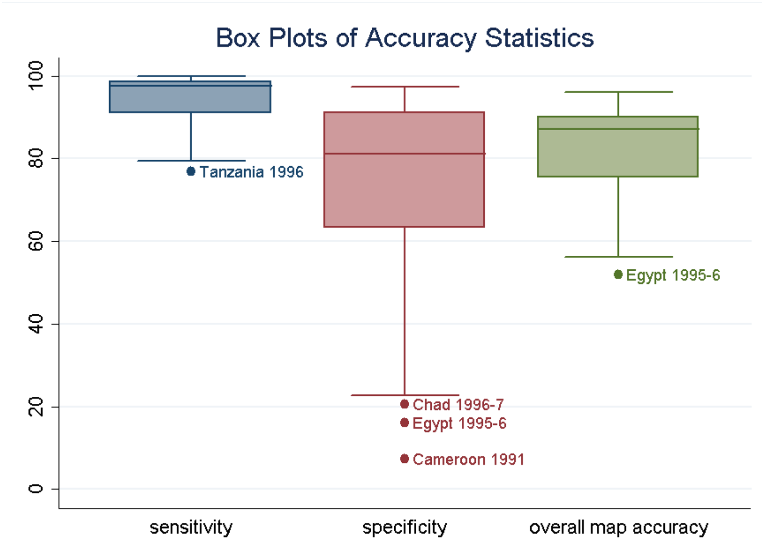
Among DHS clusters that were classified as urban, 90 percent were identified as urban in the sense of lying located within a GRUMP extent. Likewise, of all DHS clusters classified as rural, 69% lie outside GRUMP extents. Borrowing the language of epidemiology, GRUMP extents are *sensitive* in that they detect up the majority of urban clusters but they are not very specific, as GRUMP extents also pick up a large portion of rural localities. Overall map accuracy (OMA, a measure of agreement), using DHS as the standard, is 79%.[8] When we adjust for the probability that some of the agreements are by chance (a.k.a. Cohen's Kappa Statistic), the overall agreement falls to 59%. According to Landis and Koch (1977) the Kappa Statistic of 59% indicates moderate agreement; this is expected since the two data sources are based on different but correlated urban definitions.

What is the probability that the DHS clusters within GRUMP are all classified by DHS as urban? Looking at the classification of DHS clusters that fell within GRUMP extents, 66% were classified as urban, therefore 34% (n=1,204) were rural clusters identified by GRUMP as urban. Similarly, of all the clusters identified as rural by GRUMP (i.e., those that fall beyond the urban extent borders), 5% (n=137) were classified as urban by the DHS.

[8] Overall Map Accuracy (OMA) = (a+d)/n (see appendix).

Figure seven illustrates the results of the by country map agreement measures. At the national level we see that GRUMP is sensitive but has lower specificity especially in Chad, Egypt, and Cameroon.

Figure 7. Box plots of accuracy statistics for GRUMP using country specific urban definition from our sample of 20 DHS surveys as validation. This figure shows three measures of accuracy at the country level (a) sensitivity (or producer's accuracy), (b) specificity (or user's accuracy), and (c) the overall map accuracy. Outliers are labeled. Accuracy statistics approach 100 when DHS urban definition agrees with GRUMP urban definition.



Data sources: Demographic & Health Surveys; Global Rural Urban Mapping Project (CIESIN).

<u>What accounts for the lack of sensitivity? Why were some clusters classified as urban by DHS not classified as urban by GRUMP?</u>

GRUMP is primarily based on nighttime lights, therefore one of the main explanations for the lack of inclusion of DHS urban clusters within GRUMP light extents could be electrification. Of the 137 urban clusters found outside of GRUMP we had electrification information was available for 120 clusters. Nigeria did not have any electrification information, and is therefore omitted from this analysis. Of these urban clusters, 79% (95) were clusters where less than 50% of households were electrified. The electrification of these urban clusters might have been too low to be captured by the night-time lights. (This is likely the case in Tanzania: the 22 DHS urban clusters not captured by GRUMP light extents had a mean electrification of 5.6 %.) The remaining 21% (25) were well-lighted (more than 50% electrified) but they may have been too small to be captured by GRUMP. This was confirmed by looking at these 25 locations in the satellite view of Google Maps. All but one of these clusters are located in small towns of less than two square kilometers (as measured by scale on Google Earth).[9]

[9] The exception was the cluster in Dubreka, Guinea which appeared to be near a city. The coordinates for this cluster location are 9.7892N, 13.5188W.

On average, these DHS urban clusters are significantly more electrified and have better access to improved water and sanitation, flooring and adequate living area compared to clusters classified as rural by both DHS and GRUMP. However these clusters were not better off than the clusters that were classified as urban by both GRUMP and DHS (Table 5). Thus, DHS's urban classification closely conforms to GRUMP's urban classification for surveys within a five-year period of the night-time lights. DHS urban clusters that were excluded from GRUMP extents were mostly non-electrified clusters.

<u>What accounts for the low specificity? Why were some clusters classified as rural by DHS classified as urban by GRUMP?</u>

A large number (1,204) of DHS rural clusters were located within GRUMP light extents. Possible explanations for the lack of specificity include suboptimal geo-referencing data quality, rural electrification (and other characteristics associated with urban areas), proximity to urban area, and or outmoded or meaningless country-specific urban/rural classification.

As mentioned in the data quality section, we found that in some countries, rural clusters were assigned the same coordinates as urban clusters. There were 230 DHS rural clusters with coordinates also identified by the DHS as urban that were captured by GRUMP light extents. The majority of these poorly geo-referenced clusters were in Chad, the Central African Republic, and Cameroon, which helps explain GRUMP's poor specificity in these countries.

High levels of electrification and therefore high household characteristics might also account for the inclusion in the GRUMP extents of these DHS rural clusters. The DHS rural clusters included in GRUMP extents possessed significantly more "urban" characteristics than DHS urban clusters not captured by GRUMP; however they were not as electrified as DHS urban clusters captured by GRUMP. The relationship is stronger after removing the 230 poorly referenced DHS rural clusters (Table 5). Therefore, the disagreement between these two definitions suggests another possibility: they may be peri-urban localities.

Table 5a. Mean proportion of households with access to electricity, improved sanitation and water, durable flooring, and adequate living area based on contingency matrix (unweighted).

Urban Continuum	# of Clusters[a]	Electrification	Improved Sanitation	Improved Water	Durable Flooring	Adequate Living Area
GRUMP and DHS rural	2578	0.0603946	0.119254	0.3067162	0.2239631	0.7131693
GRUMP rural and DHS urban	113	0.2368877	0.1861295	0.4361309	0.4136449	0.720191
GRUMP urban and DHS rural	1120	0.4084512	0.3349198	0.4802813	0.3084192	0.7079743
GRUMP urban and DHS rural[b]	903	0.5008032	0.3964219	0.5318696	0.3651794	0.6942406
GRUMP and DHS urban	2183	0.6154588	0.4819171	0.7871711	0.760987	0.7875115

Notes: (a) Does not include Nigerian Clusters (b) Does not include the 230 DHS rural clusters with coordinates also identified by the DHS as urban.

Table 5b. Mean proportion of households with access to electricity, improved sanitation and water, durable flooring, and adequate living area based on contingency matrix (weights included).

Urban Continuum	Electrification	Improved Sanitation	Improved Water	Durable Flooring	Adequate Living Area
GRUMP and DHS rural	0.123761	0.1637283	0.462076	0.1329438	0.7056759
GRUMP rural and DHS urban	0.2849952	0.1586059	0.5198371	0.3097992	0.7208729
GRUMP urban and DHS rural	0.5867141	0.4687608	0.6673034	0.3233521	0.722218
GRUMP urban and DHS rural[a]	0.6115607	0.4877364	0.684625	0.332684	0.7205874
GRUMP and DHS urban	0.8236859	0.678375	0.9119793	0.7916697	0.8174339

Notes: (a) Does not include the 230 DHS rural clusters with coordinates also identified by the DHS as urban.

These localities may be located on or near the edges of GRUMP light extents and therefore could represent peri-urban localities (located on the edges of cities). To test this hypothesis, we calculated the average distance between the edge of the GRUMP extents and the DHS clusters located within that GRUMP extent. DHS clusters classified as rural clusters were closer to the edge of the GRUMP extent than clusters classified as urban (mean distance equals 1.86 km (std. error 0.802) and 2.30 km (std. error .093) respectively).

Table 6. Mean distance(km) to GRUMP extent edge and electrification of DHS clusters within GRUMP extents by DHS rural/urban classification.

	Distance to GRUMP edge		*Mean Electrification*	
DHS Name	**DHS urban**	**DHS rural**	**DHS urban**	**DHS rural**
Bangladesh_1999_00	2.28	1.45	76%	36%
Benin_1996	1.64	1.87	21%	11%
Burkina_Faso_1992_93	2.88	2.88	18%	0%
Cameroon_1991	2.36	2.34	54%	10%
Central_African_Rep_1994_95	2.51	2.45	2%	0%
Chad_1996_97	2.07	2.07	2%	0%
Cote_dIvoire_1994	1.71	1.18	59%	19%
Egypt_1995_96	2.69	1.78	99%	95%
Ethiopia_1999	1.99	1.26	78%	4%
Ghana_1993_94	2.11	1.65	66%	12%
Guinea_1999	1.83	0.64	47%	13%
Kenya_1998	2.90	1.54	51%	11%
Madagascar_1997	2.72	2.42	36%	15%
Mali_1995_96	1.55	1.80	19%	0%
Niger_1998	1.47	1.32	26%	0%
Nigeria_1990	3.55	2.87	-	-
Senegal_1997	1.98	1.49	59%	23%
Tanzania_1996	1.76	1.47	63%	7%
Togo_1998	1.61	1.40	25%	6%
Zimbabwe_1999	6.89	0.93	93%	39%

To summarize the rural clusters captured by GRUMP, tend to be well electrified and possess many "urban" characteristics. Many of these also appear to be peri-urban.

V. DISCUSSION AND CONCLUSION

Large highly electrified localities are more likely to fall within GRUMP extents than poorly electrified or small localities. A significant portion of the poorly electrified DHS clusters fell within GRUMP extents that were not based on nighttime lights suggesting that the DHS data serve to cross-validate urban locations that were too small or transient to be captured by the nightlights censor. Furthermore, due to the heterogeneous nature of urban neighborhoods, many poorly electrified clusters also fell within GRUMP light extents (including those based on nighttime lights). When used together, it is possible to place these poorly electrified clusters in their urban contexts.

Our results are in line with other studies that have found that GRUMP has a high urban sensitivity, which means that almost all of the locations considered urban by other data sources fall within GRUMP light extents, but a lower specificity because many locations considered rural also fall within the GRUMP extents (Tatem et al. 2005; Potere et al. 2009; Schneider et al. 2009). However, here we show that GRUMP's low specificity especially when validated by the country specific national definitions should not been seen as an error. GRUMP's relatively low specificity appears to be due to GRUMPs ability to capture peri-urban areas.

When the survey data surpasses the lights measurement by five or more years, we find lower correspondence between the cluster's urban classification and GRUMP (not shown). This implies that new DHS surveys may be used as a tool to detect the emergence of new settlements and quantifying urban spatial growth in future night-light or other satellite data series.

One end product of this research is that users of DHS datasets can now use GRUMP light extents as a measure of urban instead of the country specific definitions. Another benefit is that DHS dataset users now have info on city size both in terms of population and physical size. The dataset created for this analysis can also be used to analyze intra-city variation in access to electricity, improved water and sanitation, durable flooring, and adequate living area.

Insofar as recommendations for the data providers and other data users, a mixed data quality record issues encountered with the DHS raises concerns. While there appear to be fewer errors in the more recent surveys, uncritical use of early rounds of DHS geocodes may lead to flawed inferences. We caution readers with the use of the Chad, Cameroon, and Central African Republic surveys. The DHS does not routinely cross-validate the geocoded clusters with GRUMP, however. This exercise would recommend it as a routine matter. Our analysis was also limited by the temporal resolution of the GRUMP dataset. The number and diversity of countries with DHS surveys has increased over time. A more recent version of GRUMP would have allowed us to include many more countries in Latin America and Asia.

We will consider adding population density to the analysis since density is often used in defining urban areas. Future work will also include comparing the GRUMP and DHS datasets with an agglomeration index that is more closely tied to the economic definition of an urban area. We plan to use the World Bank's *World Development Report 2009* methodology to create an urban/agglomeration index. The WDR agglomeration index focuses on the economic significance of urban areas (Uchida and Nelson, 2008). The agglomeration index is based on population size, population density, and travel time. Specifically, an area of 1 square kilometer is defined as urban if it satisfies the following three conditions: 1) population density is greater than 150 persons per square kilometer; 2) the area has access to sizable settlement(s) within 60 minutes by road; and 3) the settlement it has access to has more than 50,000 inhabitants. We also plan to change the threshold/criteria combination to test which one is most synonymous with the GRUMP extents. The agglomeration index will provide a benchmark against which both GRUMP and DHS can be compared.

APPENDIX:

List of DHS surveys included in our analysis, the number of clusters in each survey and the estimated population of the country at the time of the survey.

Count	**DHS Survey Name**	**Num. of Clusters**	**Population ('000) at time of survey**
1	Bangladesh_1999_00	341	135,466
2	Benin_1996	200	5,820
3	Burkina_Faso_1992_93	230	9,087
4	Cameroon_1991	149	12,230
5	Central_African_Rep_1994_95	231	3,506
6	Chad_1996_97	247	7,157
7	Cote_dIvoire_1994	246	14,380
8	Egypt_1995_96	934	59,352
9	Ethiopia_1999	539	62,279
10	Ghana_1993_94	400	17,054
11	Guinea_1999	293	8,154
12	Kenya_1998	271	29,123
13	Madagascar_1997	269	14,377
14	Mali_1995_96	300	9,426
15	Niger_1998	268	10,196
16	Nigeria_1990	298	96,604
17	Senegal_1997	320	9,845
18	Tanzania_1996	357	30,392
19	Togo_1998	288	4,457
20	Zimbabwe_1999	230	11,733

Source: Demographic and Health Surveys, U.S. Census Bureau International Database

Formulas used for contingency table and map agreement measures.

		DHS urban classification	
		Urban	**Non Urban**
GRUMP Classification	**Urban**	A	b
	Non Urban	C	d
Sensitivity		a / a + c	
Specificity		d/ d + b	
Overall Map Accuracy		a + d / n	
Cohen's Kappa Statistic		$\frac{\left(\frac{a+d}{n}\right)-\frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}}{1-\frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}}$	
Probability that a cluster falling within GRUMP was urban		a/ a + b	
Probability that a cluster falling outside of GRUMP was rural		d/d + c	

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