The Generic Slum Ontology: Can a Global Slum Repository be created?

Divyani Kohli
Urban and Regional Planning and Geo-information Management
University of Twente / Faculty ITC
Enschede, the Netherlands
d.kohli@utwente.nl

Monika Kuffer
Urban and Regional Planning and Geo-information Management
University of Twente / Faculty ITC
Enschede, the Netherlands
m.kuffer@utwente.nl

Caroline M. Gevaert
Department of Earth Observation Science
University of Twente / Faculty ITC
Enschede, the Netherlands
c.m.gevaert@utwente.nl

***Abstract*— Slums are home to approximately one quarter of the world's urban population, in most cities of the Global South the majority of the urban population lives in such areas. In support of global slum eradication and transformation policies, such as the SDG goal 11 which aims to reduce slums by ensuring inclusiveness of urban areas and developments, consistent global information about the amount and spatial distribution of slums across cities in the Global South is needed. We explore the generic slum ontology (GSO) and available spatial data to seek for robust and transferable indicators for global slum mapping. The initial results of our analysis demonstrate that indicators such as building density and road characteristics in an image are potentially useful to describe differences between slum and non-slum built-up areas. In conclusion, this study highlights the opportunities of the GSO for the development of a global slum repository but also show the need of local adaptations and hence, the importance of the conceptualization of real-world features into image domain features.**

Keywords*— *slum; informal settlement; slum ontology; spatial metrics; urban morphology; image analysis

I. INTRODUCTION

Slums are home to approximately one quarter of the world's urban population, in most cities of the Global South a large part of the urban population lives in such areas [1]. In support of global slum eradication and transformation programs, consistent information about the amount and spatial distribution of slums across cities is needed [2]. Such information is important for monitoring progress on the Sustainable Development Goal (SDG) 11.1, which particularly aims to reduce slums by ensuring the inclusiveness of urban areas and developments [3]. However, most globally available datasets do not provide such information on slums [4]. Data collected for SDG 11.1 at the national level are reported by national statistics offices, where individual countries have diverse reporting strategies. For example, countries may use census enumeration for data collection on slum households while others may completely lack data on the existence of slums [5]. Thus, there is often incomplete and inconsistent knowledge about the amount and spatial distribution of slums across different countries [6]. Moreover, when considering cities across the globe, often official statistics on slums may vary with different organizations reporting different number of slum areas or slum population [7]. There is thus a need to develop consistent methods within and, across cities and countries to have reliable estimates on the proportion of the urban population living in slums, informal settlements or with inadequate housing.

Many remote sensing based approaches have been developed in the last decade that utilized the increasing availability of very high resolution (VHR) imagery in combination with object-based or more recently, machine learning based methodologies (e.g., [8-10]). To develop an earth observation based slum mapping approach, we need to have a clear definition of slums for mapping such areas in VHR imagery. Such a conceptualization is the main basis of any expert and rule-based system to map such areas. Furthermore, for the more recent developments on convolutional neural networks (CCNs), which are in principle self-learning systems, also criticized as black boxes, a fundamental conceptualization to generate robust and unambiguous training and reference data for interpreting outputs is important. Most of these published methodologies do not start with a systematic conceptualization of the morphological differences between slum and non-slum areas. For this purpose, Kohli et al. [5] developed a framework to conceptualize morphological characteristics of slums for mapping such areas using VHR imagery i.e., the generic slum ontology (GSO).

There is still limited knowledge about robust indicators that may allow monitoring slum developments and show the effect of improvement policies across the globe. Thus UN-Habitat is interested to add to the aggregated country and city level statistics, also locational information on slums, informal settlement and inadequate housing to the SDG 11 and the indicator 11.1. To address this, it is important to identify a set of robust indicators that are transferable and adaptable globally. This study uses the already available GSO as a basis to illustrate a set of morphological indicators that are potentially robust for a global slum-monitoring program. For this purpose, we use available data of three cities from three continents: Asia, Africa and South America that are known to have large slum areas (i.e., Ahmedabad, India; Dar es Salaam, Tanzania; Rio de Janeiro, Brazil). Therefore, the main aim of this study is to explore potentially useful indicators in support of global slum mapping programs.

A. The dilemma to define slums when mapping them from space

The globally recognized definition of slums is the one of UN-Habitat, defining a slum household as lacking any one of the following indicators: improved water, improved sanitation, tenure security, living in overcrowded living environment or durable housing. To identify slums using an image, information regarding these indicators is ideally required. However, most of these indicators, e.g. sanitation, cannot be directly observed from an image. Alternately, the identification of slum areas using VHR images may be

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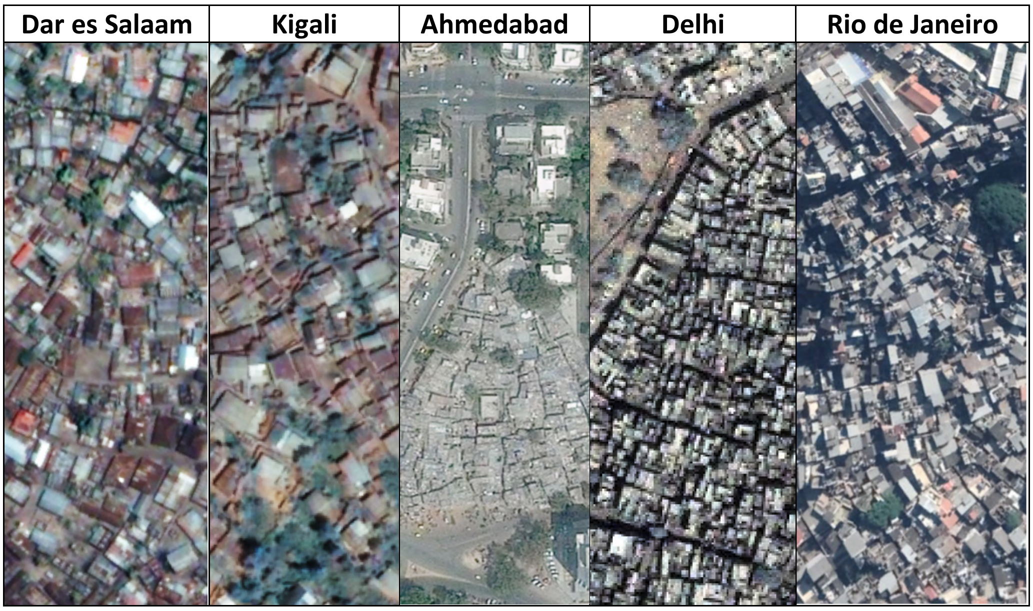

Fig. 1. Examples of the morphology of deprived areas (at the scale 1: 1,500).

possible via physical proxies [9]. Such proxies refer to the morphologic characteristics of deprivation visible in images (Figure 1), i.e., high densities, irregularity in patterns, the absence of planned infrastructure, small (building) object sizes and general environmental conditions (e.g., the absence of green areas, location in hazardous zones). These characteristics relate to the 'overcrowding' and 'durable housing' indicators of the UN-Habitat definition. The GSO is also based on the same indicators and provides a clear conceptualization of physical proxies that can be derived through VHR images [11]. Whereas the framework presented in GSO provides an organized conceptualization, quantitative assessment of how slums differ from non-slum settlements across different cities does not exist.

Commonly, for slum mapping studies, image feature sets are developed by trial and error, or more recently using feature selection approaches. However, such studies lack the analysis on which physical aspects or image features can explain the morphological differences of slum and non-slum areas. A recent study by Taubenböck et al. [6], illustrated the spatial structure of settlements in 44 cities by exploring their spatial patterns (i.e., building density, building orientation and heterogeneity) and their building morphologies (i.e., building size and height). However, we still have insufficient knowledge on which morphological features can be best transferred for a global slum mapping approach. Thus, the logical step would be to start with the conceptualization of which morphological features are more important for slum identification when compared to others taking the GSO as a basis.

B. The GSO from global to local level

Considering the complexity and vagueness in the definition of slums across different contexts, Kohli et al. [5] developed a framework for the global conceptualization of slums – the so called generic slum ontology (GSO) as discussed above (shown in Figure 2). The GSO characterizes slums at three spatial levels, namely the object, settlement and environs level respectively.

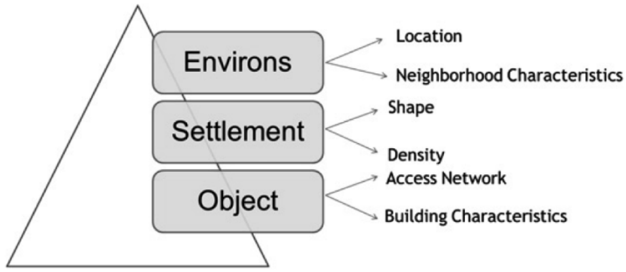

Fig.2. The generic slum ontology [5].

II. METHODOLOGY

To define potentially robust indicators, we selected one city each from three different continents. Each indicator from the GSO was analyzed for each city respectively. The following sections explain the different steps in the analysis.

A. Selection of case studies

Case studies were selected based on availability and access to slum boundaries of the respective cities. To have a comprehensive analysis and to cover diverse slum morphologies, three cities each from Asia, Africa and South America were selected: Ahmedabad, India is dominated by relatively small slums areas spread across the city. Many slums have developed in central locations, however, in the last few years, there has been a large scale resettlement of these centrally located slums to resettlement colonies in the outskirts of the city [12]. Dar es Salaam, Tanzania, has most of its city developed as informal areas with around 70% of the population living in such areas [13]. In Rio de Janeiro, Brazil, slums can be found throughout the city and are locally referred to as favelas. More centrally located favelas have been rapidly changing in the last years, showing trends of gentrification [14].

B. Operationalizing the GSO

The GSO consists of three spatial levels with indicators and related metrics as shown in Table 1. For this paper, we quantify differences in the indicators over the three selected cities using the GSO as a conceptual basis. The aim is to show the value of the different indicators for developing a

Table 1 Different spatial levels, indicators and related metrics of the GSO

Dimension/ Spatial Level	*Indicators*	*Metrics*
Environs	Location	Slope (SRTM DEM, 30 m) Location within the city: centrality
	Neighbourhood Characteristics	Surrounding land use (200 m distance)
Settlement	Shape	Settlement shape: Fractal Dimension
	Density	Density of building footprints (OSM data) Mean NDVI value
Object	Access network	Regularity of road network – number of vertices
	Size	OSM building footprints: average size

conceptual basis for a global slum analysis. For each dimension and indicators level, metrics are used to quantify the difference of slum and slum areas within the three cities and comparing the results across the cities. Data were extracted from Open Street Map (OSM) and procured through other local sources. The three levels of GSO, and the related metrics are defined as follows.

- Environs

Environs comprise the location of slums with respect to socio-economic status, neighborhood characteristics and hazard-prone areas. Slum areas tend to be located in areas where planned development may not take place due to the hazardous nature of a locality, e.g., many slums areas are located on steep/unstable slopes, in flood-prone areas, along railway lines/highways. In addition, slums also tend to be in locations where it is easy to find employment, e.g., close to central business district (CBD), industrial areas and high-income neighborhoods.

To quantify this indicator, slope and land use maps were used. Mean and maximum slopes were calculated for slum areas across the three cities. Land use within the proximity of 200 meters (to approximate the immediate neighborhood) of slum areas was derived and mean distance from the center of the city (centrality) was calculated. For Ahmedabad, the municipality was considered as the center whereas for Dar es Salaam, the CBD acted as the center point. For Rio, the center was the same as marked in the OSM maps.

- Settlement level

Settlement level consists of the development characteristics of the settlement referring to the overall shape and density. Slum areas tend to have irregular shapes due to the unplanned nature of these settlements. For example, the elongated shape of a settlement along a river or railway lines. There also seems to be very high densities of buildings in a slum. Average built-up densities were calculated for sample areas of each city. To have a consistent approach across all cities (in many cities slum buildings are only available for very few areas), small areas of complete building outlines were selected and divided by the boundary (patch envelop) of the area to quantify built-up densities.

Fractal dimension (FRAC) was calculated for the slum areas to derive the shape complexity of the settlement. FRAC measures shape complexity across spatial scales and allows to compare the complexity of slum boundaries within and across cities. A fractal dimension greater than 1 for a 2-dimensional patch indicates a departure from Euclidean geometry (i.e., an increase in shape complexity). The value approaches 1 for shapes with very simple perimeters such as squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

- Object level

The object level comprises of building characteristics and access network characteristics. From the OSM data, building footprints in terms of average and minimum building sizes were derived for the buildings in slum areas. We used the number of vertices per kilometer for the roads as an approximation of irregularity, thus for calculating this metric.

III. RESULTS AND DISCUSSION

A. Environs

At environs level, the majority of slums in Ahmedabad seems to be close to (formal) residential areas followed by industrial and commercial zones. There are slums close to railways and green areas too. Since, Ahmedabad is relatively a flat terrain, the maximum slope for the location being 30% and a mean of 4.2%. In terms of neighborhood characteristics, the majority of slums are between approximately 3 to 5 km from the center, spread out and declining towards the periphery at approx. 15 km.

In Rio de Janeiro, a high percentage of slums exist close to green/recreation and formal, residential areas. These are commonly (locally) known as favelas, and often exist at the outskirt of the city with poor accessibility. A relatively low percentage of slums are close to industrial, transport and commercial areas, which is a contrast to the situation in Ahmedabad. In terms of centrality, it exhibits variable percentages of slums spread out up to approximately 58 km from the center of the city with a mean distance from the center being approx. 21 km. With a city with an undulating terrain, slums are situated on slopes with the mean value of approx. 14% and maximum being approx. 57%.

In Dar es Salaam, slums seem to be concentrated in high percentage in and around residential areas (formal) in contrast to other land uses. However, a minimal amount of slums are located close to reservoirs, green and military areas. Regarding the distance to the center, slums in Dar are close to the center spreading out up to 32 km towards the periphery.

Slums are situated on slopes with the mean value of approx. 5.7% and maximum being approx. 36%.

B. Settlement level

At settlement level, indicators are quantified using built-up density and fractal dimension. For built-up densities, 10 sample areas for all the cities were considered. Ahmedabad had a range of densities with the minimum, maximum and average of approximately 46, 86 and 67 percent respectively (Figure 3). For Rio, these percentages were 47, 88 and 70 respectively. Dar es Salaam displays contrasting values to both the areas with lower densities with a minimum and maximum of 28 and 51 percent respectively. The mean density of Dar is also much lower at 43 percent which shows a much more dispersed pattern of slum buildings compared to the Asian and South American case. However, the fractal dimension is comparable with a value of approx.1 for all the three cities (Figure 4).

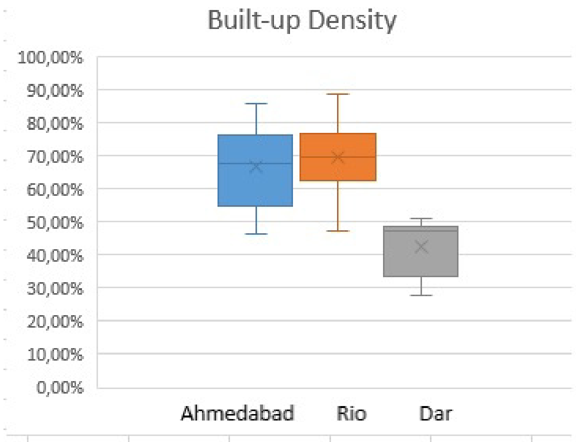

Fig. 3. Built-up density based on samples of slum areas.

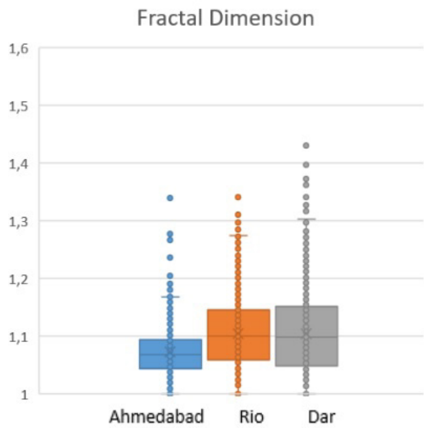

Fig. 4. Fractal dimension for the three cities at settlement level.

The NDVI values were derived from Sentinel-2 images, freely downloadable from the ESA website. The values of NDVI varied for slum and formal settlements within and across the cities (Figure 5). In Rio, the mean NDVI is substantially different for slum and non-slum areas with the values of 0.3 and 0.6 respectively signifying greener formal areas. Whereas in Dar and Ahmedabad the values for both slum and formal areas seem to be similar with not much difference in the amount of green spaces in the two kinds of settlements.

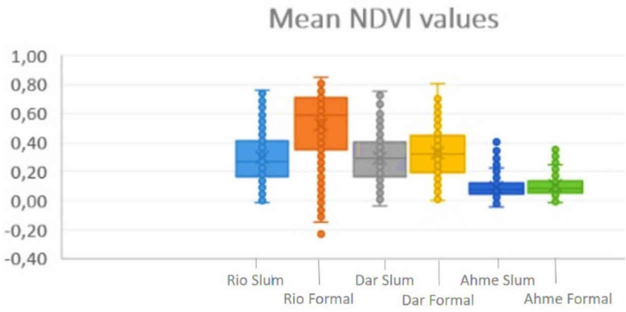

Fig. 5. Mean NDVI for formal and slum areas for the cities.

C. Object level

At Object level, size of buildings and characteristics of access network were used. For Ahmedabad and Rio, the average building size is less than 100 sq. meters whereas for Dar, it is 100 sq. meters (Figure 6). This shows that the buildings in the African city are larger than the other contexts. The number of vertices per kilometer for the roads were 60, 57 and 78 for Ahmedabad, Rio and Dar respectively, showing relatively more irregularity of the access network for Dar.

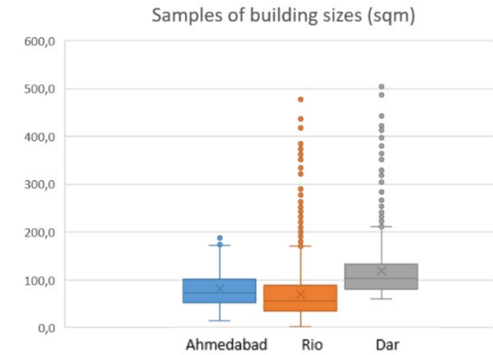

Fig. 6. Average buildings sizes in slum areas for the three cities.

IV. Conclusions

Image analysis should be based upon a sound concept translated into methodological steps which are used to recognize the objects of interest. To formulate a strategy to consistently identify slums from images, it is important to address the different morphological diversity in slum areas across the globe. In this paper, we use the generic slum ontology (GSO) as a basis to identify potentially robust indicators for slum identification. We used three different cities from three continents to capture the diversity of contexts. Results show that indicators at environs, settlement and object levels show similarity as well as variations in indicators. Overall, the selected cities do show some differences in slum morphologies, in terms of locational and physical characteristics. For example, in a more arid city (Ahmedabad) less vegetation is found in slums as well as in formal areas compared to Rio de Janiero, where formal areas seem to be much greener than slum areas. Built-up densities seem to be much higher in Ahmedabad and Rio de Janiero compared to Dar es Salaam. More research is needed to come up with robust indicators that can be used to differentiate slum and non-slum areas in a regional as well as global context. Our current research focuses on quantifying the indicators of GSO for more cities across the globe to create a representative set that could potentially be used as a basis for a global slum repository.

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