

Spatial Patterns of Slums

Comparing African and Asian Cities

Monika Kuffer, Felix Orina, Richard Sliuzas

Faculty of Geo-Information Science and Earth Observation
(ITC), University of Twente, PO Box 217, 7500 AE
Enschede, The Netherlands; E-mail: m.kuffer @utwente.nl

Hannes Taubenböck

German Remote Sensing Data Center (DFD), German
Aerospace Center (DLR), Oberpfaffenhofen, D-82234
Wessling, Germany

Abstract— Spatial data on slums are commonly either generalized, outdated or not available. Thus, very limited knowledge exists on spatial and locational factors of slums across cities in the Global South. Therefore, this study compares slum characteristics of six cities (three Asian and three African). These characteristics were analyzed at landscape, settlement and object level using available datasets (e.g. Open Street Map) and a set of indicators that are able to describe spatial commonalities and differences at these three spatial levels. The results indicate that slums show at environ level commonalities across six selected cities, while object and settlement level characteristics display more variations between African and Asian cities. Yet, slums are dominated by small buildings, high densities and good locations in terms of accessibility but poor in terms of land suitability.

Keywords—Global South; informal settlements; slums; spatial metrics; spatial patterns; urbanization

I. INTRODUCTION

Slums house approximately one quarter of the world's urban population, while in many cities of the Global South a majority of the urban population is living in such deprived areas (around 62% in African and 30% in Asian cities) [1]. Global policies such as the MDGs (Millennium Development Goals) and the SDGs (Sustainable Development Goals) have been addressing this issue, aiming at the reduction of slums [2]. In support of such policies, global datasets are required to monitor their implementation. However, spatial information on slums are often generalized, outdated or not available [3]. Information that would allow comparing the patterns of slums and spatial factors that influence the generation of such patterns across cities are very scarce. However, the knowledge on spatial factors that influence slum formation contributes to the global knowledge repository on slums that could support the better targeting of pro-poor policies.

Only few studies [4-6] mapped slums across several cities that would allow analyzing similarities and variations of spatial patterns of slums. For example, [4] mapped slums across four rather different cities (i.e., Caracas, Kabul, Kandahar, La Paz) or [6, 7] mapped slums in several Asian and African cities (i.e. Dar es Salaam, Mumbai, Ahmedabad, Kigali, Delhi). Such studies show that slums share similar morphological features that allow their classification from VHR (very high resolution) satellite imagery. However, differences and uncertainties about such differences limit the development of a global slum inventory via advanced remote sensing analysis techniques [8], as it is not

clear which key indicators could be employed across cities. This knowledge gap [9] led to the development of a generic slum ontology that allows systematic detection of slums in VHR imagery. Several studies compared urbanization patterns of rapidly developing cities in the Global South [10, 11], quantifying their spatial development patterns via a set of measures (e.g. spatial metrics). However, data availability still restricts similar studies on the spatial patterns of slums. In many cities, slums are omitted in official maps, where “hundreds of millions of people informally residing in Black Spots are often invisible to their governments and international actors” [12] (p. 40). We still know too little about commonalities and differences of slums, their locations, their morphology, etc. across cities in the Global South. Therefore, this paper addresses a first exploration of such commonalities and differences using globally available datasets, e.g. Open Street Map (OSM), SRTM DEM (Shuttle Radar Topography Mission digital elevation model) and slum maps from some selected cities.

II. METHODOLOGY

The methodology consists of four main steps. First, several accessible archives are explored to select suitable slum datasets, spatial data on slums are commonly not publically available. As a result, three Asian and three African cities are selected for this study. Second, data consistency and uncertainties are analyzed, another major limitation for comparative studies on slums across cities. Third, a set of suitable indicators to analyze the spatial patterns of slums are selected. Fourth, based on the selected indicators commonalities and variations on spatial patterns of slums are analyzed for the six cities.

A. Study Areas and Data

Most publically available datasets, such as OSM do not contain slum boundaries, therefore, the selection of cities is restricted to datasets which are accessible at ITC or DLR. The selected cities house a large amount of slum dwellers. The African cities are located in Sub-Saharan Africa, (East), while the Asian cities are two large Indian and one Indonesian city. Dar es Salaam has a current population of 2.7 million, with 70% living in slums. Kampala features 1.5 million inhabitants with more than 60% living in slums. Nairobi is a similar case, where 60% of its 3.1 million live in slums. In the two Indian cities a large part of the population lives in slums, in Mumbai 42% (total city population: 12.4 million) and in Ahmedabad 34% (total city population: 5.4 million). The slum population figures in Jakarta

vary depending to the definition by different organizations, but at least 20% of its 30 million inhabitants (metropolitan area) live in slums. For all cities we acquired data on slum boundaries, with the exception of Jakarta, where the delineation uses ‘slum neighborhoods’, administrative areas that are dominated by slums. For all cities, OSM and SRTM (DEM) data have been downloaded. For Kampala, Dar es Salaam and Ahmedabad we have also access to municipal base data (Table I).

TABLE I. DATASETS

City	Data set	Data source	Year
Kampala	Slum boundaries	City Council	2010
	Auxiliary data	OSM, City Council	2010/6
Nairobi	Slum boundaries	Orbital GeoInformation	2014
	Auxiliary data	OSM, City Council	2014/6
Dar es Salaam	Slum boundaries	Ardhi University	2012
	Auxiliary data	Ardhi University	
Ahmedabad	Slum boundaries	AUDA	2010
	Auxiliary data	OSM	2010/5
	Auxiliary data	OSM	
Jakarta	Slum neighborhoods	DKI, Jakarta	2013
	Auxiliary data	OSM	2016
All cities	DEM	SRTM	
	Slum population	UN Habitat, Worldbank databases, Census	Most recent

B. Data consistency and uncertainties

The comparability of the employed datasets is analyzed, considering spatial, temporal and attribute consistency. To assess uncertainties, the discrepancy between auxiliary data and VHR imageries (Google Earth) was analyzed.

C. Indicators

Spatial slum characteristics can be categorized into three main dimensions (D), i.e., object (O), settlement (S) and environ (E) [9], besides general characteristics (GC) such as area and population (Table II). These indicators allow analyzing the three dimensions with available datasets.

TABLE II. INDICATORS ANALYZING SLUM CHARACTERISTICS

At environ level, distance to center, transport and rivers and

D	Indicator	Description ^a
GC	Total slum area	in km ²
GC	Percentage of slums	% slum of total city area
GC	Slum population	percentage of total population
GC	Largest patch index LPI	$LPI = \frac{\max(a_{ij})}{A} \times 100$
GC	Mean settlement size	in ha
E	Mean distance to center in m	in kilometer
E	Distance slum centroid to city center	in kilometer
E	Mean nearest neighbor. distance	in hectometer
E	Mean distance to main road	in hectometer
E	Percentage within 100 m from rivers	in meter
E	Slope average in %	percentage
E	Mean height difference slum and planned areas in m	$Diff_{DEM} = \mu_{planned} - \mu_{slum}$
S	Shape index	$SHAPE = \frac{p_{ij}}{\min p_{ij}}$
S	Fractal dimension index	$FRAC = \frac{2 \ln (.25p)}{\ln a_{ij}}$
S	Aggregation index	$AI = \left(\frac{g_i}{\max \rightarrow g_{ij}} \right) (100)$
S	Built-up density	$B_{dens} = (A_{built} / A_{slum}) \times 100$
O	Mean building size	in m ²

^a_{ij} = area (m²) of patch ij, A =total area (m²); p_{ij} = perimeter of patch ij in terms of number of cell surfaces, min p_{ij} = minimum perimeter of patch ij; p_{ij} = perimeter (m) of patch ij, a_{ij} = area (m²) of patch ij.
μ: Mean, D: Dimension, O:Object level, S: Settlement level, E: Environ level, BS: Basic stats.

topography is considered, knowing that slum dwellers often trade off good accessibility with hazardous locations [4]. At settlement level, shapes and densities are analyzed, slums are often of irregular shape and have high built-up densities [13]. At object level, the building sizes are analyzed, their footprints are commonly small, contributing to overcrowding [6].

D. Commonalities and variations of slum characteristics

Employing the available boundaries of slums their patterns and spatial characteristics are analyzed. Main focus lies in the commonalities within the dimensions and indicators across cities that have the potential for providing robust indicators for image based slum detection.

III. RESULTS AND DISCUSSION

A. Slum maps

All six cities show large areas of slums spreading across the city. In Dar es Salaam (Fig.1), the remote and more rural area in the South is not covered by the slum map.

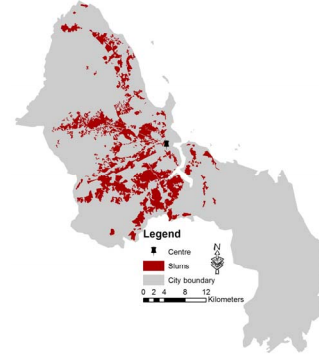


Fig. 1. Slums in Dar es Salaam.

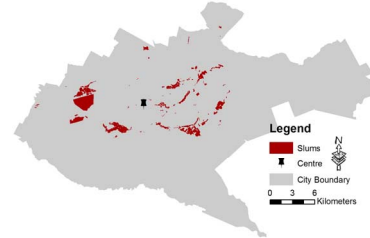


Fig. 2. Slums in Nairobi.

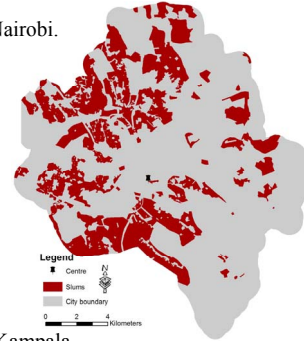


Fig. 3. Slums in Kampala.

In Nairobi (Fig. 2), slums are much less spread compared to Kampala (Fig. 3) where slums are found in all directions outside the city center. In Mumbai and Ahmedabad (Fig. 4), larger but also many small slums spread across the city. In

Jakarta (Fig. 5), slums are found in all parts of the city with a concentration towards the coast (North).

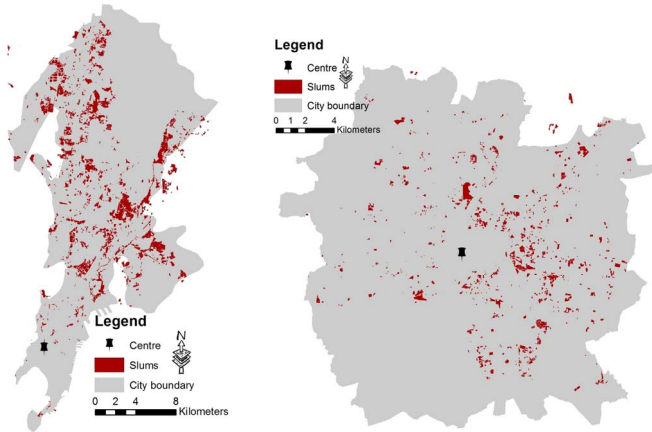


Fig. 4. Slums in Mumbai (left) and Ahmedabad (right).

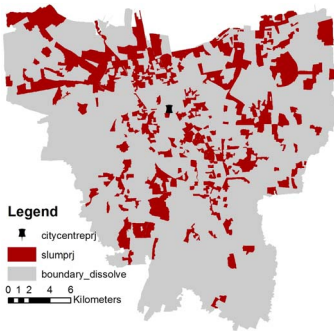


Fig. 5. Slums in Jakarta.

B. Data consistency and uncertainties

Data consistency is a major limitation of comparative studies, which to some extent is an issue here. The employed slum boundaries have different levels of generalization, e.g. boundaries in Mumbai, Ahmedabad, Kampala, Nairobi, Dar es Salaam follow mostly the morphology of slums (i.e. areas of highest density, small and low buildings or shacks, organic layout), while slum neighborhoods in Jakarta contain other land uses (due to administrative boundaries which do not perfectly conform with the morphology of slums). Auxiliary data such as main roads, rivers from OSM show good comparability, but data on building footprints show different coverage in slums. In Dar es Salaam, all buildings within the urban core have been digitized and are available via OSM, for Kampala a building layer from the municipality was used (which has also not full coverage in slums), while of all other cities only for very few slums all building footprints are available (required for the built-up density calculation). Frequently, only larger buildings are digitized. Therefore, only for few selected locations (with full coverage) the building density and sizes could be used for the analysis. Thus the analysis of building density and size relies on sample locations. Thus, in particular object and settlement level analysis is restricted due to limited data availability. While the environ level analysis is much better supported by data via OSM.

C. Indicators

The percentage of slum areas compared to the total administrative area varies across the cities, e.g. 27% in Kampala, 12% in Dar es Salaam, 11% in Mumbai and only 2.5% in Ahmedabad (Fig. 6). In Nairobi 60% of the total population is living in slums on only 2.5% of the administrative area of the city. Such figures differ when considering the percentage of slums compared to the total built-up area, e.g. in Dar the figure would be close to 70% while in Nairobi slums still make only 4% of the total residential area. This is also reflected by variations in built-up densities. Nairobi, Mumbai and Ahmedabad have average built-up densities in slums of 67-69% (with areas of 80-90%), while built-up densities in Dar and Kampala are on average 31% and 40% respectively. Jakarta shows average built-up densities of around 50%. Mean settlement sizes differ, Dar and Kampala have large and continuous areas of slums, while Ahmedabad has on average the smallest slums, which are scattered within the city. The largest patch index (LPI) shows that Nairobi followed by Kampala and Jakarta are most dominated by one large (continuous) slum area, while Ahmedabad and Mumbai have the lowest LPI.

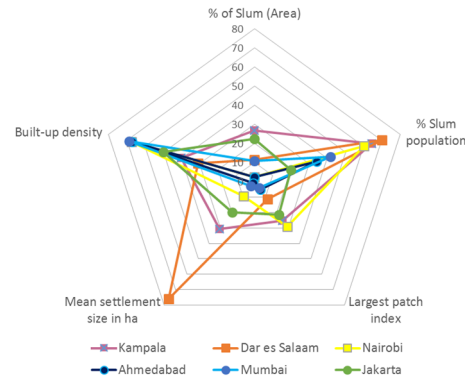


Fig. 6. General slum characteristics.

In general, slums are located in close proximity to main roads, with the exception of Dar es Salaam, where the average distance is with 600 m larger. Furthermore, in most cities slums are located towards the center, with the exception of Mumbai and Dar es Salaam (Fig. 7). In both cities, the geography limits close proximity to the city center. In all cities, slums show a tendency towards clustering (average nearest neighborhood distance having significant z score and $p < 0.05$). Slopes depend on the general topography of the city, but in all cities slums feature a higher spatial share in areas of relative high average slopes, with maximum values up to 60%. Thus, the analysis shows that slum areas tend to have higher spatial concentrations on steep slopes, in close proximity to waterbodies (e.g. rivers) or wetlands. Thus, slums often use less suitable land resources. Buildings in slums are commonly small (Fig. 8). Average sizes range from 50 m² in Jakarta to 133 m² in Nairobi. In Nairobi but also in other cities such as Dar and Kampala (105 and 97 m²), Mumbai and Ahmedabad (59 and 63 m²), building sizes can vary, from very small shelters of below 20m² (inhabited by one family) to larger dwellings shared by several families (often rented). In general, settlements are much aggregated (Fig. 8). Shape complexity of settlement boundaries is in the African cities slightly higher than in the Asian cities, that are having

more often physical infrastructure lines (e.g. roads) as boundaries.

but use the limited and often less suitable land resources of the much crowded cities.

IV. CONCLUSION

This study confirms that slums across cities of the Global South share distinct locational commonalities. Slums are often found in areas of good accessibility (e.g. main roads) but are forced into land resources with low suitability (e.g. along rivers, steep slopes), showing a tendency towards clustering. Besides some variations in object and settlement level characteristics, slums are dominated by small building footprints and high built-up densities. Such knowledge on slums across cities in the Global South, has the potential to further develop global slum mapping approaches. These characteristics can be developed into robust and transferable indicators that allow slum mapping with VHR imagery. However, more case studies are necessary to conclude on robust global slum characteristics.

REFERENCES

- [1] UN-Habitat, "Informal Settlements," New York, USA, 2015.
- [2] Leadership Council of the Sustainable Development Solutions Network, "Indicators and a monitoring framework for the sustainable development goals launching a data revolution for the SDGs," New York, USA, 2015.
- [3] H. Taubenböck and N. J. Kraff, "The physical face of slums: A structural comparison of slums in Mumbai, India, based on remotely sensed data," *J. Hous. and the Built Environ.*, vol. 29, pp. 15-38, 2014.
- [4] J. Graesser, A. Cheriadat, R. R. Vatsavai, V. Chandola, J. Long, and E. Bright, "Image based characterization of formal and informal neighborhoods in an urban landscape," *IEEE J. Sel. Top. Appl. Earth Observ. and Remote Sens.*, vol. 5, pp. 1164-1176, 2012.
- [5] P. Hofmann, T. Blaschke, and J. Strobl, "Quantifying the robustness of fuzzy rule sets in object-based image analysis," *Int. J. Remote Sens.*, vol. 32, pp. 7359-7381, 2011.
- [6] M. Kuffer, J. Barros, and R. Sliuzas, "The development of a morphological unplanned settlement index using very-high-resolution (VHR) imagery," *Comput. Environ. Urban Syst.*, vol. 48, pp. 138-152, 2014.
- [7] M. Kuffer, K. Pfeffer, R. Sliuzas, and I. Baud, "Extraction of slum areas from VHR imagery using GLCM variance," *IEEE J. Sel. Top. Appl. Earth Observ. Remote Sens.*, vol. 9, pp. 1830-1840, 2016.
- [8] M. Kuffer, K. Pfeffer, and R. Sliuzas, "Slums from space—15 years of slum mapping using remote sensing," *Remote Sens.*, vol. 8, p. 455, 2016.
- [9] D. Kohli, R. V. Sliuzas, N. Kerle, and A. Stein, "An ontology of slums for image-based classification," *Comput. Environ. Urban Syst.*, vol. 36, pp. 154-163, 2012.
- [10] H. Taubenböck, M. Wegmann, A. Roth, H. Mehl, and S. Dech, "Urbanization in India – spatiotemporal analysis using remote sensing data," *Comput. Environ. Urban Syst.*, vol. 33, pp. 179-188, 2009.
- [11] H. Taubenböck, T. Esch, A. Felbier, M. Wiesner, A. Roth, and S. Dech, "Monitoring urbanization in mega cities from space," *Remote Sens. Environ.*, vol. 117, pp. 162-176, 2/15/ 2012.
- [12] D. E. Batson, "Black spots are no treasure island: Land tenure and property rights in megacities," in *Understanding Megacities with the Reconnaissance, Surveillance, and Intelligence Paradigm*, C. Ehlschlaeger, Ed., ed. Vicksburg, USA, 2014, pp. 34-47.
- [13] J. C. Duque, J. E. Patino, L. A. Ruiz, and J. E. Pardo-Pascual, "Measuring intra-urban poverty using land cover and texture metrics derived from remote sensing data," *Landsc. Urban Plan.*, vol. 135, pp. 11-21, 2015.

Fig. 7. Environ slum characteristics.

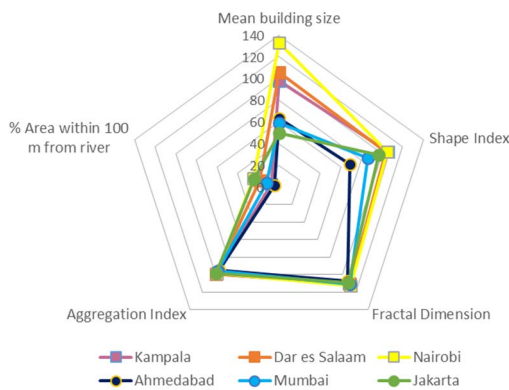


Fig. 8. Environ, settlement and object slum characteristics.

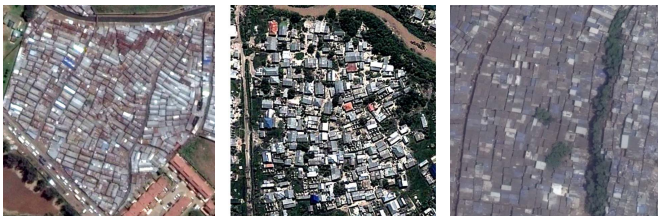


Fig. 9. Slums in Nairobi (left), Dar es Salaam (center) and Mumbai (right).

D. Commonalities and variations of slum characteristics

Slums across the six African and Asian cities show commonalities in terms of locational patterns: they follow main roads and are often found in areas close to waterbodies, land that might be less attractive for formal development due to potential flooding. In addition, areas of steep slopes often house slums. Slums tend to cluster around such 'attraction points' and develop high densities with rather small building footprints. In general, the size of buildings in African cities (with the exception of Nairobi) are larger than in Asian cities, having also higher built-up densities (see Fig. 9). Thus Asian slums consume less space