DIGITALIZATION AND URBAN DEVELOPMENT IN THE GLOBAL SOUTH: TOWARDS RELIABLE POPULATION DATA IN DEPRIVED URBAN AREAS

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INTRODUCTION

According to the United Nations (UN), 90 % of the population growth in the coming 30 years will happen in Asian and African cities. Unfortunately, the capacity of most African and Asian cities to provide low-cost housing, including basic services, to their growing population is very limited. Therefore, if present trends continue, most of this growth will occur in poor urban neighbourhoods (hereafter called deprived areas, which are commonly referred to as slums or informal settlements) (UN Department of Economic and Social Affairs Population Division 2019). The dynamics of the population living in deprived areas is also one of the main urban Sustainable Development Goal (SDG) indicators (SDG 11.1.1) (UN-Habitat 2016b). Presently key societal challenges found in such areas fall into four major categories, i.e., poverty (e.g., access to livelihood and services), climate change/ environmental conditions, security/empowerment and health threats such as pandemics. However, there are no consistent and reliable global or continental datasets available to quantify and understand the scale of these challenges, .e.g., in terms of the population that are severely impacted by increasing climate change risks or the COVID-19 crisis across cities in the Global South.

In general, digital innovations have increased the amount and availability of data for urban areas in Africa and Asia. However, most urban datasets show major gaps and/or have high uncertainties for deprived areas. To address these gaps, Earth Observation (EO) studies have increasingly developed methods to map the location, extent and dynamics of deprived areas. However, most scientific studies do not provide operational datasets. For example, there is a too limited understanding between the EO community and real urban data needs (Zhu et al. 2019). This is particularly true in the rapidly developing urban areas in Global South cities, due to the mismatch of methods developed in research labs without involving local stakeholders and without understanding local user requirements. Developed and published methods typically do not achieve impacts and do not contribute to needed changes and societal progress on the ground (Thomson et al. 2020). Making resulting spatial data available might be even harmful to local communities by revealing details of mapped communities, without their knowledge or consent.

There is a large number of methods available in the field of artificial intelligence (AI) and EO, working with very high-resolution (VHR) images (below 1 m spatial resolution) and very efficient computational method, but they are not tailored to meet the needs of local users, as they never break through the walls of scientific knowledge (Kuffer et al. 2020). Local urban data needs on deprived areas have a large range (Figure F), with many disciplines urgently requiring reliable and up-to-date data. For example, health professionals require reliable population data on deprived areas to assess the variations of health outcomes between deprived and well-serviced urban areas. Or in the case of a major disaster, people living in deprived areas often drop out of any compensation scheme (i.e., in the recovery process) as they do not have any formal records of their existence. However, producers of such data need to clearly understand what data is needed and how to minimize exposing deprived communities and preventing unwanted consequences, such as further stigmatization and harassments. In a dialogue, local communities need to be better prepared to understand the opportunities but also risks of digital knowledge, while the EO-community need to better understand how to optimize innovations for the benefits of local communities. This should ultimately aim at reducing the digital divide.

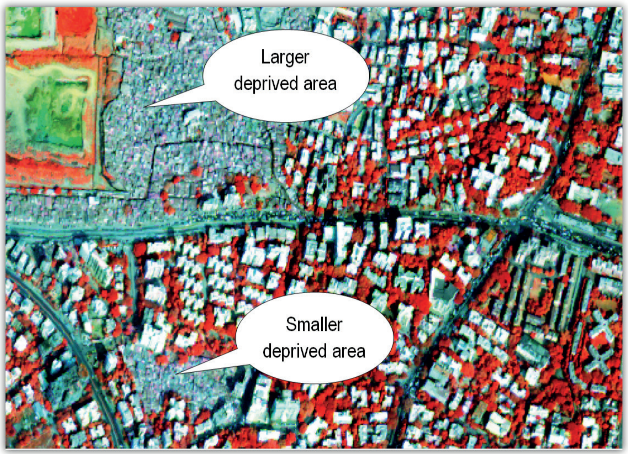
Figure F: Disciplines Requiring Urban Data and Images from Deprived Areas in Nairobi

Left: Disciplines that require data on all urban areas, in particular, deprived areas;
Right upper: drone image of Nairobi, Kenya, showing a road development project that transects Kibera slum and displaces thousands of people
Right Lower: ground photos within deprived areas in Nairobi, Kenya

Source: Monika Kuffer (left); Jonny Miller (right upper) (see also: Miller n.d.); Angela Abascal Imizcoz (right lower)

For example, a major innovation required to bridge this gap involves the development of EO and AI methods that allow the production of relevant global datasets in support of most urgent societal problems (and effectively relate research outputs to the theory of change). For example, the EO community is presently empty-handed in cities to support the most urgent data needs in the COVID-19 outbreak. For more than 1 billion people in densely built-up and deprived areas, no operational dataset exists that allows local authorities and others responding to COVID-19 to target needs assessments in such areas. Guidelines developed in the Global North, do not relate to the local realities in the Global South (Corburn et al. 2020). The absence of operational data is intrinsically related to the "tradition" that, typically, urban EO methods are developed without user and local interaction and are often tested for small areas of just a few km^2, while questions of scalability and transferability are commonly ignored (Kuffer et al. 2020). Several EO studies (e.g., Duque et al. 2017; Wurm/Taubenböck 2018; Taubenböck et al. 2018; Persello/Stein 2017; Kuffer et al. 2016) stressed the potential EO data and machine learning methods to fill these data gaps. VHR images (examples of deprived areas are shown in Figure G) can map and characterize deprivation (Kuffer et al. 2017). However, most studies neither produce city-level delineations of deprived areas (due to image and computational costs) nor is the next step taken to provide population estimates in support of policymaking (e.g., due to the unavailability of bottom-up estimation models). Top-down population estimates (e.g., very high-resolution population data of WorldPop) typically use census data, combined with covariates often extracted from EO data (Wang et al. 2019; Stevens et al. 2015). As a consequence, such data suffer from large data gaps in official census data in deprived areas (Kit et al. 2013), besides the general problem that in urban areas population densities are often underestimated. Therefore, an innovative framework is urgently required that combines of EO, local and Volunteered geographic information (VGI) data by employing machine-learning to map and estimate the population of deprived areas. Such a framework would provide a robust answer to the question: how much do official statistics on deprived areas (slums) underestimate the population living in deprived areas.

Figure G: Mumbai, India, Deprived and Formal Built up Areas



WorldView-2 image, Mumbai, India, showing deprived areas within formal built-up areas (vegetation shown in red)

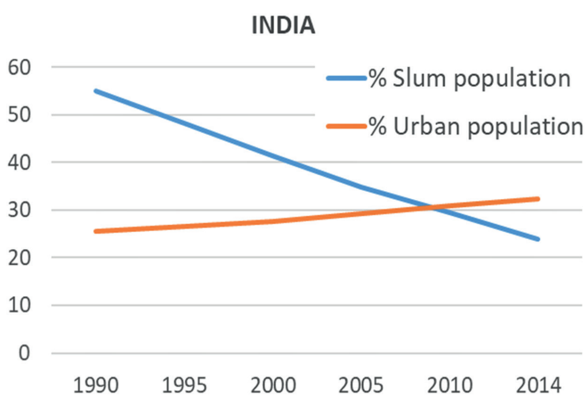
Source: DigitalGlobe

INNOVATION IN METHODS – TOWARD LOCALIZED POPULATION ESTIMATES

UN statistics state that about 25 % of the worldwide urban inhabitants are living in deprived areas (UN-Habitat 2016b). A slum household (spatial clusters of such households are seen as deprived areas) is defined as a household without appropriate access to safe water, improved sanitation, durable housing, secure tenure or sufficient living space (UN-Habitat 2016a). To support improvement strategies, accurate and up-to-date locational and population data are required. However, data are commonly inconsistent, unavailable and underestimate the deprived population. Census-based data available in rapidly growing cities is usually out-of-date by the time it is used (Mossoux et al. 2018), and commonly ignore temporary, pavement dwellings and new developments on the outskirts of cities (Carr-Hill 2013). Data reported by national governments for the slum SDG indicator suffer from many uncertainties (UN-Habitat 2016a), e.g., they contain inconsistencies related to national and local policies for recognizing areas (underreporting) (Kuffer et al. 2018), while occasionally, at a municipal level over-reporting has also been observed (Leonita et al. 2018).

Taking the example of India, official statistics reported for the SDG indicators, indicate a strong decline in "slum" population, while the urbanization rates are increasing (Figure H) (World Bank 2017). However, these figures are very uncertain. For example, in Ahmedabad (India) the census of India (2011) reported 4 % slum inhabitants, while the municipality reports 18 %. Similarly, in Bangalore (India), the census records around 8 % slum inhabitants, local records of the Karnataka Slum Development Board (n.d.) records a total of 597 slums for the city with around 23 % of the population living in slums. These figures are contrasted by a local survey, which mapped over 1,500 slums (Roy et al. 2018). In Bangalore, most omitted slums are temporary settlements (e.g., of migrant works) that are not officially recognised (Kuffer et al. 2018). As such, similar issues can be observed in many cities, i.e., typically new, temporary and small deprived areas are not included in official datasets, if such data exist at all. The few studies conducted using EO to estimate the deprived population showed that official statistics possibly exclude large proportions of inhabitants, sometimes 50 % or even more (Taubenböck/Wurm 2015; Veljanovski et al. 2012; Carr-Hill 2013). Thus, in many large deprived areas, the population is systematically underestimated, while small, new, temporary settlements are often not covered (Kuffer et al. 2018). However, rich quantitative and qualitative data, typically those collected by Non-Governmental Organisations (NGOs) or Voluntary Geographic Information (VGI), could fill this gap, but such data do not offer city-level or international coverage and have their own inherent uncertainties (Zhang/Goodchild 2002), typically requiring cross-validation.

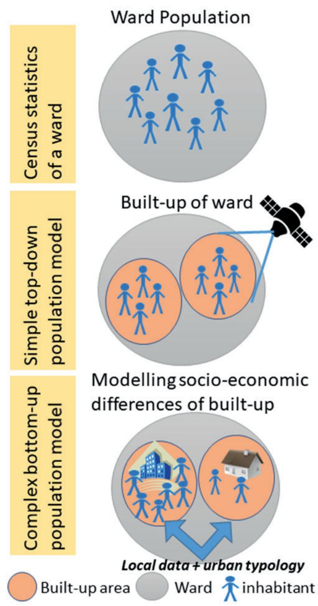
Figure H: Comparison of Urbanization Rates and the Proportion of Slum Population



Source: World Bank 2017

To map deprived areas, studies commonly use VHR images (e.g., Kuffer et al. 2017; Duque et al. 2015; Munyati/Motholo 2014). In such images, deprived areas can be clearly identified using morphological characteristics (e.g., densities, building size) (Kohli et al. 2012) (Figure G). Several studies have highlighted the value of machine-learning methods, and in particular, deep learning such as Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) for capturing complex urban areas (Szegedy et al. 2015; Farabet et al. 2013). Such methods have demonstrated to obtain high classification accuracies, even beyond 90 % (Persello/Stein 2017; Mboga et al. 2017; Zhang et al. 2016; Maggiori et al. 2017; Fu et al. 2017). A major advantage of deep learning is the ability to learn from provided training data the most relevant information (Bergado et al. 2018). However, deep learning requires large sets of training data to obtain high accuracy. Consequently, in most scientific publication around 70 % of the data are used for training (and 30 % for testing – accuracy assessment). The scarcity of ground-truth data on deprived areas is one of the major obstacles to scalability besides the large computational requirements of deep learning (Kuffer et al. 2018). This is also reflected in the fact that most studies work on very small areas, commonly using a couple of km2 (Mboga et al. 2017; Persello/Stein 2017). Therefore, several initiatives (e.g., IdeaMaps and Slumap) are working on robust city-level methods to capture deprived areas (Kuffer et al. 2020). The results will provide city-level delineations of deprived areas. These results allow feeding bottom-up population models (Cockx/Canters 2015; Nagle et al. 2014; Weber et al. 2018) to estimate the population. Commonly, population models use a top-down approach, meaning that census data (e.g., aggregated ward population) are disaggregated into smaller spatial units (Figure I) employing ancillary data (e.g., land-cover) resulting in disaggregated spatial representations of the census population distribution (Langford et al. 2008; Briggs et al. 2007; Azar et al. 2013). However, that approach is rather problematic for deprived areas due to gaps in census data. Therefore, the solution is the use of a bottom-up framework that uses the outcomes of the EO-based city-level mapping of deprived areas (and their built-up areas), optionally also the height of buildings (in case of multi-storey areas extracted from VHR-stereo images (Kuffer/Sliuzas 2014) and a combination of local data (e.g., from NGOs, VGI) to model the variation of the built-up area per person ratio across the city. Such outputs allow to produce localized estimates of the deprived population. Even such outputs have their own uncertainties, e.g., caused by input data, they allow to compare results with census estimates and build the basis for exploring data gaps (and their causes) in official statistics.

Figure I: Population Models, Comparing Top-down and Bottom-up Models



Source: Monika Kuffer

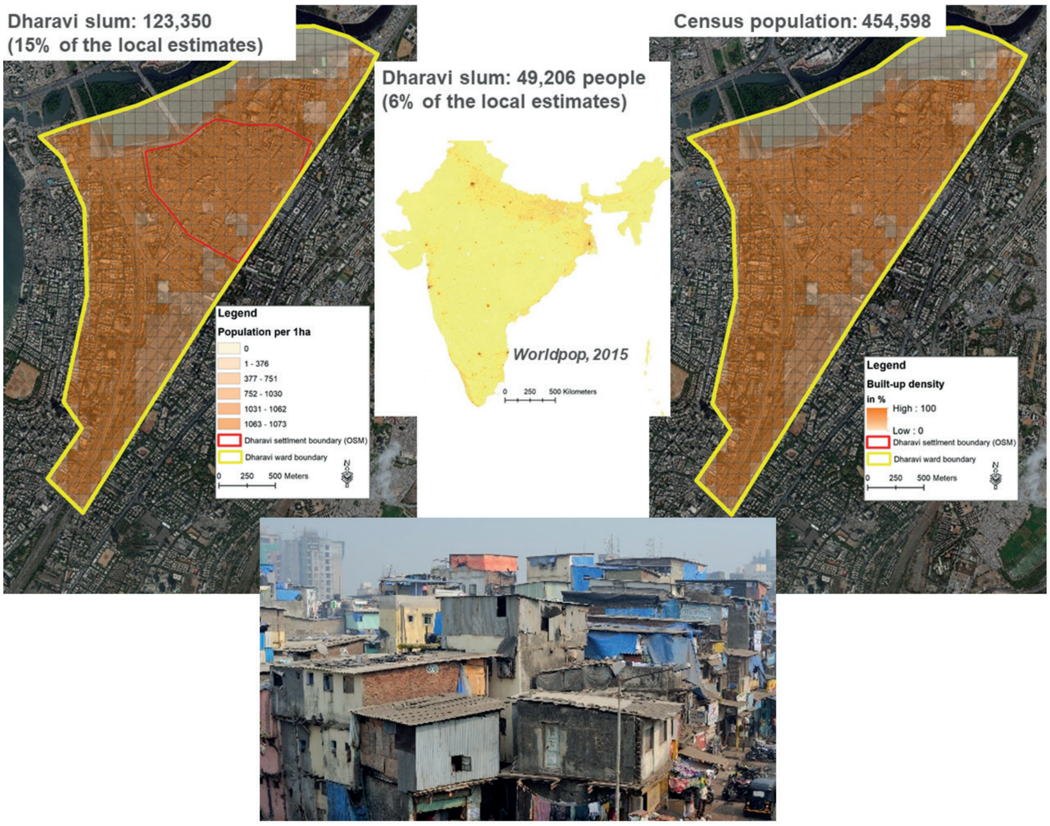
CASE STUDIES – SHOWING OPPORTUNITIES

Two cases are used to illustrate the information gaps, and the role of digital knowledge, on inhabitants of deprived areas and the potential of EO data combined with local data to support in bridging these gaps. The city of Mumbai, India and the city of Dar es Salaam, Tanzania are used to illustrate data gaps and the role of bottom-up population estimates.

THE CITY OF MUMBAI, INDIA

Dharavi in Mumbai is one of the oldest and most well-known slums in India. The area, with only around 2 km^2, is very densely built-up. Large parts of the area are a mix of residential and highly diverse commercial and manufacturing functions. Many buildings have low-rise built structures, with typically 2-3 floors. Dharavi slum (red outline Figure J left) is a small part of Dharavi ward (yellow outline). The population of Dharavi ward was accounted in the 2011 census (last census) with around 450,000 people. However, local population estimates indicate a much large population number for Dharavi slum (Taubenböck/Wurm 2015). Recent estimates assume that more than 800,000 people live within this 2 km². Using a simple top-down population modelling approach, i.e., using an EO layer (extracted from a machine learning based mapping of VHR images) that provides the built-up area and disaggregating the census population data, Dharavi slum would be accounted with around 120,000 inhabitants. Taking the most detailed global population layer (i.e., WorldPop) and overlaying the WorldPop data with the Dharavi slum boundary, the estimate would be around 50,000 inhabitants. In contrast, population numbers close to 800,000 inhabitants are obtained by an EO-based bottom-up estimate based on the extracted built-up maps combined with local statistics on household sizes and average building sizes and building height parameters.

Figure J: Examples of two Top-down Population Estimates



Examples of two top-down population estimates using a 100 m grid (population density and built-up density maps): Census population combined with built-up densities (right), Census-based population density (left), WorldPop Data of India (center) and ground photo of Dharavi slum (bottom).

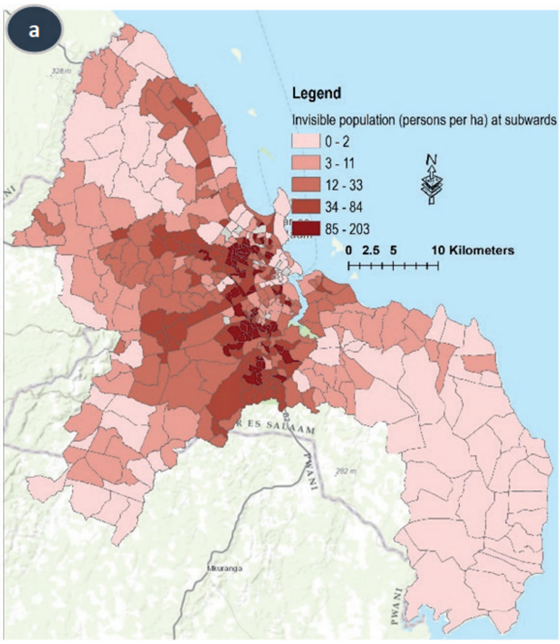
Source: Monika Kuffer; Center: Worldpop

THE CITY OF DAR ES SALAAM, TANZANIA

Dar es Salaam, the main economic hub of Tanzania, had according to the 2012 census (last census) a population of around 4.4 million people. The city belongs to the fastest-growing urban areas in Africa. The city has around 70 % of its inhabitants living in locally called informal areas (UN-Habitat 2010). In such areas, most houses are single-storey structures, also with a mix of residential and commercial functions. A large community-based mapping project, Dar Ramani Huria (2020) – meaning Open Data in Swahili, published a very rich publically available spatial dataset (e.g., available via OSM). Data include, e.g., building outlines extracted from Unmanned Aerial

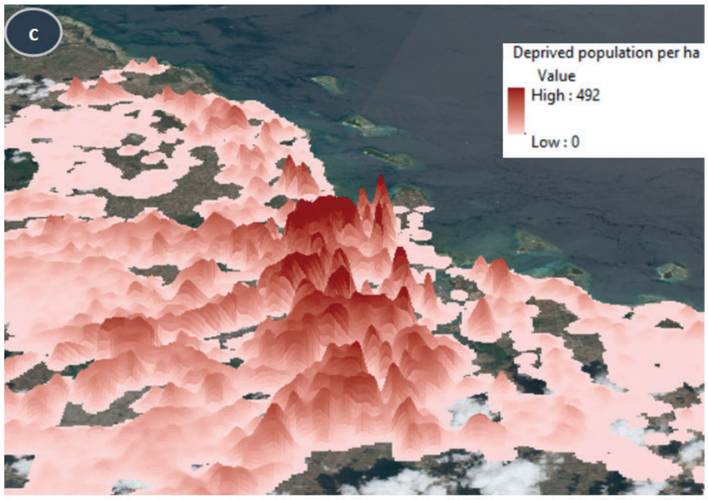
Vehicle (UAV) images. Also for many deprived areas very rich data including population counts, are available within the database built by Shack/Slum Dwellers International (SDI) at the 'Know your city' portal. Comparing a top-down (based on census data) and a bottom-up model (based on building outlines, local survey and community-based population estimates), the results show (Figure K), that the census estimate is with around 3 million deprived inhabitants much lower as compared to around 5 million people using a bottom-up model (Kuffer et al. 2019). Using the bottom-up model to account for the entire population of Dar es Salaam, the city would be estimated with a total population of around 6 million with around 80 % living in deprived areas. These figures indicate a large gap between official data and community-based information and should open a debate on how to improve population data for deprived areas.

Figure K: Estimates of Deprived Population



b

	Occupancy rate (roof area per person in m²)		Deprived population estimates (persons)	
	Census	Bottom-up estimate	Census	Bottom-up estimate
Deprived areas	16.85	10.21	3,055,179	5,043,903



a) Bottom-up estimate of the invisible population; b) estimate of occupancy rates and deprived population (total); c) density of deprived population (Dar es Salaam, Tanzania)

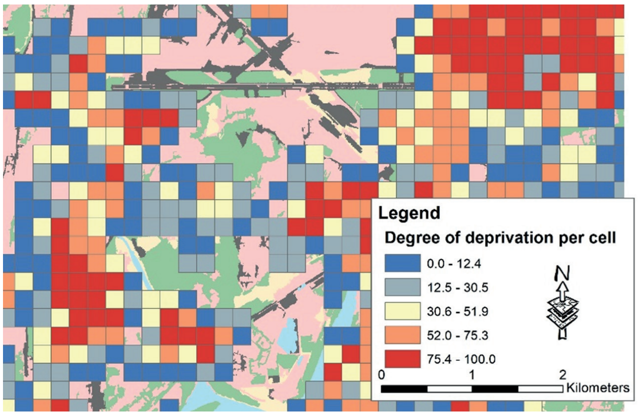
Source: Kuffer et al. 2019

DISCUSSION

The two examples (Mumbai and Dar es Salaam), show that official data do not match with local and community-based data, pointing to possible large data gaps in official data, but also the potential of digital innovation to fill these gaps. The present COVID-19 crises and the consequences for urban inhabitants of deprived areas in the Global South indicate that reliable data to manage and plan such emergencies, e.g., to plan and organize food provision, are urgently needed (Corburn et al. 2020; IdeaMapsNetwork 2020). For example, data from Lagos (Justice & Empowerment Initiatives – Nigeria (JEI) 2020), show that almost 80 % of the inhabitants in deprived areas could not meet their basic needs during the official lock-down. The food provision organized by the government was not able to meet the great demand, also due to the absence of local data. The potential of digital technology is not sufficiently used for populations in need; reasons are manifold. We need to raise the fundamental question of why such technology is used to generate a wealth of information (e.g., the cities of the Global North), and for large areas such as deprived areas in the Global South essential information is not available (Nagenborg/Kuffer 2018). Voices from communities (e.g., JEI) stress the importance to have communities included and been shown on maps, which requires a joint effort but also clear answers to privacy questions for responsible mapping versus the polities of omitting areas in official documents. Also, science needs to move. Despite the large body of EO publications on mapping deprivation areas, the majority employ single image analysis methods, work on very small geographic areas (Kuffer et al. 2020). However, the required information needs to be available at city-scale, as well as such data should be added to global urban data repositories (Thomson et al. 2020). EO data products need to be made accessible and be combined with local and community-based data to provide an account of the location and population living in deprived areas. EO-based data combined with bottom-up population estimates will allow to support local authorities in planning and management, as well as to support NGOs in advocating for the rights of inhabitants. For this purpose, the communication gap amongst the EO-community (not comprehending user requirements) and local users (not fully comprehending opportunities and risks of this rapidly evolving digital technology) need to be bridged (Pratomo et al. 2017). Therefore, much more interaction and understanding of local information needs are required within the EO-community. The EO-community should be ready to provide end-users with essential base data for the formulation of pro-poor policies. Results need to be publically accessible while respecting data sharing restrictions, privacy and ethical considerations, e.g., by better understanding what information about deprived areas can be made publically available.

To achieve that, the development of ethical data sharing guidelines is urgently required (Kuffer et al. 2018). For example, VHR images and derived mapping products can fill such data gaps, but bear the danger to be misused against vulnerable inhabitants (e.g., stigmatization, evictions). To reduce these risks, gridded datasets are a promising solution (Figure L), e.g., by providing the degree of “deprivation” per cell (Kuffer et al. 2020). Users can select their locally adapted thresholds, when categorical maps are required, this protects individual and group privacies in published data, combined with transparency in methods (Thomson et al. 2020).

Figure L: Example of a Gridded Dataset, Showing the Degree of Deprivation per Cell, Part of Mumbai, India.



Source: Monika Kuffer

CONCLUSION

Deprived areas are a socio-economic by-product of the rapid urbanization in many countries of the Global South (but also newly developing refugee camps in the Global North share similar characteristics). Deprived areas are associated with poor living and housing conditions, overcrowding and tenure insecurity. Development processes in many cities are often very rapid and planning authorities do not have updated base data, as well as many city administrations do not cover such areas in their official maps. Globally, the reliability of urban population estimates for deprived areas is very low, showing a clear digital divide between socio-economic groups. High uncertainties about data that flow into SDG statistics can be concluded for deprived (slum) area. Current artificial intelligence based methods combined with EO and local data have great potentials to provide more reliable estimates of the number of inhabitants living in such areas. However, deprived areas are rather complex, dynamic and diverse with often fuzzy boundaries. Therefore, more flexible (such as gridded) mapping approaches, that combine the full potential of digital innovation but also protect privacies are required to provide flexible and policy-relevant data to diverse user groups.

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