Challenges of mapping the missing spaces

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Abstract— **Urbanization in the Global South is often characterized by the proliferation of deprived neighborhoods (frequently referred to as slums). The importance of improving the lives of the residents in these areas is highlighted by many global development agendas. Unfortunately, improvement efforts are hampered by lacking, inaccessible, or outdated spatial data. In this paper, we describe the current limitations which should be addressed to enable a widespread scaling up of remote sensing and image processing methodologies capable of providing this data. We focus on the conceptual ambiguity of what is understood as a slum, informal settlement, or deprived neighborhood. There is a wide diversity of their appearance within a single city, as well as at a global scale. This leads to existential and extensional uncertainty, causing even experts to have different assessments of a slum's boundaries. Such conceptual ambiguities make it more difficult to obtain training data for image processing algorithms, as well as validation to test their accuracy. This also makes it difficult to improve the geographic, contextual, and temporal transferability of the algorithms. After discussing what is needed to upscale current algorithms, we continue to describe the gap between the geospatial data products developed in the remote sensing community and the information needed by policymakers and other user-groups. We discuss why an objective and transparent system for monitoring slums is needed to monitor global development goals as well as support local communities and NGOs.**

Keywords— urban planning, slums, informal settlements, poverty mapping, remote sensing

I. INTRODUCTION: MAPPING THE MISSING SPACES

Accelerated urbanization in many Global South regions and the low capacity of the housing market to provide affordable housing to low-income groups contribute to the growth of slums (SDG indicator 11.1.1). Accurate, comprehensive and up-to-date spatial information of such areas, as well as their evolution at city scale, are needed for local decision-making and to support pro-poor development strategies. However, available data are often inconsistent, outdated, or unavailable. Indeed slums can be "missing spaces" as they are sometimes not mapped or not included in official maps. City data, when collected, is often inaccessible to communities and cannot be disaggregated to help localized projects and hampers their use for advocacy and accountability. In most countries, administrative definitions or income-based indicators are used to differentiate urban slum and non-slum areas. The data collected is typically based on census surveys and does not provide disaggregated information about the spatial concentration or location of slum-dwellers.

Remote sensing (RS) studies have shown the capability of satellite imagery to provide consistent and timely information on the location and physical dynamics of slums [1]. Developments of the last years indicate the development of object-based [2] as well as machine-learning-based methods to provide technological solutions [3]. For example, combining RS and local (non-official) data with deep learning models (the latest generation of machine learning techniques) to extensively map, explore and understand the spatiotemporal dynamics of slums with a temporal granularity adapted to the local slum dynamics (ranging from a few months in cities of very high dynamics to one or two years). However, most studies fail to provide a clear definition and operationalization of such areas. The terms slums or informal settlements, are generally understood but contain ambiguities. The general belief, "if you see a slum you will know that it is a slum", is not entirely true, due to a gradual range from very deprived to less deprived areas. Concerning official slum definition, there are variations across countries but even within cities often different institutions do not use the same indicators to define slums [4]. Furthermore, such areas often do not have crisp boundaries and have variations in their physical and socio-economic conditions. This paper aims to highlight the conceptual ambiguity of the term 'slums' and address its implications on remote sensing techniques for creating policy-relevant information.

II. WHAT EXACTLY ARE WE MAPPING?

There is a need for techniques to get a global estimate of slums and also to address the variability both at intra-city and inter-city level. The characterization of slums spatially in a consistent manner by addressing and including the related uncertainties will potentially help to target slum intervention programs more effectively. This will further help to improve the understanding of the phenomena geographically in a wider context. The ambiguities related to the slums or informal settlements can be due to a number of reasons. To start with, slums are known to have different local names depending on location, cultural context, and material used to build dwellings and infrastructure. They can have various local names, examples include chawls in Mumbai, kachi abadi in Karachi, vijiji in Nairobi, favelas in Rio de Janeiro, jhuggi jhopri in Delhi. Even, within the same city, there can be different slum characteristics and associated names based on the composition and often, also the tenure status of a slum settlement. The physical diversity is due to factors such as variations in locally available building materials and topographic conditions. (Figure 1). Moreover, different countries often develop their own definitions for slums. But even within countries, different government organization can have different slum definitions [4]. Slum mapping is thus not a straightforward task due to the variability in slum types across the world and also within a local context [5].

However, despite these variations, slum areas do tend to share some common features globally. The most characterizing feature is that these areas often have the highest concentrations of the deprived population with poor

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Fig. 1. Ground photos of missing spaces: Roma camp in Serbia (left, source: Flikr) and a slum in Mumbai (right, source: Dr. Karin Pfeffer).

shelter and precarious conditions. For successful remote sensing based analysis or detection of these areas, it is important to address the ambiguities as a first step. This can be done by identifying the common features that may be relevant for slum identification in various contexts.

A. *Capturing various perceptions on: 'what is a slum?'*

Recent studies have shown the importance of integration of context-knowledge for slum identification using RS [4]. Reference [2] presents *existential uncertainty,* which expresses the uncertainty about the existence of a slum on the ground, and *extensional uncertainty,* which implies that the area covered by a slum can be determined with limited certainty. To showcase the implications of such uncertainties in this study, we selected two image subsets: from Jakarta, Indonesia and Pune, India respectively. These subsets were used for slum delineations by participants of an urban symposium held at the Faculty ITC of the University of Twente. These participants were people having on-ground knowledge of slums and at least, basic level of RS.

The total participants (12) were divided into three groups of 4 each and asked to delineate slums in the provided subsets. Results showed variations in the delineations by different groups where there were clearly some areas with more agreement on being a slum than others (Figure 2). These imply both existential and extensional uncertainties which could be attributed to different levels of generalizations, the perception of slums by the group members, as well as decisions on drawing boundaries.

One of the major findings of this exercise as well as earlier studies [2] is the importance of local knowledge. Such findings also reiterate the implications that remote sensing based slum detection can have if the above-mentioned uncertainties are not addressed. Furthermore, slum map reference data is commonly generated through visual interpretation. This causing difficulties regarding the definition of adequate accuracy metrics used to assess the results of slum mapping studies.

III. Upscaling the current methods

Remote sensing studies identify physical differences in the built-up fabric which are associated with formal vs. informal areas. Lower income areas typically consist of small, dense structures with organic patterns whereas higher income areas have more regularly spaced, larger buildings with better infrastructure access [6]. A South-African journalist clearly demonstrates these differences through UAV imagery [7]. Other than visual interpretation, methods such as contour models, object-based, pixel-based, statistical, machine learning, multi-scale, textural, landscape metric, and socio-economic based approaches have been used to identify deprived neighborhoods. References [8] and [9] provide detailed overviews regarding these methods. Advancements in deep learning algorithms [3] are greatly improving image analysis techniques for restricted areas, though computational constraints may limit applications at city-scale.

Despite the high accuracies reported for machine learning algorithms, why is there not yet a 'universal' algorithm for identifying deprived neighborhoods? One issue is *geographic transferability*. Studies tend to be concentrated in specific geographical areas such as Brazil, South Africa, and India whereas other countries with reportedly high slum population estimates are left out [9]. To develop a robust workflow to work in many study areas, one must have access to input data and reference data which are representative of the different appearances of deprived neighborhoods. Workflows which utilize VHR imagery are not freely available globally; whereas free and global datasets such as Landsat and Sentinel may not provide sufficient detail. The reference data must also have a high geo-diversity [10]. OpenStreetMap is such a global open source dataset which can be utilized to provide free reference data and support the development of open workflows [11]. The quality and accuracy of such VGI datasets can be seen as a limitation, though developments in assessment methods [12] and the support of machine learning workflows may at least provide the user with an indication of the quality over a particular area.

Even with the availability of high-quality global imagery and reference data, another limitation for scaling slum mapping methods is the *contextual transferability*. The ambiguity of the definition of a slum or deprived neighborhood and the strong dependency on local context creates a wicked problem. The importance of community participation and participatory mapping approaches is vital for understanding local spatial nuances as well as community needs [13].

Changes in deprived neighborhoods over time mean that algorithms must also be *temporally transferable*. The transformation of slums from infancy to consolidation and maturity may be visible through the construction of new buildings. However, the degradation of formal areas into

Fig. 2. Delineations of slums in snapshots of Jakarta, Indonesia (left) and Pune, India (right) produced by three groups, each represented by a different color. Source: GoogleEarth

deprived neighborhoods is more difficult to capture in RS imagery.

Scaling up current methods for mapping deprived areas is obviously difficult due to their geographic, contextual, and temporal heterogeneity. When we go for global mapping, are we equipped enough to contextualize our models accordingly (i.e., to integrate local knowledge)? How can we find the balance between global definitions which provide coverage and local definitions which are capable of providing more fit-for-purpose information of deprivation?

Perhaps one way to avoid the difficulty in defining 'slums' and distinguishing 'formal' versus 'informal' areas is by mapping another indicator entirely. Reference [14] avoid this dichotomy by developing a Slum Severity Index which allows for a more nuanced description of neighborhood deprivation. Reference [15] focus on estimating population distributions. The development of alternative spatial data sources such as Unmanned Aerial Vehicles [16], street-view images [17], mobile phone data [18], night-lights [19], and social media data [20] can be used to integrate social information. These new sources of information provide socioeconomic information in the development to complement the physical characteristics captured in imagery and perhaps allow us to define new ways of integrating local context into global algorithms.

IV. The Practical Use of the Generated Knowledge

A. Who owns the data

Generally, the remote sensing community does not sufficiently understand, which data are required for different user groups, while potential users do not understand the capabilities and limitations of RS [21]. Thus it is important to ask ourselves: how far are we with producing maps that can be used by different user groups? – Are the data we are producing and the techniques we are developing suitable for local and global policy-making to support pro-poor initiatives?

For example, for the SDG indicator 11.1.1, current methods rely on nationally reported statistics. These may neglect unrecognized, newly developing, temporary and small clusters of slums. Studies that compared the recognized slums with the slums on the ground found large discrepancies [14], [22]. Such data inconsistencies do not allow to monitor the outcome of global and local efforts to eradicate poverty, proving durable housing, basic services and a safe living environment to all urban inhabitants.

To support local policies, localizing slums is fundamental. Localized information is also critical for disaster mitigation and adaptation as well as for addressing residents facing evictions. For instance, long-standing national and municipal policies that maintain the invisibility of slums often means that they face evictions when large projects get undertaken, and many large global and national financing institutions, unlike the World Bank, do not have policies that address displacement. Slum Dwellers International (SDI) and other transnational grassroots organizations address these challenges at the planning stages, where disaggregated slum data is essential. It is fundamental that data on slums in owned and accessible by communities and NGOs supporting them.

B. User groups of data

Users of information on slums are at three main scales – on a global, national and local level. International organizations (e.g., UN-organizations) require information that complements the existing survey based methodologies, allowing for localizing slum information and showing trends over time. Such information also links to other SDGs, providing essential information related to poverty. At the national and local level, governments require timely access to geographic data on the location, extent, and dynamics of slums. Access to more precise data about slums would help in developing appropriate responses to the needs of slum dwellers as well as in assessing the impact of programs and actions geared towards improving their lives. Slum communities themselves through their associations or advocacy groups would benefit from better information on of their living conditions, often hidden in urban averages.

The mapping of deprived and vulnerable population in various parts of the world raises ethical questions, and in the worst case could increase eviction pressure. The latest generation of satellite imageries provides spatial details up to a resolution of 30 cm, while machine learning allows to automatize the slum mapping and provide essential information for designing pro-poor policies. However, responsible design and use of earth observation technologies ask for careful considerations about the acquisition, processing, and use of the data. For example, data are processed with a specific accuracy, the quality of the produced data and related uncertainty need to be clearly communicated to end users and concerned communities.

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Furthermore, presently the communities and their partner associations have no access or control of data and its ownership is often with everyone but them. Organizations such as SDI promote the generation of data that is within the hand of communities and their associations.

V. Conclusions

This paper describes how the conceptual ambiguity of the term slum is an obstacle for upscaling remote sensing methods, which otherwise have demonstrated high accuracy in observing slum boundaries from space. This is frustrating, as an objective and transparent monitoring of slums would increase the effectiveness of international development agendas as well as empower local communities and NGOs. At the same time, it is indeed the variations in physical appearance, local understanding, and information needs, which are challenging the development of a holistic definition of slums and methods for monitoring them. Should we, therefore, focus RS research efforts on identifying the common denominator of slums? To identify the key RS characteristics which *are* transferable? Another strategy could be to depart from the binary vision of slums versus non-slum, accept that boundaries are fuzzy, and instead use RS to derive a type of deprivation index. A third strategy could be to focus on deriving information which itself is more suitable for scaling. For example, information regarding environmental and living conditions, such as built-up density, the presence of green or open spaces, high temperatures, air ventilation, air pollution, or the lack of street lights. Such attributes should be reconsidered given the emergence of new spatial datasets. Such attributes could be used to build a settlement typology, which systematically characterizes settlements based on their physical conditions (similar to the local climate zones classification system). Whichever strategy is selected, future directions should focus on the development of methods scalable at a global level to monitor the temporal dynamics of slums at a larger scale, while understanding the local needs and potential of people living in these 'missing spaces'.

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