doi:10.20944/preprints201910.0242.v2

Critical Commentary. Need for an integrated deprived area "slum" mapping system (IDeAMapS) in LMICs

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Abstract

Ninety percent of the people added to the planet over the next 30 years will live in African and Asian cities, and a large portion of these populations will reside in deprived neighborhoods defined by slum conditions, informal settlement, or inadequate housing. The four current approaches to neighborhood deprivation mapping are largely silo-ed, and each fall short of producing accurate, timely, comparable maps that reflect local contexts. The first approach, classifying "slum households" in census and survey data and aggregating to administrative areas, reflects household-level rather than neighborhood-level deprivation. The second approach, field-based mapping, can produce the most accurate and context-relevant maps for a given neighborhood, however it requires substantial resources, preventing up-scaling. The third and fourth approaches, human interpretation and machine classification of satellite, aerial, or drone imagery, both overemphasize informal settlements, and fail to represent key social characteristics of deprived areas such as lack of tenure, exposure to pollution, and lack of basic public services. The latter, machine classification of imagery, can be automated and extended to incorporate new and multiple sources of data. This diverse collection of authors represent experts from these four approaches to neighborhood deprivation mapping. We summarize common areas of understanding, and present a set of requirements to produce maps of deprived urban areas that can be used by local-to-international stakeholders for advocacy, planning, and decision-making.

Keywords
satellite imagery, social indicator, urban, poverty, SDG

Introduction

Most low- and middle-income countries (LMICs) are in the midst of urban transitions, or will be soon, and are facing rapid growth of slum-like communities. Although urbanization has been associated with some of the greatest achievements in human history, including reduced mortality and the production of material wealth, it is also closely linked with socioeconomic inequalities that trap generations of families in perpetual cycles of poverty and insecurity (UN-Habitat, 2003).

The United Nations (UN) expects that between 2018 and 2030, megacities such as Kinshasa (D.R. Congo), Delhi (India), and Dhaka (Bangladesh) will each add more than 700,000 people per year on average through 2030 (UN-DESA, 2019). An estimated 2.5 billion people will be added to the planet by 2050, with 90% of that population increase concentrated in Asian and African cities alone (UN-DESA, 2019). This is cause for concern given that many of the LMICs within these regions are currently facing various development challenges, which impede their ability to adequately accommodate this future population growth (Mahabir et al., 2016).

To help cities better plan for future population growth, Sustainable Development Goal (SDG) 11 aims to "make cities and human settlements inclusive, safe, resilient and sustainable." Progress towards SDG 11 is measured, in part, by identifying the "proportion of urban population living in slums, informal settlements or inadequate housing" (UN-DESA, 2018). Decision-makers use neighborhood deprivation maps to estimate numbers of people living in these areas (Angeles et al., 2009), allocate public services (Gruebner et al., 2014), plan and evaluate health policies and campaigns (Weeks et al., 2012); respond to humanitarian disasters (Bramante and Raju, 2013), and make long-term development decisions (Chitekwe-Biti et al., 2012).

Despite more than two decades of effort, slums, informal settlements and areas of inadequate housing are not mapped accurately and routinely across LMICs. The problem is twofold. First, there is no universal definition of deprived areas. Second, there are no established, universally applicable best practices to map such areas. As a result, there are no data repositories of consistent, up-to-date, publicly accessible maps on deprived areas within cities. This paper, with contributions from a diverse group of international experts, outlines the need to integrate and leverage the strengths of existing approaches to routinely, and accurately map deprived urban areas in LMIC cities to support SDG 11 and decision-making.

Slum are versus slum household

The term "slum" has been used to belittle and marginalize groups in some contexts, and it is used as an identity-marker among residents in other contexts (Nuissl and Heinrichs, 2013). "Favela", "ghetto", "barrio", or "shantytown" are also common terms in some cities; however, each of these labels comes with a specific political and social history. Recognizing these limitations, we instead use the term "deprived areas" to refer to urban residents of slums, informal settlements and inadequate housing in line with SDG 11.

A number of efforts have been made to define deprived urban neighborhoods including expert meetings (UN-Habitat et al., 2002; Sliuzas et al., 2008; UN-Habitat, 2017); published frameworks

(Lilford et al., 2019; Mahabir et al., 2016); and operational definitions within Earth Observation (EO) research (Kohli et al., 2012; Kuffer et al., 2014; Mahabir, et al., 2018a). Despite efforts over the last 20 years, no universal definition or methods have been achieved to map deprived urban areas. This is due, in large part, to the enormous diversity and dynamism of slums and informal settlements, and because perceptions of neighborhood deprivation is relative to other nearby communities (Nuissl and Heinrichs, 2013).

UN-Habitat provides a widely accepted definition to classify a household or group of individuals as a "slum household" if they lack any of the following: durable housing, sufficient living space, safe water, adequate sanitation, or security of tenure (UN-Habitat, 2007). Household tenure, however, is generally not measured in censuses and surveys, so it is routinely excluded from this definition in practice. Although relatively easy to operationalize, a household-level definition of deprivation fails to account for important area-level social, environmental and ecological risks that result from living in deprived areas (Table 1). Living in a deprived area can increase the incidence of disease via exposure to animal vectors and crowding of buildings, injuries such as fire, vulnerability to extreme weather events, higher incidence of crime, and physical and social barriers to services (Ezeh et al., 2017). The "slum household" definition reflects household-level poverty, which poses unique risks such as crowding within the home and economic barriers to services. Furthermore, the household-based definition has been shown to overestimate deprived areas in some contexts, classifying neighborhoods as "slums" that are not considered as such locally (Engstrom et al., 2013) and labelling almost entire cities as "slums" (Lemma et al., 2006).

Table 1. Definition of a deprived area (slum, informal settlement, area of inadequate housing) versus "slum household"

Deprived Area	**"Slum Household"**
Reflects *social, environmental, and ecological risk factors* to health and wellbeing above and beyond household and individual characteristics	Reflects *household poverty* risk factors to individual health and wellbeing
Indicators include: ● Social risk - e.g. no social safety net, crime ● Environmental risk - e.g. flood zone, slopes ● Lack of facilities - e.g. schools, health facilities ● Lack of infrastructure - e.g. roads, bus service ● Unplanned urbanization - e.g. small, high-density, disorganized buildings ● Contamination - e.g. open sewer, trash piles ● Land use/rights - e.g. non-residential zoning	Indicators include: ● Non-durable walls, floor, or roof ● Too few sleeping rooms ● Lack of safe water source ● Lack of adequate toilet ● Lack of tenure of home (usually not measurable)

The risks of belonging to a "slum household" within a deprived area act simultaneously to exacerbate individual health and wellbeing, and all residents of deprived areas, regardless of household wealth, face multiple area-level risks. (Figure 1). Different policies and interventions are

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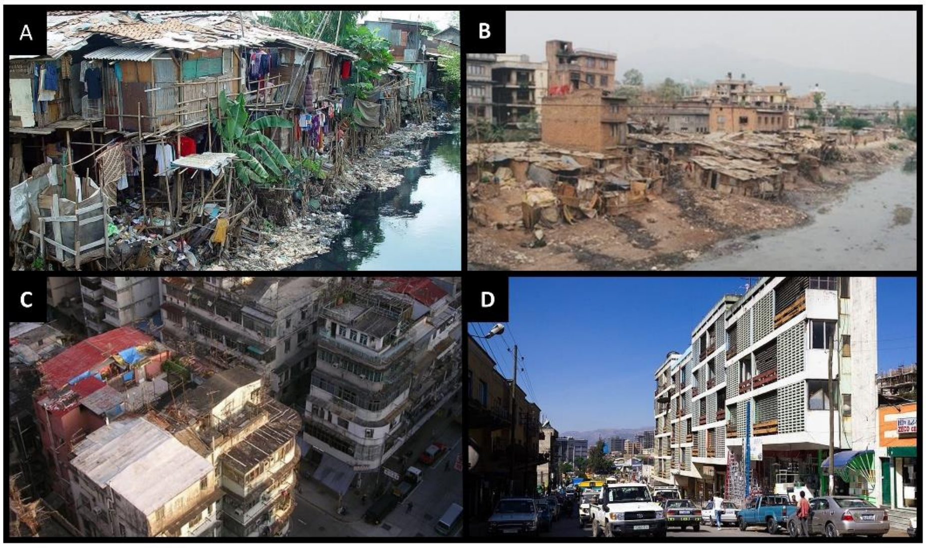
needed for households located in deprived versus non-deprived areas, and thus it is imperative to map area deprivation in addition to “slum households.”

Figure 1. Four ways in which “slum household” and deprived area risks intersect

“slum household” in deprived neighbour-hood

non-slum household in deprived neighbour-hood



“slum household” in not deprived neighbour-hood

non-slum household in not deprived neighbour-hood

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Requirements for area deprivation mapping

As mentioned before, no universal definition of a deprived urban area yet exists; however, the following seven requirements have been clearly articulated. Urban area deprivation maps need to be:

1) *Reflective of area physical characteristics.*

Deprived urban areas are often characterized by their morphology in the urban environment. Physical indicators of area deprivation include building size, shape, and height; road and other access networks; building density; settlement shape; and settlement location with respect to public green or blue spaces, steep slopes, flood zones, and proximity to railways and high voltage power lines (Kohli et al., 2012).

2) *Reflective of area social characteristics*.

Deprived urban areas are characterized by a wide range of features in the social environment. Social indicators of neighborhood deprivation include presence of crime; presence and practices of law enforcement; coverage and quality of solid waste, water, sanitation, and power systems; proximity and accessibility to schools, health facilities, shops, employment, and public infrastructure; and social capital derived from community-based organizations and among neighbors with shared identities (Lilford et al., 2019).

3) *Context dependent*.

The physical and social characteristics that define a given deprived area differ across cities and countries and even within the same neighborhood (Kuffer et al., 2016). Furthermore, neighborhoods are not static in that the specific characteristics that define deprivation at a moment in time change as the neighborhood evolves and policies and social forces unfold (Mahabir, et al., 2018a).

4) *Comparable across cities and countries*.

To adequately support national planning and programs, and to be used in global initiatives such as the SDGs, a level of consistency in deprived urban area definitions are needed across cities and countries (Ezeh et al., 2017).

5) *Updated frequently with timely data*.

Deprived urban areas are highly dynamic and can be transformed over very short periods. As deprived areas transition through different development stages, from low- to high-density, and as they experience major shifts in population due to demolitions or "overnight invasions" of new residents, frequent updates to deprived area maps are needed based on very timely data (Mahabir et al., 2018a). Further, areas previously classified as deprived need to be able to be classified as non-deprived as infrastructure and services improve, sometimes because of gentrification.

6) *Protective of individual privacy, and vulnerable populations*.

Given the relatively high spatio-temporal resolution of neighborhood maps, approaches must ensure individual privacy in EO and other data, as well as transparency in the mapping methods. There may additionally be a need to selectively filter or obfuscate exact boundaries of deprived areas to protect already vulnerable populations (Thomson et al., 2019).

7) Developed via an inclusive multi-stakeholder process.

Urban "slums" do not emerge at random. Existence of deprived urban areas reflect stories of social inequality, exclusion, and/or oppression. For a deprived area to transition into a place that is "inclusive, safe, resilient and sustainable," the policies and social attitudes that permitted its formation need to be addressed. Neighborhood transformation requires involvement of communities, local authorities, and national governments (Ezeh et al., 2017; Lilford et al., 2017).

Existing approaches to area deprivation mapping

Existing efforts to map deprived urban areas follow one of four general approaches or a combination of these: (1) aggregation of "slum household" data; (2) field-based mapping by residents; (3) human visual interpretation of EO imagery (satellite, aerial, and drone) ; and (4) semi-automatic classification of EO imagery with machine algorithms. These approaches have operated in parallel over the last two decades, largely in isolation, and each has strengths and limitations. Importantly, none of the existing approaches alone meet all requirements for area deprivation maps (Table 2).

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Table 2. Strengths and limitations of existing approaches to area deprivation mapping

Requirements	Aggregated "slum households"	Field-based mapping	Human imagery interpretation	Machine imagery classification
1) Reflective of area physical characteristics	✗	✓	✓	✓
2) Reflective of area social characteristics	?	✓	?	?
3) Context dependent	✗	✓	?	?
4) Comparable across cities and countries	✓	✗	✗	✓
5) Updated frequently with timely data	✗	✗	✗	✓
6) Protective of individual privacy, and vulnerable populations	✓	✓	?	?
7) Developed via an inclusive multi-stakeholder process	✗	✗	✗	✗

1. Aggregated "Slum Households" Approach

The widely cited statistic - 1 billion slum dwellers globally - is calculated by classifying urban "slum households" in censuses or surveys, and then aggregating to country or sub-national region (UN-Habitat, 2003). Academics have similarly used the "slum household" definition to classify household survey data for statistical analysis, and interpret the results as representative of slum dwellers (e.g. Fink et al., 2014). Some experts from the social sciences recommend classifying census enumeration areas or survey clusters as "slum areas" when 50% or more of households meet the "slum household" definition (Lilford et al., 2017).

This approach has two major limitations. First, the indicators of a "slum household" do not reflect the social, environmental, and ecological factors that define deprived urban areas (Thomson et al., 2019). Second, this approach can exclude small pockets of deprived areas within larger non-deprived areas because a typical "slum area" is just 1.6 hectares (Friesen et al., 2018).

2. Field-based mapping

Field-based mapping is commonly performed by community NGOs, and linked to advocacy for slum dwellers' recognition and rights (Slum Dwellers International, 2016; Panek and Sobotova, 2015; Nairobi City County, 2018). In many cases, the approach is wholly participatory, where organized community members map and enumerate their settlement to gather planning data and catalyze community action (Map Kibera Trust, 2009). When field-based mapping is performed by outsiders such as academics or governments, the approach often begins with a review of EO imagery and identification of potential informal settlements before field validation with, or without, the involvement of community members (Improving Health in Slums Collaborative, 2019). Many field-based approaches rely on handheld digital devices such as GPS units, and the collected data may be collated to reflect the, sometimes overlapping, land claims in informal settlements (e.g. GLTN, 2017).

While field-based mapping strongly represents local context, area-level physical characteristics, and area-level social characteristics, the approach on its own is extremely difficult to upscale to whole cities and countries. In addition, field-based mapping results in area deprivation maps that are highly variable across cities and countries.

3. Human Imagery Interpretation Approach

Earth observation data are sometimes used to manually digitize informal settlements. This approach is typically based on *a priori* definitions of deprivation, for example, defining deprived areas only as informal settlements with high built-up density, irregular layout pattern, small or no internal access roads, small buildings and lack of green spaces. The use of imagery to identify and delineate informal settlements does not depend on predefined areal units and thus may approximate actual informal settlement boundaries (Lilford et al., 2019); however, the boundaries of more formalized deprived areas may be missed using this approach.

Such delineations may be performed by local (Angeles et al., 2009) or outside (Wurm and Taubenböck, 2019) experts, and are labor intensive but can provide high-quality, detailed maps required by planners. Manual delineation is sometimes performed to minimum requirements, and if done by several interpreters, might be inconsistent (Leonita et al., 2018). Furthermore, local experts might disagree in complex setting about the delineation of informal versus formal areas (Kohli et al., 2016). Although local experts may be from the cities being mapped, delineation of informal settlements is generally performed without involvement of people living in those areas, ignoring local opinions, privacy, and geo-ethics. The degree to which human imagery interpretation reflects local context depends entirely upon who is doing the interpretation and delineation.

4. Machine Imagery Classification Approach

Semi-automatic "supervised" imagery classification is performed with EO imagery, as well as other spatial datasets such as road intersections which allows the scaling-up of deprived area classifications (e.g. Verma et al., 2019; Ibrahim et al., 2019). Developments in deep learning show that well-trained models can achieve classification accuracy of more than 90% (Kuffer et al., 2018). However, such methods require a large number of high-quality training data, expensive very high-resolution imagery, and are computationally demanding. Consequently, most machine-learning efforts are proof-of-concept studies that typically cover small study areas within a single city.

In practice, the input data overwhelmingly represent physical characteristics such as building morphology, slope, and flood zone (Kuffer et al., 2016; Mahabir, et al., 2018a), with few models considering social characteristics such as trash piles, open sewers, crime rates, or zoning designations (Thomson et al., 2019). A majority of image classification models result in maps with discrete boundaries between area types, however, deprived areas may not have sharp boundaries (Leonita et al., 2018). Further, a majority of these models do not account for disagreement among experts who delineate training datasets (Verma et al., 2019). Both of these issues can be addressed with models that classify informal and other deprived neighborhoods on a continuous scale (e.g. degree of deprivation) in tiny units such as grid cells (Kohli et al., 2016).

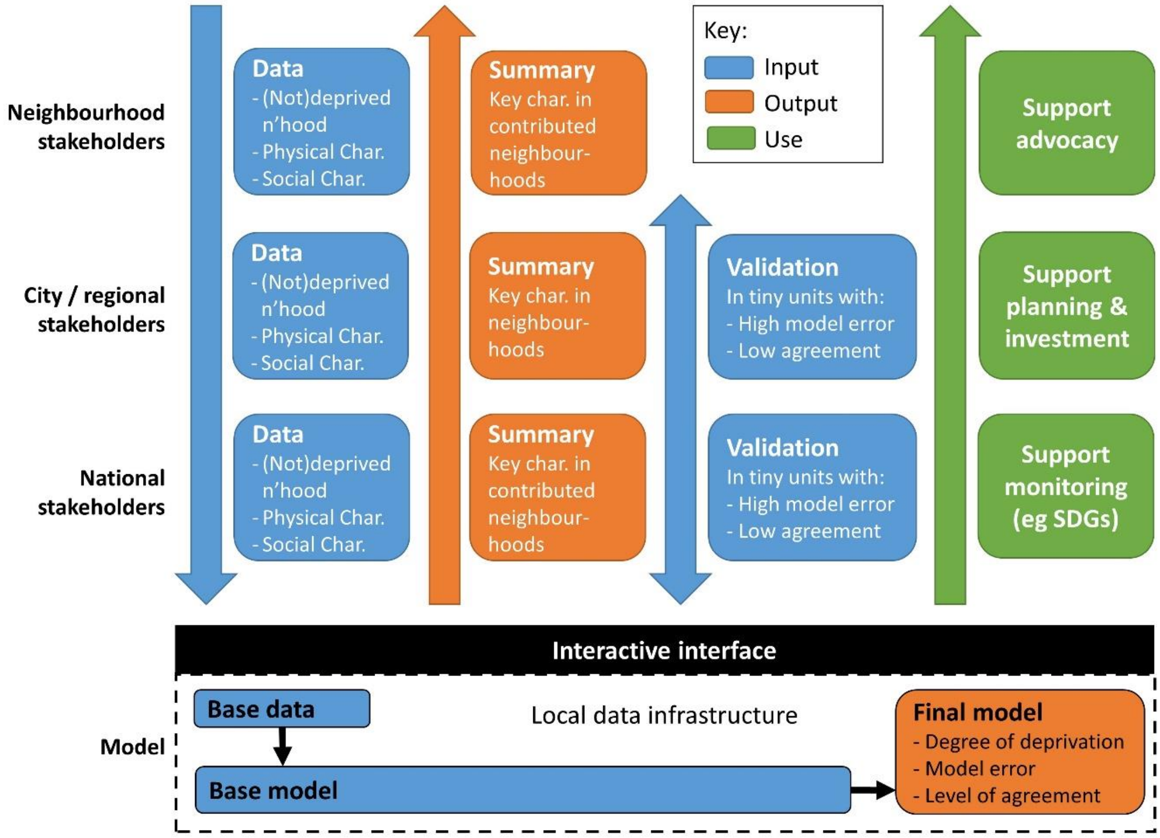
Proposing an integrated deprived area mapping system (IDeAMapS)

Alone, each of the current approaches has substantial limitations, however these approaches can be integrated to leverage their strengths and meet all of the area deprivation modelling requirements. Below and in Figure 2, we outline an integrated deprived area mapping system (IDeAMapS) that:

- leverages continual contributions of updated data from an ecosystem of national and local stakeholders,
- reflects the social and political realities on the ground, and
- provides a simple interface with predefined geospatial models allowing users to decide which datasets are suitable to model neighborhood deprivation for their specific needs, generating an up-to-date custom map on demand.

The backbone of the IDeAMapS approach would be a base model and universal datasets embedded in a locally housed, open data infrastructure. A sizable amount of work would be needed up front to develop universal covariates that reflect both physical and social area-level characteristics. New social datasets would need to be created, for example, informal tenure by comparing real-estate website activity with population density (Mahabir, et al., 2018b), or using feature extraction techniques to identify trash piles in EO imagery (Thomson et al., 2019).

Figure 2. Diagram of an integrated deprived area mapping system (IDeAMapS)



IDeAMapS would not only rely on universal datasets; it would also need **continual contributions** of custom, local covariates and classified neighborhood-level training datasets from a **range of stakeholders** at multiple levels. Contributions of deprived/not deprived area training datasets could be incentivized by returning **summary statistics for each contributed and classified neighborhood** such as total population and percent of area covered by buildings, roads, or water to be used for local planning and advocacy projects. By allowing multiple stakeholders to contribute delineated and classified area boundaries, the system **eliminates the need for a single global deprived/"slum" area definition**, and rather accumulates a rich database of classified training data.

The output of IDeAMapS should be **formatted as a gridded dataset** in which degree of deprivation is estimated for each grid cell. Gridded datasets allow the output to be aggregated to any number of spatial units such as census enumeration area or city wards. Furthermore, a sensibly sized grid cell (e.g. 50 x 50 meters) would allow for a high level of spatial detail across a city while obfuscating exact settlement boundaries. Neighborhood names and specific geographic boundaries should never be publicly reported in this system to protect the privacy and security of residents in deprived areas. Many users will desire degree of deprivation to be translated into a classified map (i.e. "slum"/"non-slum"), thus a user-specified threshold of deprivation could be included.

An important step in the IDeAMapS approach would be **iterating the model** by seeking additional training data from users depending on the results of the first model iteration. By running a first model with the available universal and contributed dataset, grid cells in which the model performs poorly, and grid cells in which only one training dataset is available, could be sampled and presented to a locally-based user. These users would classify the cell as deprived/not deprived to feed back into the final model, both improving statistical certainty, and allowing for a measure of agreement about what is, and is not, a deprived area.

Users would need a simple **interactive interface** that is linked to a **locally-based data infrastructure.** Many government, NGO, and community groups may hesitate to contribute if their data will be extracted from the country. Additionally, contributors need control over their data, including the ability to validate, contest and revise contributed data. We envision this platform as a public good, freely accessible to national and local governments, community groups, NGOs, researchers, international agencies, and the public. Given the unique needs of national and local governments to produce official "slum area" maps for SDG and other official reporting, special support should be provided to government agencies with the ability to filter approved covariates and training datasets. We recognize that this is an ambitious endeavor that requires clear terms of reference, sustained resources, commitment, and trust in the governance structure (see UTEP Consortium, 2019 for how this might work).

Discussion

The authors of this commentary hail from the four existing approaches to area deprivation mapping - aggregated "slum households," field-based mapping, human imagery interpretation, and machine imagery classification. Through a series of workshops in 2018 and 2019, we came to understand the strengths and limitations of each other's approaches, and outlined this approach to an integrated deprived area mapping system (IDeAMapS). We have summarized our thoughts here to stimulate discussion within and across our disciplines, and to connect with new and diverse stakeholders who share our goals to identify deprived urban areas in LMICs and improve the wellbeing of those residents. Our work together thus far has highlighted several important areas of understanding.

First, "slum households" and deprived areas, while related, are different phenomena. Deprived areas are defined by physical and social risks and outcomes such as absence of public services, while "slum households" are defined by risks and outcomes in households such as limited-income. To effectively target vulnerable populations with policies and programs, we need to locate both "slum households" and deprived urban areas, and understand the unique risks that face "slum households" in deprived, as well as not deprived, areas.

Second, a wealth of area-level physical characteristic maps exist in LMICs, however, few maps of area-level social characteristics are available. Methods for area deprivation mapping that use satellite imagery or spatial data focus almost exclusively on small, disorganized buildings or streets; however, deprived areas are not synonymous with informal settlements (Nuissl and Heinrichs, 2013). Many of the risks and outcomes that define life in deprived areas are social in nature, and can co-exist with organized streets and permanent buildings. The creation of social area-level datasets, such as areas of insecure tenure or trash pile locations (Mahabir et al., 2018b; Thomson et al., 2019), stand not only to improve the accuracy of area deprivation maps, but also serve as valuable decision-making tools on their own.

Third, area deprivation mapping can have both positive and negative effects on individuals who live in deprived areas. The mapping of deprived areas has been used to advocate for the rights of slum dwellers and help them access basic public services (Panek and Sobotova, 2015), as well as to fuel demolition campaigns and harass residents (Roy, 2009). Critically, it is involvement of residents in the mapping process that determines the effect of such maps (Lilford et al., 2017; Panek and Sobotova, 2015). Community groups based in slums and other deprived areas must be central to any area deprivation mapping initiative, especially large-scale initiatives such as the one we propose.

Finally, existing evidence points toward seven basic requirements for area deprivation maps: (1) reflects physical risks, (2) reflects social risks, (3) is context dependent, (4) is comparable across cities and countries, (5) is updated frequently with timely data, (6) protects individual privacy, and vulnerable populations, and (7) is developed via an inclusive multi-stakeholder process. We believe all seven requirements can be achieved through an IDeAMapS approach. The simple classification of deprived/not deprived areas enables reporting on slums, informal settlements and areas of inadequate housing for SDG 11, and provides the spatial information needed to disaggregate other population-based SDG indicators. An integrated mapping system further enables key dimensions of deprivation to be mapped to support critical budget and planning decisions for local and national governments. For example, IDeAMapS might separately identify areas of a city where pollution, or unplanned housing, or social risks are predominant problems. Self-identified slum communities who hold mapping campaigns can benefit from receiving data summaries of characteristics that have been mapped by others in their neighborhoods for use in planning and advocacy. Those deprived communities that do not have active mapping campaigns would benefit from being represented in national statistics and subsequent policies and programming.

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Acknowledgements

Special thanks to the following people who contributed to key workshops and meetings that gave rise to this paper: Donatien Beguy, Daniel Githira, Julius Majale, Shipra Narang-Suri, Walter Oriedo, Kerstin Sommer, Daniela Di Filippo, and Faith Barorot from UN-Habitat; Kenneth Mubea from the Global Partnership for Sustainable Development Data (GPSDD), Sergio Freire and Alice Siragusa from the European Commission Joint Research Centre; Blessing Mberu from the African Population & Health Research Center; Andrew Tatem from the WorldPop Team at the University of Southampton; Steven Ramage from the Group on Earth Observations, Philipp Ulbrich and Godwin Yeboah from the Institute for Global Sustainable Development at the University of Warwick, and Robyn T. Emerson an urban development consultant and author.

Author contributions

All co-authors helped to conceptualize this paper, and read and approved the final version. DRT and MK performed the literature investigation, and DRT, MK, JPA, CK, GB, and TG wrote the initial draft. The following people contributed to visualizations: CA, JPA, GB, SC, TG, BH, CK, MK, NM, and DRT. The following people performed project administration: JPA, BH, CK, MK, DM, and DRT.

Competing interests

We declare no competing interests.

Funding

This work is unfunded.