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Need for an Integrated Deprived Area "Slum" Mapping System (IDEAMAPS) in Low- and Middle-Income Countries (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 siloed, and each fall short of producing accurate, timely, and comparable maps that reflect local contexts. The first approach, classifying "slum households" in census and survey data, 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 (visual) interpretation and machine classification of air or spaceborne 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 public services. We summarize common areas of understanding, and present a set of requirements and a framework to produce routine, accurate maps of deprived urban areas that can be used by local-to-international stakeholders for advocacy, planning, and decision-making across Low- and Middle-Income Countries (LMICs). We suggest that machine learning models be extended to incorporate social area-level covariates and regular contributions of up-to-date and context-relevant field-based classification of deprived urban areas.

Keywords: urban; poverty; SDG; slum; deprivation, spatial model

1. 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, and 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. This paper outlines the need for an Integrated Deprived Area Mapping System (IDEAMAPS) in Section 2, provides two case studies to underscore limitations of existing data in Section 3, proposes a framework for IDEAMAPS in Section 4, and discusses considerations for implementation of such a framework in Section 5.

2. Need for an Integrated Deprived Area Mapping System (IDEAMAPS)

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 (Mayne 2017). 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. 2018b). 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 are 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. Despite being 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 as neighborhood effects. Deprived areas are defined by social, environmental, and ecological risks to health and well-being such as lack of legal access to land, social amenities such as access to schools and health centers, or basic infrastructure such as roads and sewer lines (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; Friesen et al. 2020). 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 overestimates the population living in deprived areas in some cities by classifying neighborhoods within them as "slums", though they may not be considered as such locally (Engstrom et al. 2013), or entire cities may be classified 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 needed for households located in deprived versus non-deprived areas, and thus it is imperative to map area deprivation in addition to "slum households."

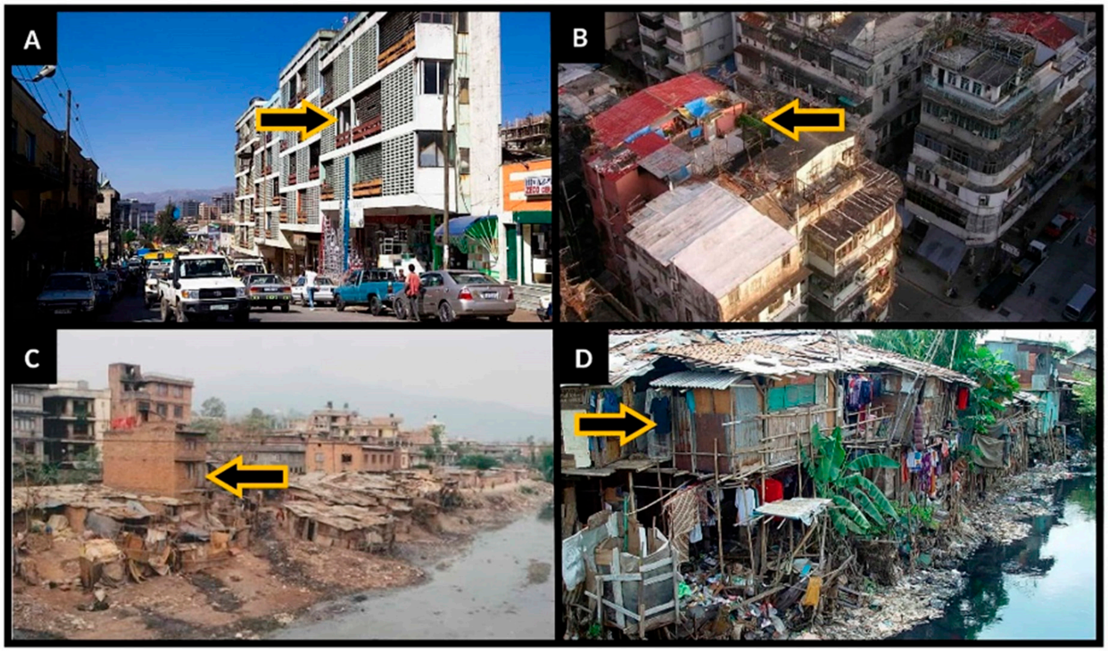


Figure 1. Four ways in which "slum households" and deprived area risk factors intersect. (**A**) Non-slum household in non-deprived area, (**B**) Slum household in non-deprived area, (**C**) Non-slum households in deprived area, and (**D**) slum households in deprived area.

2.1. 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 may include crime levels; 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. 2018b).
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. 2018b). 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. For example, public release of ultra high resolution drone imagery which shows trash piles behind property walls or inside roofless latrines is considered sensitive by citizens and should probably be avoided (Gevaert et al. 2018). 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. The existence of deprived urban areas reflects histories 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 the involvement of communities, local authorities, and national governments (Ezeh et al. 2017; Lilford et al. 2017).

2.2. 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 (i.e., 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 with its own strengths and limitations. Importantly, none of the existing approaches alone meets all requirements for area deprivation maps (Table 2).

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

IDEAMAPS Requirements	Aggregated "Slum" Households	Field-Based Mapping	Human (Visual) Image Interpretation	Machine Image 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	✕	✕	✕	✕

Key: ✓ requirement met, **?** requirement partial met, ✕ requirement not met.

2.2.1. 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).

2.2.2. 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., Global Land Tool Network 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. Urban deprivation manifests differently across LMICs and their cities due to local differences in their environment, policies, and history. This makes a single definition of urban deprivation unlikely to be developed for local field-based mappers to follow. Even when local experts use the same "slum" definition, they draw different boundaries for deprived areas in the same city (Pratomo et al. 2017; Kohli et al. 2016). Together, these issues mean that field-based mapping results in area deprivation maps that are highly variable across cities and countries.

2.2.3. Human (Visual) 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 a high built-up density, irregular layout pattern, small or no internal access roads, small buildings, and a 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 the 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.

2.2.4. Machine Learning 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 a 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. 2018b), with few models considering social characteristics such as trash piles, open sewers, crime rates, or zoning designations (Thomson et al. 2019). As a result, these methods mainly reflect informal settlements, and are less useful in contexts where the urban poorest live in durable housing but face multiple deprivations. Furthermore, 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). 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).

3. Case Studies: Methods and Results

The first case study from India demonstrates classification of deprived urban areas during routine household surveys, and provides clear evidences of differences between deprived neighborhoods and slum households. The second case study from Bangladesh demonstrates the classification of deprived urban neighborhoods using human interpretation of satellite imagery and field verification, and highlights opportunities and limitations of using secondary spatial data sources for deprivation area mapping.

3.1. Eight Cities, India

The 2005–2006 and 2016–2017 National Family Health Surveys (NFHSs) in India were among the first routine national household surveys to use urban "slum" areas in their sample design. Both NFHSs used officially registered "slums" to stratify the urban sample in eight of the country's largest cities: Chennai, Delhi, Hyderabad, Indore, Kolkata, Meerut, Mumbai, and Nagpur (IIPS and Macro International 2007; IIPS and ICF International 2017). In the field, a survey supervisor reclassified each sampled cluster by whether it met the 2011 census definition of an identified slum, defined as "a compact area of at least 300 populations or about 6–70 households of poorly built congested tenements, in an unhygienic environment usually with inadequate infrastructure and lacking in proper sanitary and drinking water facilities (MHUPA 2013)." This resulted in a representative sample of 597 clusters in 2005–2006 and 687 clusters in 2016–2017 with a field-referenced and standardized classification of deprived/non-deprived areas.

We further calculated the percent of households that met the UN-Habitat "slum household" definition in each of the eight cities using the 18,575 households sampled in 2005–2006, and 13,414 households sampled in 2016–2017 (IIPS and Macro International 2007; IIPS and ICF International 2017). Households that met any of the following conditions were considered a "slum household" according to the UN-Habitat definition (UN-Habitat 2007): unimproved water source (i.e., from an unprotected well or spring, surface water, or truck/cart); unimproved toilet (i.e., flush toilet not connected to sewer lines, open pit, no facility, or a toilet shared by more than six households); non-durable structure (i.e., mud/earth/dung floor, or mud/thatch/cardboard wall, or mud/thatch/plastic roof); or over-crowding (i.e., more than 3 people per sleeping room). Analyses were performed in Stata 15, applying household sample probability weights via svy commands to produce population-representative estimates in each city.

The results reveal heterogeneous distributions of populations in "slum households" located in deprived neighborhoods (field-referenced identified slums) versus non-deprived neighborhoods (field-referenced non-slums), as well as changes in these distributions over time. Figure 2 summarizes the percent of population in non-"slum households" in non-deprived neighborhoods (top left), in "slum households" in non-deprived neighborhoods (top right), in non-"slum households" in deprived neighborhoods (bottom left), and in "slum households" in deprived neighborhoods (bottom right). If most "slum households" were located in identified "slums," as is often assumed, then the top right and bottom left boxes in each diagram would be small or non-existent.

Figure 2. Distribution of population in "slum households" and deprived neighborhoods across eight Indian cities in 2005–2006 and 2016–2017 based on National Family Health Surveys.

However, the diagrams show that in seven of the eight cities, in 2005–2006 as well as 2016–2017, an equal or larger portion of the population resided in "slum households" in non-deprived areas compared to deprived areas (Figure 2). The combination of deprived area maps with measures of "slum households" paints a new nuanced picture of urban poverty, and can guide decision-makers toward interventions and policies that are most likely to be effective toward alleviating poverty at the local level. For example, cities with large portions of "slum households" residing outside of deprived areas, social protection programs (Ortiz and Cummins 2011), and/or investments in mixed-income neighborhoods are key for poverty reduction, while cities with large portions of the population living in slum areas (bottom two boxes in each diagram) will find participatory slum upgrading programs important in city strategies (Turley et al. 2013). In India, this would include Mumbai, Indore, Meerut, and Kolkata where more than a quarter of the population lived in a deprived area in 2016–2017 (Figure 2). The intersection of "slum households" and deprived areas can also be used to monitor progress over time. For example, the cities of Chennai, Nagpur, Delhi, and Hyderabad each saw sizable reductions in the percent of population residing in deprived areas between 2005–2006 and 2016–2017 (Figure 2).

3.2. Dhaka, Bangladesh

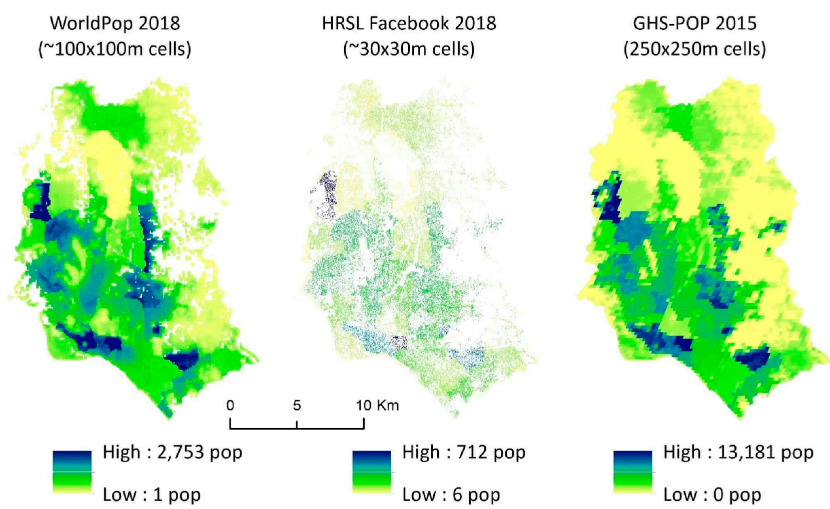
Working with the city government of Dhaka, researchers used very high resolution satellite imagery and field visits to identify areas of informal settlement and manually delineate "slums" across the Dhaka metropolitan region in 2006 and in 2010 (Gruebner et al. 2014) (Figure 3). Publicly available "slum" area boundaries like these are used by city governments, researchers, non-governmental organizations, and international agencies for planning, monitoring, and research, and are often combined with other secondary data sources. In this case study, we demonstrate use of a deprivation area map and three publicly available population datasets to estimate Dhaka's total "slum" population and population density (population per square kilometer).

The featured datasets include WorldPop 2018 (WorldPop 2020), Facebook's High Resolution Population Density Maps 2018 (Facebook 2020), and the Global Human Settlement population layer (GHS-POP) for 2015 (European Commission 2017), each of which is detailed and compared elsewhere (Leyk et al. 2019). Broadly, all three datasets disaggregate 2011 Bangladesh UN-projected census population counts to small grid squares using geo-statistical models and spatial covariates such as roads and land cover types. The original spatial resolution is approximately 30 × 30 meter cells in the Facebook dataset, approximately 100 × 100 meter cells in the WorldPop dataset, and 250 × 250 meter cells in the GHS-POP dataset. The top three maps in Figure 3 show cells with the greatest population density in blue, cells with the least dense population in yellow, and cells classified as non-settled as white. To calculate population totals and densities, we resampled the WorldPop and GHS-POP datasets to 25 to 30 meter cells, and performed zonal statistics in ArcGIS 10.6 for each "slum" and non-"slum" area across Dhaka's wards and unions. The bottom-right graphs in Figure 3 show population density per meter in each of Dhaka's slum and non-slum areas.

Secondary dataset sources such as these support numerous development and humanitarian use cases, but also present challenges. By now, the reader has noted that the years of these datasets do not align. Neither the Dhaka city government, nor the research team who produced the "slum" map, have publicly released an updated version of "slum" area boundaries in the last decade. Any activities based on this map will, therefore, exclude new "slums" and areas of "slum" growth, likely excluding areas in which infrastructure and services are less developed than established "slums." At the time of this writing, WorldPop had released annual estimates from 2000 to 2020, Facebook had released one population estimate for 2018, and GHS-POP had released four estimates for 1975, 1990, 2000, and 2015. At an aggregated scale, the featured population estimates produced similar total "slum" population counts of 1.2 to 1.4 million inhabitants, or 11.5% to 13.4% of Dhaka's population (Table 3). These figures might vastly underestimate the "slum population", which might be more than 3 million (Islam et al. 2006). However, in any given slum, the population estimates and densities varied widely across the three datasets (Figure 3). The variations within each "slum" and non-"slum" area were due to different modeling approaches and input datasets; WorldPop methods are known to underestimate the highest density cells, GHS-POP is known to over-estimate population density and exclude sparse rural settlements, and the Facebook dataset is so recent that accuracy assessments and comparisons are limited (Leyk et al. 2019).

Table 3. Total population and population density in Dhaka, Bangladesh according to three secondary population datasets.

Population	Slum	Non-Slum
Total (%)		
WorldPop 2018	1,394,977 (12.1)	10,097,443 (87.9)
Facebook 2018	1,442,960 (13.4)	9,324,747 (86.6)
GHS-POP 2015	1,236,851 (11.5)	9,520,949 (88.5)
Area (sq. km.)	25.8	281.1
Density per sq. km.		
WorldPop 2018	54,027	35,919
Facebook 2018	55,885	33,170
GHS-POP 2015	47,902	33,868



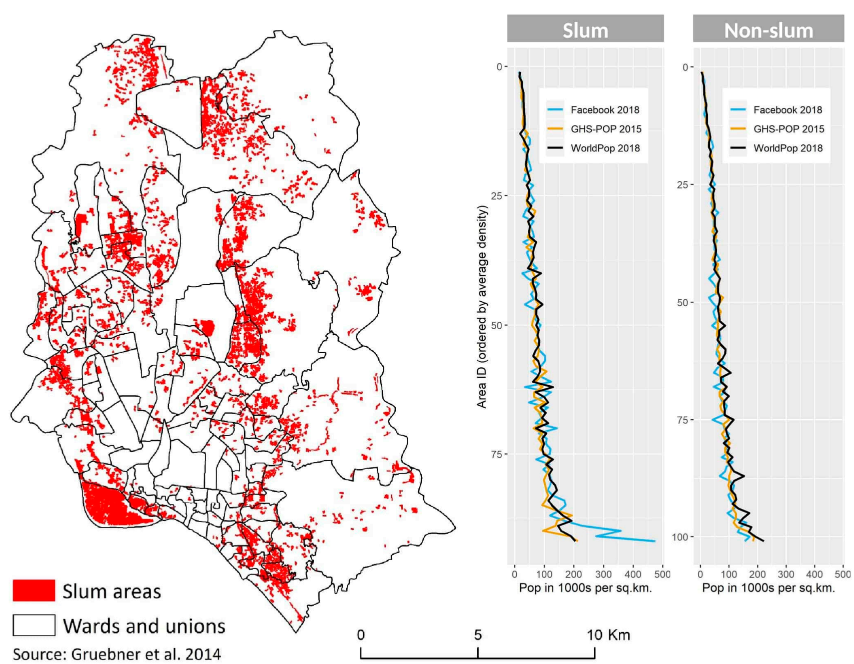


Figure 3. Three gridded population estimates and "slum" area boundaries in Dhaka, Bangladesh with "slum" and non-"slum" area population density estimates.

In general, gridded population accuracy assessments are performed at aggregated scales on secondary data (e.g., 4th-level administrative units) rather than at the cell-level (Leyk et al. 2019), and field-referenced population counts are rarely, if ever, used to evaluate gridded population model accuracy. If deprivation area and population maps are to be useful for local activities such as participatory slum upgrading, vaccination campaigns or household surveys, accuracy assessments need to be performed at fine geographic scale. Given the highly dynamic nature of cities, it is also essential that these datasets are updated routinely in a timely manner so data are not obsolete upon release. Despite being freely and publicly available, the datasets featured here are difficult for slum communities to view and access, in part because intermediate GIS skills and tools are needed to simply open the datasets. Bangladesh is a particularly data-rich country and thus these datasets are among the most detailed and accurate available; however, errors in modeled data are exponentiated in data-sparse settings due to limited, coarse, and outdated inputs from other secondary sources (e.g., census, OpenStreetMap).

In the next section, we highlight ways in which data producers can integrate communities, local governments, and other field-based partners into a modeling workflow to achieve multiple benefits: improved map accuracy across space and time, familiarity by researchers with data needs and limitations, and communication channels by which field-based experts can lend insights the inputs to improve data suitability for planning, interventions, advocacy, and more.

4. IDEAMAPS Framework

Alone, each of the current approaches to deprivation area mapping has substantial limitations, however, these approaches can be integrated to leverage their strengths and meet all of the area deprivation modeling requirements. Below and in Figure 4, we provide a framework for 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 framework should 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. 2018a), or using feature extraction techniques to identify trash piles in EO imagery (Thomson et al. 2019).

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 × 50 m) 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 for the 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 governments, NGOs, and community groups may hesitate to contribute if their data will be extracted from their 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).

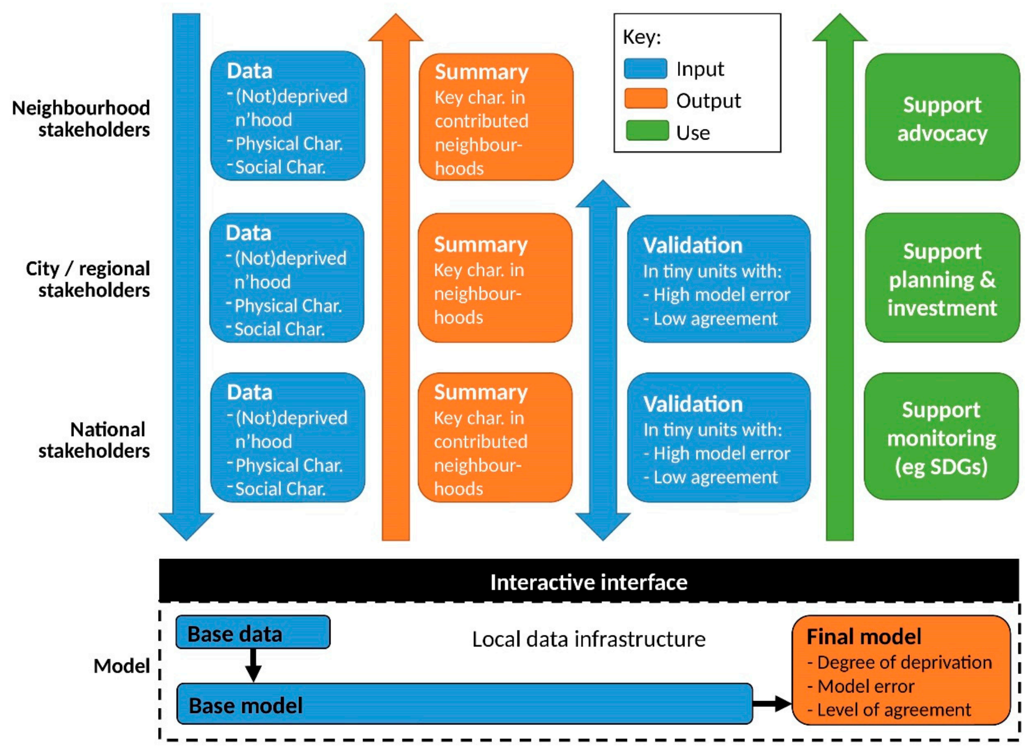


Figure 4. Framework for an Integrated Deprived Area Mapping System (IDEAMAPS).

5. Discussion

The authors hail from the four existing approaches to area deprivation mapping—aggregated "slum households," field-based mapping, human visual imagery interpretation, and machine learning 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 that result from neighborhood effects and area-level outcomes such as an absence of public services. In contrast, "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. This is particularly true in LMICs with social housing programs that provide durable, serviced housing to the poorest, but where severe social deprivation still persists. The creation of social area-level datasets, such as population density, areas of insecure tenure or trash pile locations (Mahabir et al. 2018a; 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. The present COVID-19 emergency underscores the urgent need for timely data about population density, absolute numbers of population stratified by age group, availability of quality health facilities, water, sanitation, transportation networks, and other characteristics, to inform critical decisions in the COVID-19 response.

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). To gain a proper understanding of deprived area characteristics that vary across countries and contexts, any mapping initiative must include the perspectives of community and grassroots organizations, which must be actively involved in the production and analysis of new data on the areas they live in. 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. This way, community mapping can not only generate new context-sensitive training datasets as "equitable ground-truth" for machine learning models, but simultaneously enable a dialogical engagement with communities (Albuquerque and de Almeida 2020) that yields social learning and creates an evidence basis for advocacy of local improvements. The mapping community needs to be aware that labeling an area as a "slum" might contribute to harassment, fines, evictions, violence, or stigma faced by residents. The coauthors who work and live in established slums have experienced both, though the situation varies widely by city and context. We underscore the need to involve local communities in defining the format of mapped outputs to ensure that fine-scale data is available for decision-making without creating unintended risks for residents. We have established the IDEAMAPS Network to facilitate meaningful exchange among stakeholders involved with area deprivation mapping (IDEAMAPS Network 2020).

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, including further efforts to improve the existing evidence basis.

6. Conclusions

We argue that current approaches to mapping deprived urban areas in LMICs are, on their own, not able to produce accurate, timely, scalable and inclusive outputs in support of the SDG 11 targets. However, we argue, that if existing approaches are integrated under a deprived area mapping system (IDEAMAPS) framework, it is possible to leverage the strengths of current approaches and produce city-level maps of slums, informal settlements, and areas with inadequate housing or other vulnerabilities which are context-specific, accepted as accurate, and available on a routine basis across multiple cities and countries. The IDEAMAPS framework requires earnest engagement and contributions from neighborhood, city, and national stakeholders. We outline a data ecosystem that encourages meaningful stakeholder engagement at all levels by providing use-case ready data outputs, and an iterative process of data validation by local and national authorities to maintain acceptability of map outputs.

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