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"Domains of Deprivation Framework" for Mapping Slums, Informal Settlements, and other Deprived Areas in LMICs to improve urban planning and policy: A Scoping Review

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ABSTRACT

The majority of urban inhabitants in low- and middle-income country (LMIC) cities live in deprived urban areas. However, statistics and data (e.g., local monitoring of Sustainable Development Goals - SDGs) are hindered by the unavailability of spatial data at metropolitan, city and sub-city scales. Deprivation is a complex and multidimensional concept, which has been captured in existing literature with a strong focus on household-level deprivation while giving limited attention to area-level deprivation. Within this scoping review, we build on existing literature on household- as well as area-level deprivation frameworks to arrive at a combined understanding of how urban deprivation is defined with a focus on LMIC cities. The scoping review was enriched with local stakeholder workshops in LMIC cities to arrive at our framework of Domains of Deprivations, splitting deprivation into three different scales and nine domains. The Domains of Deprivation framework provides a clear guidance for collecting data on various aspects of deprivation, while providing the flexibility to decide at city level which indicators are most relevant to explain individual domains. The framework provides a conceptual and operational base for the Integrated Deprived Area Mapping System (IDEAMAPS) Project for the creation of a data ecosystem, which facilitates the production of routine, accurate maps of deprived "slum" areas at scale across cities in LMICs. The Domains of Deprivation Framework is designed to support diverse health, poverty, and development initiatives globally to characterize and address deprivation in LMIC cities.

KEY WORDS

global south, indicators, urban, city, poverty, neighborhood-level

INTRODUCTION

Today more than half of the world's population (55%) live in urban areas – a share projected to reach 68% by 2050 (UNDESA, 2018). The rate and scale of growth presents daunting challenges, especially in low and middle-income countries (LMICs) where urgent and significant investments are required in transportation, housing, sanitation, energy, education, and health as well as social and physical infrastructure (Azcona et al., 2020; UN-Habitat, 2020b). Ninety percent of global population growth in the next 30 years will occur in African and Asian cities; for example, Lagos (Nigeria), Delhi (India), and Dhaka (Bangladesh) are each expected to increase by an average of 650,000 to 870,000 people per year through 2035 (UNDESA, 2018). Increasing urbanization exacerbates growth of slums, informal settlements, and other deprived areas (hereafter called deprived areas). Despite this staggering reality, no operational dataset is available that provides statistical and spatial information about the location and diversity of deprived areas across the Globe. This calls for the development of a data system that not only characterizes deprivation, but also helps a diverse range of stakeholders respond to it.

In response, the IDEAMAPS Network is developing a data ecosystem that provides open-access information on the location and diversity of deprived areas across and within LMIC cities (Thomson et al., 2020). IDEAMAPS is piloting the production of routine, accurate maps of deprived areas across cities in LMICs by combining different mapping traditions, including machine learning with Earth Observations (EO), census and survey aggregation, and community mapping. This is facilitated by a data ecosystem designed for users in local governments, community based organizations, NGOs, universities, and elsewhere to exchange and integrate geographic data. For the development of such a data ecosystem, it is fundamental to conceptualize key domains of deprivations to guide which data are used to label deprived areas and improve them. To avoid a common trap of using data simply because it has been used before (precedent) or it is available (convenience) (Radford and Joseph, 2020), the IDEAMAPS framework maintains a focus on data user applications, data requirements, and conceptualizations of deprivation.

Although 'deprivation' may refer to the lack of basic necessities at an individual-, household- or area-level, the focus here is on area-level deprivation including the accumulation of individual- and household-deprivations in an area, as well as exposure to unhealthy living conditions, or living in a marginalized or neglected area. We focus this review on academic and grey literature which conceptualize deprivation beyond economic poverty, specifically in cities. This was an explicit choice, as urban (and peri-urban) deprivation requires a different framework as compared to rural deprivation, though both are equally important for global poverty reduction. Given that deprivation frameworks from high-income countries (HICs) have strongly influenced the development of frameworks in LMICs, it was necessary to include global conceptualizations of deprivation in this review.

With the aforementioned aims and scope in mind, the research questions addressed in this review include:

- How is urban deprivation conceptualized within the academic and grey literature focusing on cities/urban areas globally?
- How are these conceptualizations translated into domains of deprivation?
- If, and how, are these domains associated with indicators that measure aspects of deprivation within cities?

Brief overview of the deprivation literature

Initial published conceptualizations of deprivation were mainly focused on HICs with attention on deprivation at the individual- and household-level. Over the last half century, these frameworks have expanded to include theories and frameworks of deprivation within LMICs, and more recently understandings of deprivation have shifted to thematic and geographic concerns, for example, the nature of deprivation within cities and urban areas (Figure 1).

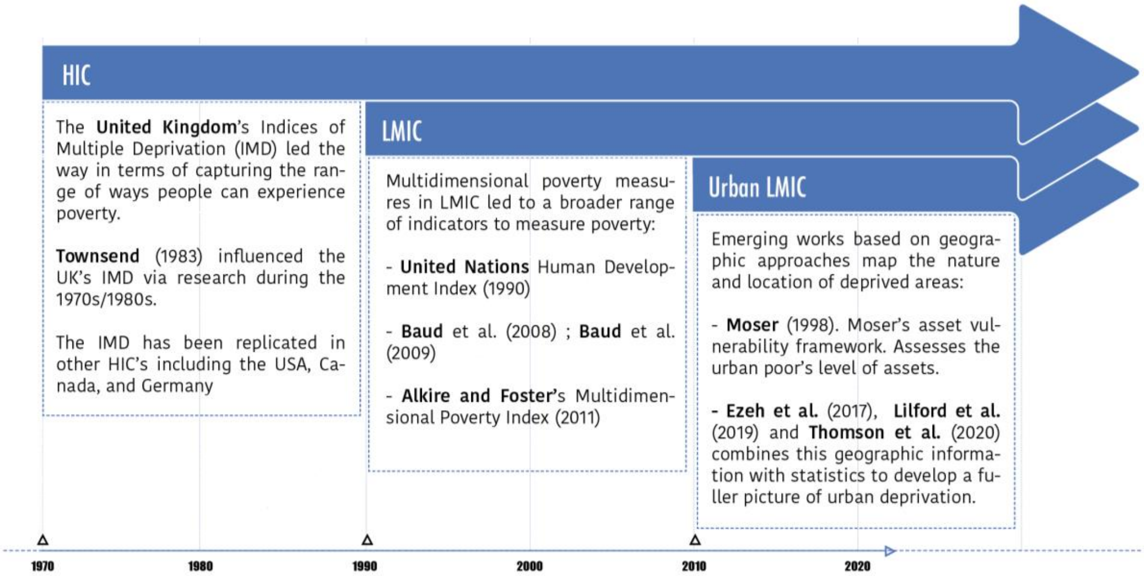

Figure 1. Evolution of frameworks related to multiple deprivations in LMIC urban settings

Multiple-deprivation indices in HICs

UK indices of multiple deprivation (IMDs) were seminal to how deprivation has been conceptualized and quantified in both HICs and LMICs. These indices shifted from measuring deprivation broadly from national census and survey data, to disaggregating census data to local administrative units, exposing area-level patterns in household indicators. In time, area-level indicators were introduced to indices such as levels of outdoor air pollution or numbers of road-traffic accidents. Today the English IMD, for example, reflects seven domains of deprivation related to income, employment, education and skills, health and disability, crimes, barriers to housing, and services and living environment, and is as measured by 39 census and other government indicators in areas of approximately 1500 people, or 600 households (Dymond-Green, 2020; OCSI, 2021).

Other similar UK indices measured household deprivation within small areas but with fewer indicators and/or domains. Sally Holtermann (1975), for example, used eighteen variables representing housing conditions, unemployment, and occupational social class, to investigate geographic variations in deprivation in the UK. In the 1980s, the Townsend Deprivation Index (Townsend et al., 1988), Jarman Underprivileged Area Score (Jarman, 1984), and Carstairs Index (Carstairs & Morris, 1991) were all developed around four census indicators of car ownership, home ownership, overcrowding, and unemployment, but differed in their methodological application. Other HICs have developed and used similar multidimensional indicators of deprivation over the decades, including the U.S. Area Deprivation Index (Singh, 2003), 2006 Canadian Marginalization Index (Matheson et al., 2012), and Accessibility/Remoteness Index of Australia (ARIA) (Hugo Centre for Population and Housing, 2020).

Multiple-Deprivation Indices in LMICs

During the 1990s, quantitative measures of multiple deprivation were applied and tailored to LMIC settings and were shaped by thought leaders such as Amartya Sen (e.g., 1992, 2009; Dreze and Sen, 1990). Sen's Capability approach conceptualizes development as the removal of 'unfreedoms' to enable each person to fulfill their potential or 'capabilities' (1999). For a girl living in India, for example, regulations to prevent child marriage may help to remove her 'unfreedom' of curtailed education, as girls often leave school when married early. Sen did not specify these 'unfreedoms' as domains or indicators, but others attempted to do so to operationalize his ideas. Martha Nussbaum, for example, developed a capability model that could be used to envisage social justice for women (2000, 2011).

Concurrently, improvements in the quantification of deprivation occurred as donor countries and agencies supported LMIC governments to invest in routine national household survey programs (Fabic et al., 2012). A proliferation in household-level data on population health and wellbeing in LMICs fed into monitoring of Global goals such as the 2000-2015 Millennium Development Goals (MDGs), and the current UN Sustainable Development Goals (SDGs) (Alkire 2014). As the SDGs were kicking off, Sabine Alkire (2015) pioneered the Multidimensional Poverty Index (MPI) with a broad range of indicators, and the MPI has gone on to influence poverty and deprivation studies in LMICs including articles reviewed below (e.g., Altamirano et al., 2016; Zakaria et al., 2017). For decades, household-level surveys have been the main source of data to measure deprivation and poverty in LMICs because administrative systems have often lacked investment (Setel et al., 2007), and spatial data about infrastructure and environmental characteristics in LMICs have been missing, fragmented across organizations, incomplete, or cost prohibitive (Dotse-Gborgbortsi et al., 2018; Mahabir et al., 2016). Surveys, however, are rarely designed to be representative of small areas, and surveys that include spatial locations randomly geo-displace them to protect respondent anonymity, severely limiting analysts' ability to link data about individuals and households with other datasets at fine geographic scale (Perez-Heydrich et al., 2016).

Given that household census and survey data have been essentially the only comparable data across countries for decades, both the MDGs (7.10) and SDGs (11.1.1) use household-level data to measure the population living in slums, informal settlements, and other deprived areas, an area-level phenomenon. Both MDG7 and SDG11 measure "slum households" as lacking any of the following assets: improved water, improved sanitation, durable building material, sufficient living space, or secure tenure, and then aggregate "slum households" within urban areas (UN-Habitat et al., 2002). In practice, tenure status is rarely measured in censuses or surveys, leaving four household assets to define the complex concept of "slums" across diverse, dynamic cities (e.g., Fink et al., 2014). Not only is the exclusion of tenure status problematic, this approach implicitly - and incorrectly - assumes that "slum households" are concentrated in slum areas. In one survey covering eight Indian cities where slum areas were mapped and field-verified, more than half of "slum households" were located in non-slum areas (Thomson et al., 2020). Another limitation of census and survey data is that they generally only differentiate urban and rural areas, which means that the needs of the urban poorest become masked in urban averages (Elsey et al., 2016). The creators of the "slum household" definition acknowledged its limitations as a household-based measure and advocated for it to be replaced with an area-level measure by drawing slum/non-slum boundaries into official census maps based on local context, as is already done for urban/rural boundaries (UN-Habitat et al., 2002).

One further shortcoming of urban indices, as well as surveys and censuses, is that they are not, as yet, adequately mainstreaming gender issues. Mainstreaming gender is carried out via an initial gender analysis of needs and experiences followed by indicator formulation that can lead to the monitoring of, and progress towards, gender equality and women's empowerment. A first step as mandated at the 1975 Beijing Conference for Women was the collection of sex-disaggregated data, but decades on from this, sex-disaggregated data remains patchy particularly in relation to urban issues. Although the engendering of data and indicators is slowly changing - with the SDGs paying closer attention to this, and UN Women among other organizations championing the need for gendered measurement - much remains to be done to ensure this becomes a reality. As such, we seek to understand if, at a minimum, sex-disaggregation is included in urban indices and we isolate patterns in terms of which gender issues are counted.

Multiple Deprivation Measures in LMIC cities

In the early 2000s, geographers and physical data scientists began developing their own concepts of urban deprivation as newly available Earth Observation (EO) and spatial data became available. The explosion in new technologies, computing power, and spatially detailed data cannot be understated: in the last 20 years, free very high-resolution satellite imagery and sensor data, ubiquitous use of mobile phones and GPS devices, the introduction of Volunteered Geographic Information (VGI) such as OpenStreetMap, and new platforms to easily share open spatial data all became realities (Lang et al., 2020; Ramadan 2017; Yan et al., 2020). The conceptualization of deprivation by physical data scientists, however, has predominantly focused on the form and morphology (physical arrangement) of features such as buildings and roads (Duque et al., 2017; Leonita et al., 2018; Taubenböck et al., 2018; Wang et al., 2019; Wurm & Taubenböck, 2018). Divyani Kohli and colleagues, for example, published a seminal "ontology of slums" that defined whether an area was a slum based on characteristics at three scales; specifically, of building and road "objects", shape and building density of the "settlement", and its location and characteristics relative to other features in the "environs" such as proximity to power lines (Kohli et al., 2012). This framework, and others like it (e.g., Kuffer et al., 2014; Mahabir et al., 2018) tended to exclude issues such as education, employment, or social capital because these factors cannot be directly measured via EO data.

A literature review by Monika Kuffer and colleagues (2016) summarized the first 15-years of "slum" mapping with EO data and concluded that contextual knowledge on the diversity of deprived areas across the globe is still limited among physical data scientists, and a more systematic exploration of deprived area characteristics is required for innovation in this field. A challenge for physical data scientists when operationalizing deprivation frameworks by social scientists is the lack of detailed spatial data about the domains and indicators included; while a challenge for social scientists to contribute to spatial modelling of slums and informal settlements is complexity of methods, data sources, and terminology used (Thomson et al., 2020).

Several attempts have been made to bridge understanding among social and physical data scientists, including at the 2002 meeting led by social scientists and practitioners from UN-Habitat, the UN Statistics Division, and Cities Alliance, which resulted in the "slum household" definition widely used today and discussed above (UN-Habitat et al., 2002). A similar group of experts were convened by Alex Ezeh and Richard Lilford in 2017 in Bellagio, Italy (UN-Habitat, 2017) following their publications on the importance of geography to the health and wellbeing of individuals in LMIC slums (Ezah et al., 2017; Lilford et al., 2017). This group drafted a framework for measuring deprived areas, reflecting social and physical science perspectives in five domains: Social/environmental risk, Lack of facilities/infrastructure, Unplanned urbanization, Contamination, and Lack of Tenure (Thomson et al., 2019). This conceptualization informed other frameworks (e.g., Lilford et al., 2019), and was a catalyst in forming the IDEAMAPS Network (Thomson et al., 2020).

As LMIC cities face unprecedented scenarios of urbanization, the framing of deprivation through quantitative measures has crucially shaped how authorities view and respond to slums, informal

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settlements, and other deprived areas. Negative perceptions of deprived areas lend to resettlement and eviction policies; while positive measures lend to engagement of community leaders, in-situ housing and infrastructure upgrading, and improved connectivity between deprived areas and other parts of the city (Plummer, 2000). One of those to view the potential of urban areas has been Caroline Moser, an urban social anthropologist, and she has been instrumental in framing and measuring assets that households can draw on to improve wellbeing, and offer to their community and city (Moser, 1998, 2007; Moser & Dani, 2008).

State of the field

The most established poverty and deprivation frameworks are rooted in a period when government census, survey, and administrative data (mainly HICs) were chief sources of information about poverty, and measurement of area-level deprivation depended on aggregation of household data to either small neighborhood-sized areas (HICs) or across all urban areas in a country (LMIC). The emergence of crowd-sourced and publicly available spatial data has resulted in a parallel stream of thinking about the measurement of poverty among geospatial experts. Establishment of the IDEAMAPS Network is just a recent milestone among several recent attempts to bridge disciplinary silos to measure the multiple dimensions of deprivation faced by the poorest in LMIC cities using a multitude of datasets produced by diverse stakeholders.

METHODOLOGY

Literature review

We performed a scoping review on the extent and nature of urban deprivation literature in both the social and physical sciences to define an integrated framework of deprivation for cities. Academic articles (empirical and applied research), as well as international and national reports, were examined. We began with a systematic keyword search within Scopus, covering the dates 1 January 2000 through 20 June 2020, using the following expression: [urban OR city OR cities] AND [indicator* OR index OR indic* OR domain* OR asset*] AND [poverty OR deprived* OR slum OR informal OR vulnerability* OR inequit* OR livelihood] AND [framework OR concept OR model*]. The review had a global geographic coverage, and included articles with national-to-local focus; however, articles that focused exclusively on rural deprivation were excluded. All articles published in a language that our author team could read - Romance, Slavic, and Germanic languages - were included. Scopus search results included English, French, Spanish, German and Portuguese language articles, all of which were included, and Chinese language articles, which were excluded. The search did not result in any African language publications. This resulted in 2,447 publications from Scopus. We then used “snowballing” to identify 28 additional scientific and grey literature publications which were referenced in these Scopus articles. A total of 2,475 publication titles and abstracts were screened, and 350 publications were reviewed for a proposed and/or applied deprivation framework. After reviewing full texts, 116 publications were retained for analysis (Figure 2).

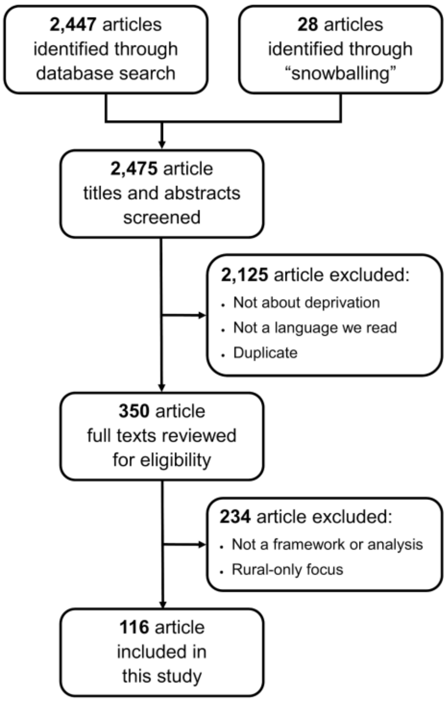

Figure 2. Diagram of systematic literature review criteria

Coding of articles

First, we used a list of questions to extract standardized information from each of the 116 articles into Excel about the coverage, sources, and approaches used to define and/or apply each deprivation framework. The questions coded for each article were:

1. Geography:
    a. What is the finest geographic scale used for analyzing the indicators of deprivation (e.g. census enumeration area, neighborhood)?
    b. Which countries or regions are covered by the included papers?
2. Data source:
    a. Are the data used for the development of the indicator(s) open?
    b. If applied, e.g. to a case study/geographic area, are data from community engagements used?
    c. In general, what type of data are used?
    d. If applied, are Earth Observation data (e.g., satellite images) used?
3. Approach:
    a. Is the result also providing a composite output (e.g., in form of an index)?
    b. Is the publication only a (theoretical) framework or is it applied?
4. Mapping:
    a. If applied, is the output mapped at the level of settlement (i.e., community, neighborhood, census enumeration area)?
    b. If applied, is the output mapped at the level of administrative boundaries (i.e., ward)?
    c. What is the scale of data collected (i.e., household, census block, etc.)?
    d. What are the methods used in publications?
5. Influence: We classified publication influence as the average number of citations (based on Google Scholar) adjusting for year of publication: $Number\ Citations\ /(\ 2020 - Publication\ Year)$

Coding of indicators, and development and validation of framework

Next we coded each indicator and domain mentioned in the 116 articles using a coding framework. Our first iteration of the coding framework was based around the five Bellagio workshop domains: social/environmental risk, lack of facilities/infrastructure, unplanned urbanization, contamination, and lack of tenure (Figure 3) (Thomson et al., 2019). We chose this framework as a starting point because it had been developed by a mix of social and physical scientists, explicitly acknowledged the difference between household-level and area-level data, and was designed to define LMIC urban deprivation. Through three iterations of this process, we decided to split two domains, and add two domains (Figure 3).

Second, we (a) documented each indicator as defined by the original author(s), (b) recorded any domain label assigned by the author(s) according to their framework, and (c) coded whether the indicator was either disaggregated by sex, or sex-specific. This resulted in 1,897 indicators from the 116 papers.

Third, we iteratively developed and applied our coding framework of domains and indicator groups (i.e., specific indicator topics). This process followed recommended qualitative analysis techniques for multi-disciplinary research (Gale et al., 2013), and splitting indicators among co-authors to apply the framework, spot-checking each other's work and discussing our coding decisions, adjusting the coding framework (e.g., to reflect concepts or measures that had been missed), and then repeating the entire process until we all agreed on the coding framework and code assignments to each of the 1,897 indicators.

Fourth, we arranged the domains and indicator groups from our coding framework into a visual Domains of Deprivation Framework. We found inspiration from existing framework figures in the literature (Appendix A), specifically those that reflected the spatial hierarchy of deprivation and/or data used to measure deprivation (e.g., Kohli et al., 2012; Taubenböck et al., 2018).

Fifth, we presented and sought feedback on a first draft of our Domains of Deprivation Framework at a workshop in Accra, Ghana in October 2020. Twenty workshop participants were purposefully invited to represent community, local assembly, local government, civil society, private sector, and national government perspectives. In breakout groups, participants spent one hour discussing and providing suggestions to improve the framework layout and content, and reported back in plenary.

We received resounding feedback that governance should be considered a distinct domain in the Domains of Deprivation Framework. Although governance had only been named explicitly as a domain in one article that we reviewed (Asadi-Lari et al., 2013), several others included governance-related indicators as part of other domains (Borzooie et al., 2019; Jarman, 2001; Pairan et al., 2018; Sphere, 2018), and together these corroborated the argument for governance to be measured as a distinct issue. Workshop participants also highlighted the need for safety indicators and specifically mentioned street lighting, the need for functioning drainage systems in addition to water and sewage systems, and measurement of ecological diversity. Based on workshop feedback, we revised our coding framework a final time (Figure 4), reapplied it to the indicators, and revised our Domains of Deprivation Framework (presented below).

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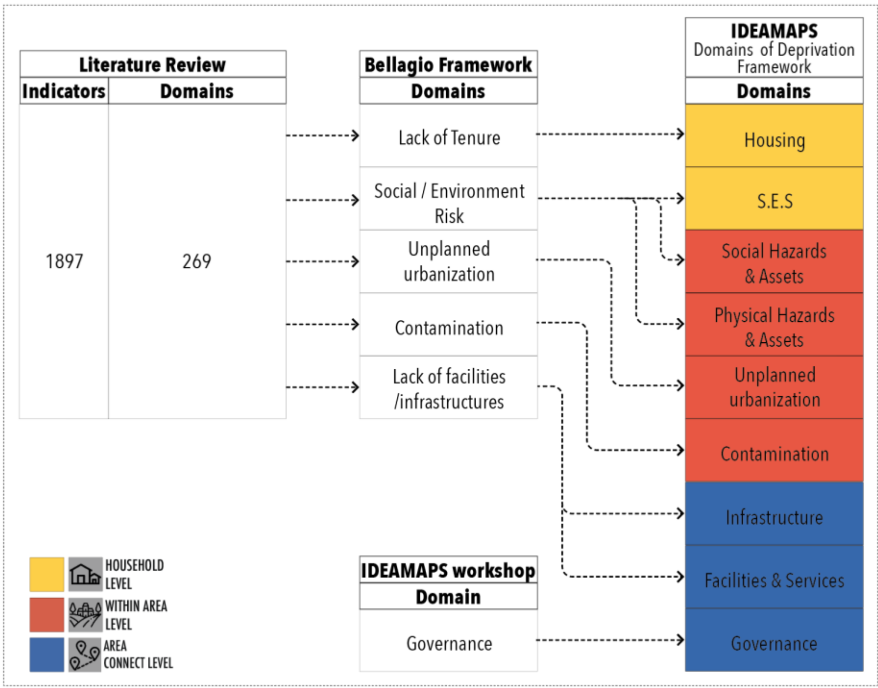

Figure 3. Diagram of design process for the Domains of Deprivation

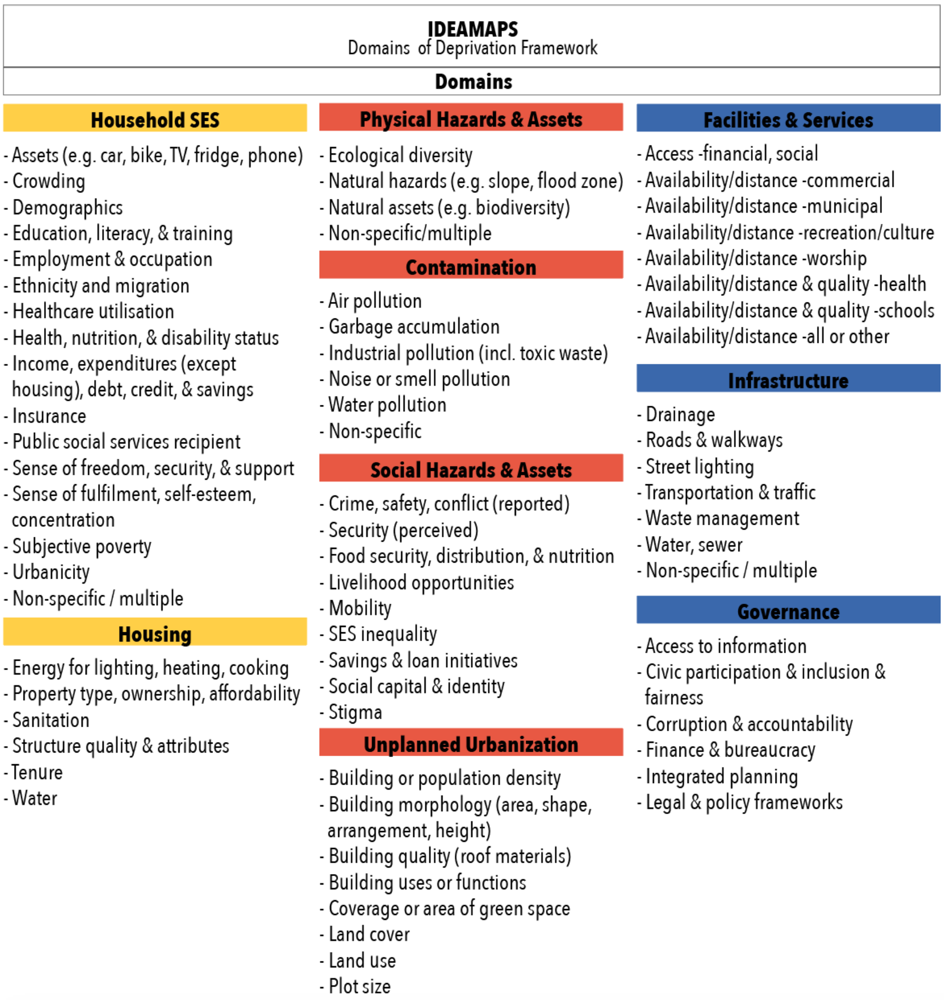

Figure 4. Final Coding Framework

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RESULTS

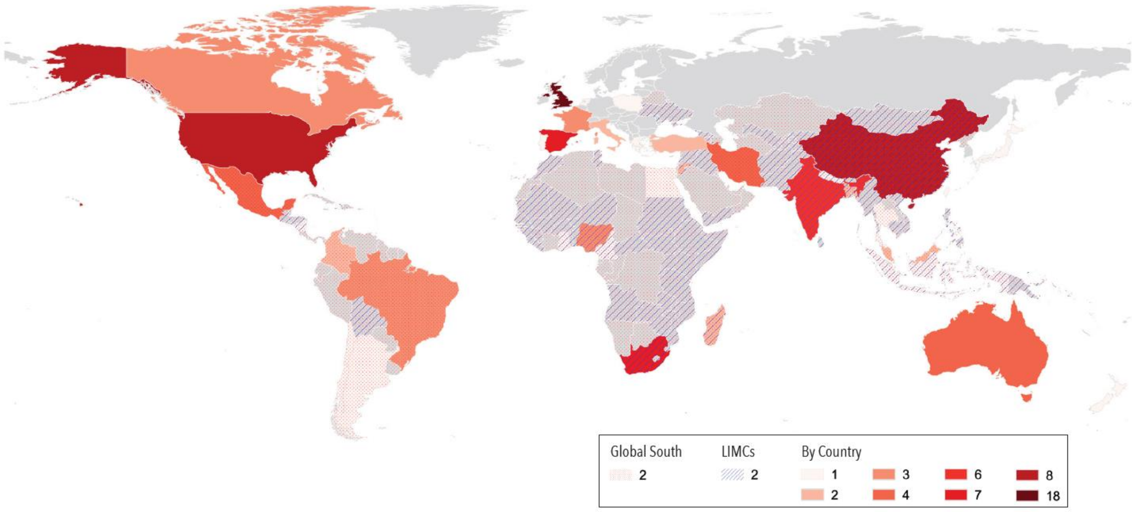
The results section is split in four sections. First, we provide an overview of the findings to key questions of the literature review. Second, we analyze the frequency of domains and indicator groups in the literature to allow for an overall grouping of indicators. Third, we provide an overview of the most influential frameworks to better understand the importance of different domains. Finally, based on the findings of section one to three, we present the resulting IDEAMAPS Domains of Deprivation Framework.

Findings to key questions of the literature review

This section summarizes characteristics of the literature we reviewed in terms of framework geographics, data sources, approaches, and mapping characteristics.

Geography

A large number of the frameworks were developed for use in the UK and countries historically linked to the UK including the US, India, South Africa, and Australia (Figure 5). Over 50% of the articles were developed in, or applied to, LMICs (Table 3). The regional splits of these studies shows that Europe as well as Eastern and Central Asia received the bulk of attention (28.2% and 21.4%, respectively) with Africa, the Middle East and Latin America lagging behind in terms of number of studies (Table 3). Few frameworks have been developed for application in a Global or Global South context.



*Regions	%	Citations
Central & South America	7.8	(Feres & Mancero, 2001; D'Ambrosio& Rodrigues, 2008; Del Carmen Rojas *et al.*, 2008; Alves, 2013; Hacker *et al.*, 2013; Caicedo & Jones, 2014; Altamirano et al., 2016; Seguel & Villaroel, 2018; Builes-Jaramillo & Lotero, 2020)
Eastern & Southern Asia	20.7	(Fukuda *et al.*, 2007; Baud *et al.*, 2008; Ling, 2009; Baud *et al.*, 2009; Tipayamongkholgul, Podang & Siri, 2013; Chen & Wang, 2015; Mahadevan & Hoang, 2016; Webster *et al.*, 2016; Chowdhury & Mukhopadhaya, 2016; Akter & Rahman, 2017; Ge et al., 2017; Manap et al., 2017; Wan and Su, 2017; Wu & Qi, 2017; Zakaria *et al.*, 2017; Mitra & Nagar, 2018; Saif-Ur-Rahman *et al.*, 2018; Bag & Seth, 2018; Yuan *et al.*, 2018; Ajami *et al.*, 2019; Pairan et al., 2019; Chen et al., 2019; Gao & Sun, 2020; Ensor *et al.*, 2020)

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Europe & Central Asia	28.4	Jarman, 1983, 2001; Kearns, Gibb & Mackay, 2000; Bradshaw & Finch, 2003; Harris & Longley, 2004; Jordan et al., 2004; Scottish Executive, 2004, 2006; Niggebrugge *et al.*, 2005; Noble *et al.*, 2006; Eskandrani, 2007; Eroğlu, 2007; Havard *et al.*, 2008; European Commision, 2010; Marí-Dell'Olmo *et al.*, 2011; Martínez & Lechuga, 2012; Payne & Abel, 2012; Bayram et al., 2012; Coromaldi & Zoli, 2012; Bocquier *et al.*, 2013; Alguacil & Camacho, 2014; DCLG, 2015; Guillaume *et al.*, 2016; Jacobsen, 2016; Arribas-Bel, Patino & Duque, 2017; Swiader et al., 2017; Cornado *et al.*, 2017; Ministerio de Fomento, 2018; Venerandi et al., 2018; Abarca-Alvarez et al., 2019; Mclennan *et al.*, 2019; Page et al., 2019; Panori et al., 2019
Middle East & North Africa	5.2	Abu-kharmeh, 2009; Asadi-Lari *et al.*, 2013; Najjary *et al.*, 2016; Bérenger, 2017; Borzooie et al., 2019; Zandi et al., 2019
North America	11.2	Messer *et al.*, 2006; Bell et al., 2007; Johnson, 2007; Casas et al.,2009; CONEVAL, 2010; Krishnan, 2015; Wang & Fox, 2017; Fuentes et al., 2018; Jenerette, 2018; Reckien, 2018; Medina Perez et al., 2019; Roy et al, 2020
Oceania	4.3	Baum, 2006; Saunders et al., 2008; Pawson *et al.*, 2012; Hulse *et al.*, 2014; Exeter *et al.*, 2017
Sub-Saharan Africa	11.2	Duclos et al., 2006; Barnes *et al.*, 2007; Oldewage-Theron & Slabbert, 2008; Günther & Harttgen, 2009; Noble *et al.*, 2010; Noble & Wright, 2013; Ajakaiye *et al.*, 2014; Yakubu *et al.*, 2014; Steinert *et al.*, 2016; Deinne & Ajayi, 2019; Han et al., 2019; Beck et al., 2020
Global	7.8	Moser, 1998; Davis, 2003; UN-Habitat, 2003; Ompad *et al.*, 2007; Nations, 2009; WHO, 2012; Anindito et al., 2018; Sphere, 2018; Oxford Poverty & Human Development Initiative, 2020
Global South	3.4	Alkire & Santos, 2010; Kohli *et al.*, 2012; Taubenböck et al., 2018; Wilkinson *et al.*, 2020

Figure 5. Country or region* of deprivation framework origin for 116 reviewed publications

Data source

From the articles we reviewed, 48.3% utilized or made available open source data, and only 7.8% of the studies definitely did not. There were, however, 44.0% of the articles in which it was hard to discern if the data was openly available (Table 3). Out of the 116 articles reviewed, 85.3% applied concepts and/or measurements of deprivation to specific case studies (Table 3), for example, to a specific geographic context (e.g., Baud et al. 2008) or sector such as health or environment (e.g., Caicedo et al., 2014, Mishra et al., 2018). The majority of frameworks were based on a single country (84.5%), reflecting the importance of geographic context when measuring and addressing deprivation (Table 3). Of those studies which applied a framework to measure deprivation, census data were used in 61.6% of articles, and survey data in 58.6% (Table 3).

Furthermore, 47.5% authors consulted with stakeholders such as local communities, or those involved with government (Table 3). This is a promising result in terms of the conceptualization of deprivation because stakeholders within the community are more likely to have insight regarding what constitutes deprivation in that context. Only 8.1% of the articles which applied a framework used EO data (Table 3). Many of these studies measured deprivation as a one-dimension concept of unplanned urbanization based on a physical classification of buildings, roads, and other features (Arribas-Bel et al., 2017). There are also authors who attempted to expand the number of domains and datasets to cover access to services, transportation infrastructure, and environmental risk by incorporating spatial data from volunteered geographic databases and bespoke geo-located household surveys (Hacker et al., 2013; Ajami et al., 2019; Roy et al., 2020).

Table 3. Summary of literature review results

Indicator	Percent
Finest Geographic Scale (N=116)	
National	48.3
Sub-national	47.4
Not applicable	4.3
Coverage, extent (N=116)	
Single country	84.5
Multiple countries	15.5
Coverage, World Bank 2020 designation (N=116)	
Low Income Country	1.7
Lower-Middle Income Country	15.5
Upper-Middle Income Country	34.5
High Income Country	41.4
Not applicable (Global coverage)	6.9
Indicator data are open/available (N=116)	
Yes	48.3
No	7.8
Unclear	44.0
Composite Index (N=116)	
Yes	68.1
No	30.2
Unclear	1.7
Framework is presented with applied example (N=116)	
Yes	85.3
No	14.7
If applied example, data from stakeholder engagements used (N=99)	
Yes	47.5
No	52.5
If applied example, census data used (N=99)	
Yes	61.6
No	38.4
If applied example, survey data used (N=99)	
Yes	58.6
No	41.4
If applied example, EO data used (N=99)	
Yes	8.1
No	91.9
If applied example, local (settlement-level) map presented (N=99)	
Yes	14.1
No	85.9

Approach

A majority of the articles that applied a framework (68.1%) produced a multiple deprivation index based on a summative (composite) approach where indicators were weighted, based on equal or expert weighting systems (Baud et al., 2008; Baud et al., 2009; Exeter et al., 2016; Mclennan et al., 2019). To reduce the high dimensionality (large number) of indicators that reflect deprivation and to deal with high correlation between indicators, several studies used dimension reduction strategies, such as factor analysis or principal component analysis as well as data-driven methods that allow the generation of clusters (Marí-Dell'Olmo et al., 2011; Krishnan, 2015; Roy et al., 2020) (Figure 6). In recent years, advancements in methods such as artificial intelligence (AI) have enabled additional analyses of multiple deprivation (Ajami et al., 2019), as well as the development of deprivation measures in relation to fuzziness of concepts (Gao & Sun, 2020). Developments such as these are designed to address limitations of simple summative indices that obfuscate the complexity of deprivation.

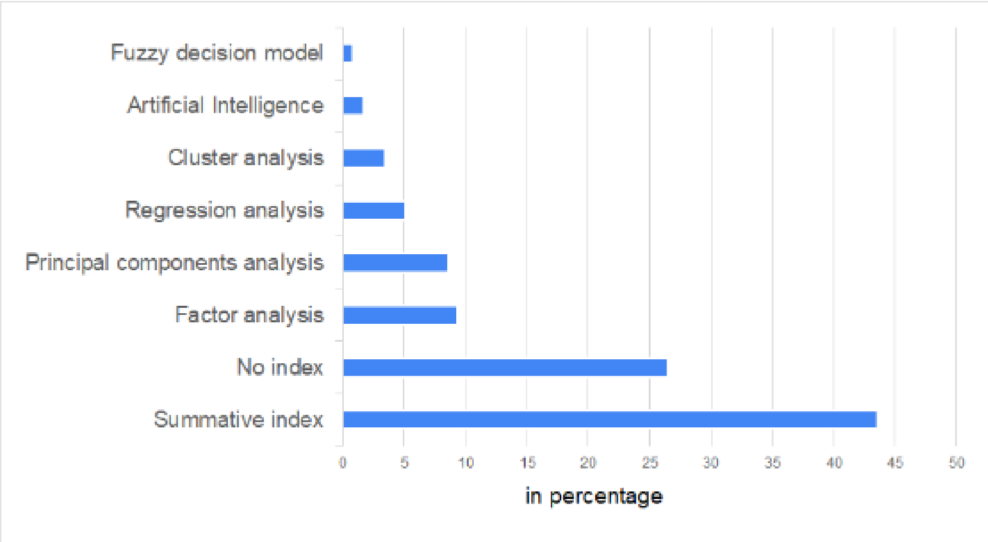

Figure 6. Approaches used in studies to calculate a multiple deprivation index (N=116)

Mapping

Few articles (14.1%) that applied a deprivation framework mapped deprived areas at fine-scale such as settlement or census enumeration area (Table 3). This was unsurprising given the emphasis of frameworks on census and survey data, as census data are generally not released at the enumeration area level to ensure privacy, and survey data are rarely representative below the second administrative unit (e.g. district). Mapping of settlement-level deprivation tended to occur in studies that used EO data (Harris & Longley, 2004; Taubenböck et al., 2018; Ajami et al., 2019).

Frequency of Domains and Indicator Groups in the Literature

Existing deprivation frameworks overwhelmingly emphasize indicators of household-level SES (58.7%) and Housing (15.1%) deprivation, which can be easily measured in census and survey data (Table 4). The next three most commonly measured domains in the literature were Facilities & Services (7.1%), Social Hazards & Assets (6.0%), and Unplanned Urbanization (5.9%) which are generally measured with volunteered geographic information (VGI) such as OpenStreetMap, EO data, or one-off household surveys on such topics as community social capital and safety (Table 4). If our Domains of Deprivation Framework is meaningful, and Physical Hazards & Assets (0.8%), Contamination (2.1%), Infrastructure (2.9%), and city Governance (1.5%) are important domains for indicators to measure area deprivation (Table 4), then this review highlights major gaps in the literature to measure, and therefore, label and address these challenges and assets.

Table 4. Frequency of indicators by domain

Scale	Domain of Deprivation	Indicator	
		Frequency	Percent
Household-level	SES	1,114	58.7
	Housing	286	15.1
Within area-level	Social hazards & assets	113	6.0
	Physical hazards & assets	15	0.8
	Unplanned urbanization	111	5.9
	Contamination	39	2.1
Area connect-level	Infrastructure	55	2.9
	Facilities & services	135	7.1
	Governance	29	1.5
	Total	1,897	100.0

Within the nine Domains of Deprivation, a few key indicators tended to be measured. In the most commonly measured domain, SES, household demographics, and individual education, employment, income, and health status were commonly used to define SES, while sense of freedom or fulfillment were rarely measured (Figure 7). In the less common domain of Facilities & Services, distance to (or number of nearby) health facilities was most commonly measured, whereas distance to (or number of nearby) schools was rarely used as a measure (Figure 7). In the uncommon domain of Contamination, air and noise pollution were most often measured, but water pollution and garbage accumulation were rarely measured (Figure 7).

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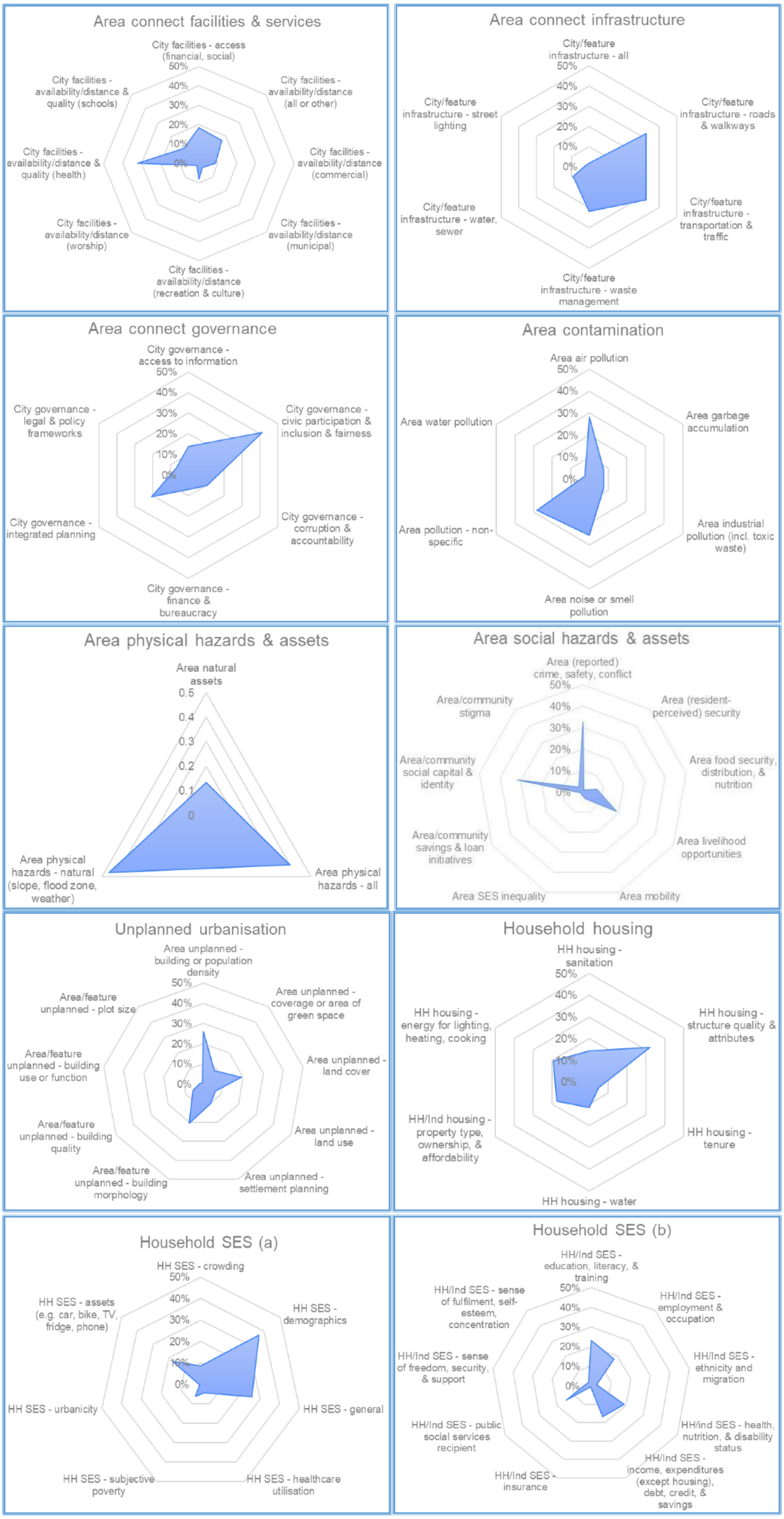

Figure 7. Percentage of Indicators group contributions within the major domains.

Out of the 1,897 indicators, only 51 (2.7%) had a sex disaggregated component (Table 5). Sex indicators tended to focus on whether the house was led by a female, or disaggregated education and employment by male/female (Table 5).

Table 5. Sex disaggregated indicators

Domain - Indicator group	Frequency	Percent
SES - Household demographics	16	0.8
SES - Employment and occupation	10	0.5
SES - Health, nutrition and disability status	10	0.5
SES - Education/literacy training	6	0.3
SES - Income, expenditures (except housing), debt, credit and savings	4	0.2
SES - Public/social services recipient	4	0.2
SES - General	1	0.1
All gender indicators	51	2.7
Total number of indicators	1,897	100

Most influential frameworks

We measured the influence of deprivation frameworks in terms of citations per year. Nearly all of the most influential frameworks in this review were developed by academics or international organizations, though this was likely a function of our search in the scientific literature (Figure 8). Deprivation frameworks designed for HIC contexts were more represented than frameworks designed for LMIC contexts, or frameworks designed for use at a global scale (Figure 8). Along the vertical axis of Figure 8 are the data sources mentioned to apply the framework (e.g., census, EO). Influential articles that recommend use of EO data to measure deprivation have only emerged in the last decade (Figure 8). The most influential framework was developed by David McLennan and colleagues (2019), with 206 citations per year, as indicated by the darkest blue shade (Figure 8). This is “The English Indices of Deprivation 2019,” and is a composite of 35 mostly household-level indicators organized in seven domains (McLennan et al., 2019). The second most influential framework was developed by Sabina Alkire and Maria Emma Santos (2010) at the World Bank, with 133 citations per year. This publication defines and applies a Multidimensional Poverty Index (MPI) to 104 LMICs, and is composed of entirely household-level indicators in three domains (Alkire & Santos, 2010). The third most influential article was by Caroline O.N. Moser (1998) at the World Bank, with 115 citations per year. This framework was developed to assess vulnerability globally based on physical, financial, and human capital (including social and natural capital), but is not linked with specific datasets or applied (Moser, 1998). The remaining articles were cited less than 60 times per year; the authors organization, coverage, data sources, and mapping, are represented in the timeline below (Figure 8).

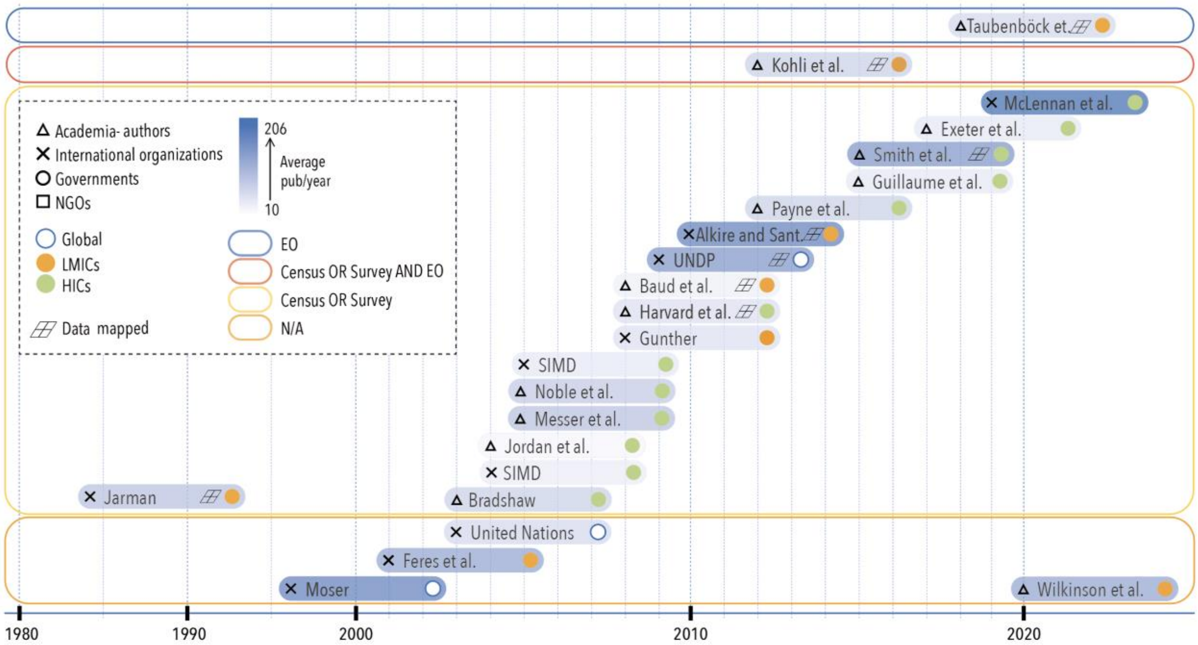

Figure 8. Timeline of the most representative frameworks.

IDEAMAPS Domains of Deprivation Framework

The most cited articles guided our design of the IDEMAPS Domains of Deprivation Framework, and our coding framework was used to define the framework's 67 indicator groups in nine domains across three scales of measurement: household, within area, and "connecting" (across areas) (Figure 9).

Household-level domains of deprivation reflect indicators measured at the individual - or household-level, often by census or survey. The first domain, Socio-Economic Status (SES), is measured with indicators that reflect individual education rates, health status, employment, and household ownership of assets. A separate Housing domain is defined to reflect characteristics of living structures such as the quality of building materials, whether it is owned or rented, the type of water and sanitation facilities, and whether the occupants have tenure rights to the land and/or structure.

Within Area domains encompass four deprivations found *within* settlements: Social Hazards and Assets, Physical Hazards and Assets, Unplanned Urbanization, and Contamination. Social Hazards include risks such as crime and lack of livelihood opportunities, while Social Assets include strong social identity or community cohesion. Physical hazards include high likelihood of flooding, landslides, and other natural threats such as earthquakes, while Physical Assets include mitigation resources and strategies such as earthquake resilient materials, or presence of trees and plants to maintain cooler temperatures and cleaner air. Indicators within the Unplanned Urbanization domain are associated with rapid and unplanned in-migration to an area that might result in tightly packed, unplanned housing, limited green space, and lack of roads. The Contamination domain reflects accumulation of garbage, water pollution, air pollution, or high levels or constant noise that affect the well-being of residents.

Area Connect domains refers to connectivity with surrounding settlements and the integration into the rest of the city. These include the Infrastructure domain, referring to water, waste, transportation, and other infrastructure systems typically managed by the municipal government, as well as the Facilities & Services domain which reflects the availability, accessibility, and affordability

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of schools, health facilities, banking establishments, shops, religions and cultural amenities, and other facilities and services needed for a thriving city. Challenges in deprived communities are prevented and addressed by transparent, effective city-wide planning and management making city Governance the final domain.

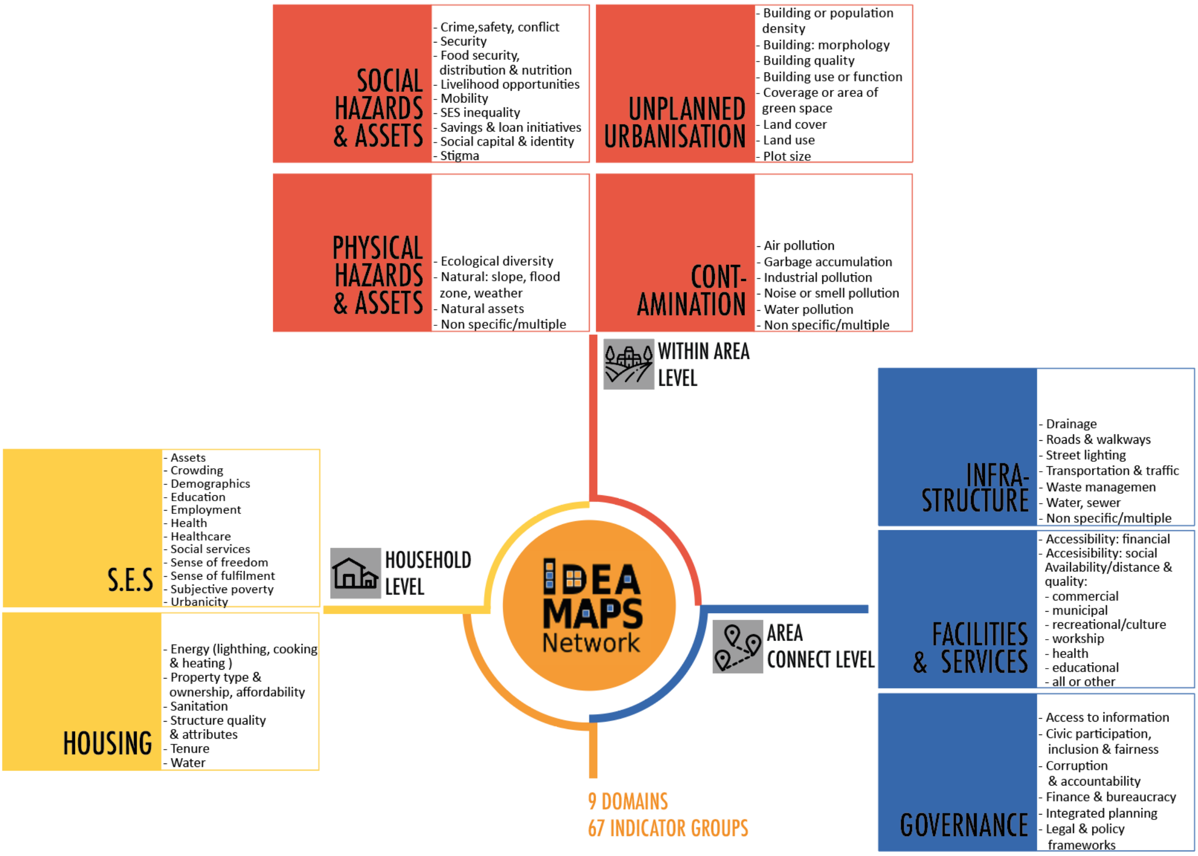

Figure 9. Diagram of IDEAMAPS Domains of Deprivation Framework

The IDEAMAPS Domains of Deprivation Framework stresses that not only household-level domains require gendered indicators, but also Within Area domains and Area Connect domains require gendered indicators. For example, is street lighting particularly important to women's safety and access to services such as public toilets? How are female-dominated versus male-dominated jobs distributed in the city; for example, do most men work outside the community while most women work inside the community? This has implications for gendered exposure to contamination, crime, traffic, and so on. A gendered lens is key to understanding how deprivation impacts communities, and their members, differently.

DISCUSSION

This paper presents a review of contemporary frameworks for conceptualizing urban deprivation in LMIC cities, integrates key concepts from social and physical sciences, and develops a novel Domains of Deprivation Framework that can support multi-disciplinary global deprived area mapping efforts. Our domains aim to be inclusive of issues that define deprivation from the individual-to-city-level, and this is reflected in classification of domains within a simple spatial hierarchy. We also, importantly, link dozens of indicator groups to each domain based on the literature review. Therefore, the IDEAMAPS Domains of Deprivation Framework is flexible to be adapted to different geographic contexts and scalable, by allowing users to "switch on and off" indicators that are more or less relevant to their context, and supports the integration of diverse household- and area-level data with the ultimate aim to support pro-poor policy-making.

Scale

The overwhelming majority of frameworks reviewed, conceptualized, and measured deprivation as a household-level socio-economic issue, focusing on indicators of household assets, access to services, and individual sense of well-being (e.g., Table 3). As with several UK indices, some indices for LMICs acknowledged the importance of area-level (e.g., pollution) and system-level (e.g., public utilities) factors in shaping and reinforcing deprivation (e.g., Baud et al., 2009). However, attempts to measure area-level domains with aggregated household data were generally inadequate as it can be challenging to aggregate information operating at different scales. For example, percent of households using a flush toilet (household-level) is not necessarily related to the percent of sewage in a neighborhood or city that is safely treated (area-level) (Baud et al., 2009). Aggregation of household data to areas also means working with arbitrary geographic boundaries that may mask or produce misleading trends, which can be termed as the modifiable areal unit problem (MAUP) (Openshaw, 1983). Within articles reviewed, it appears that area-level deprivation indicators were best studied and measured directly by either selecting a number of communities and collecting detailed community-level data (e.g., Caicedo & Jones 2014) or using Earth Observation (e.g., Ajami et al. 2019; Kohli et al. 2012).

Although many publications stress that data are needed from an "array of spatial scales" to inform policies, interventions, and research decisions (e.g., McLennan et al. 2019), a key challenge is how to spatially align and combine household- and area-level data. Deprivation indices calculated by administrative units are limited by the heterogeneity of administrative boundaries, and comparison across countries is problematic because the terminology, function, and size of administrative units varies by country. In many countries, disaggregated census data (e.g., census tracts) are not easily accessible (resulting in the use of larger and very heterogeneous areas), and if disaggregated census data are accessible they are collected at low temporal frequencies (e.g., census data are typically collected every 10 years). In many countries, census might omit the most deprived population (e.g., those living in temporary and low-income settlements, also known as slums) (Carr-Hill, 2013; Wardrop et al., 2018)

Data integration

One way to align data at a fine geographic scale is to disaggregate indicators with geo-statistical models into a regular grid of equal-sized small cells (e.g., 100x100m); these cells can then be aggregated to any larger relevant boundary. Census population counts (e.g., WorldPop, 2021) and survey indicators (e.g., Gething, 2015) are already disaggregated in this way, though models are subject to error (Leyk et al. 2005). Similar innovative solutions are being used to model non-census and survey indicators of deprivation in terms of spatially disaggregated analysis of area level deprivation, for example, the combination of Earth Observation (EO) data alongside newly emerging data sources (e.g., social media data, Taubenböck et al., 2018b), extraction of data focusing on specific aspects of deprived areas from available repositories (e.g., lack of physical accessibility extracted from OpenStreetMap; Soman et al., 2020) or the use of Artificial Intelligence (AI) and EO data to capture environmental characteristics contributing to deprivation (e.g., accumulation of waste piles; SLUMAP, 2020).

However, more innovative solutions are required to address existing data gaps. In this context, data related to tenure is typically not used to measure area-level deprivation due to unavailability of data. To bridge this data gap, Ron Mahabir and team (2018) tested the use of web-scraped data from real estate companies and gridded population data to deduce areas of potential informal tenure, knowing that formal real estate transactions will occur in areas where formal tenure systems operate. Problems with such an approach remain, given that real estate companies in LMICs do not typically serve the bottom 20-40% of the economic pyramid (Kolb et al., 2020) resulting in a segment of rental and owned property transitions taking place offline. However, this kind of innovative data integration to develop proxy indicators is a move in the right direction. Innovative proxy indicators can be supported in the age of big data by the evolution of data cubes that allow the combination of various data, modelled at homogenous areal units (e.g., grids) (De Anda et al. 2019). Data cubes provide new solutions in terms of data access, spatially disaggregated data and capturing the complexity of spatial phenomena such as deprivation.

Data disaggregation

Another gap is the lack of data disaggregated by important sub-groups such as gender. The lack of measurement of gender requires specific attention as women tend to bear more adverse effects of urban deprivation than men, and do not benefit equally from urbanization (Chant, 2013). Gender inequalities are experienced in numerous areas of daily life including: accessing decent work opportunities, increased workloads with the balancing of paid and unpaid work activities, accessing financial assets and housing security, fair tenure rights, access to services, asset accumulation, engaging in public governance structures, and personal security (Chant & McIlwaine, 2016; Moser, 2016; Tacoli & Satterthwaite, 2013; Tacoli, 2012; Reichlin & Shaw, 2015). Female-headed households are additionally associated with increased deprivation levels, likely because these households tend to depend on one income and because women often earn less than men (Ortiz-Ospina & Roser, 2020).

Data disaggregation by gender can also unmask challenges that overwhelmingly affect men, and improve the ability of civil society and officials to respond by better targeting their messages, policies, or interventions. For example, in relation to crime levels, women may be more likely to experience domestic violence (Kalokhe et al., 2018) and sexual assault in deprived areas (BBC News, 2010), but men might instead be more likely to experience mugging, and gang-related or street crime (Meth, 2017).

Policy and practice relevance

The IDEAMAPS Domains of Deprivation Framework is a global framework that is designed to be tailored to local contexts such that local experts select the most relevant indicators for each domain. This is because the most relevant indicators of, say, Social Hazards and Assets, will vary by location (e.g. Tirana versus Timbuktu) and coverage (e.g. city-wide versus continent-wide). Amy Krakowka Richmond and colleagues (2015) applied a similar approach in their study of climatic and socio-economic vulnerability in East Africa in which they defined ‘baskets’ of vulnerability factors, and worked with local leaders across countries to produce a weighted score for each basket, such that ‘baskets’ were comparable across regions. The IDEAMAPS Domains of Deprivation Framework is already being used in this way. Using an early published version of the framework (Thomson, Shonowo, et al., 2020), the Impact Initiative REACH program in Northern Nigeria developed an Area Deprivation Index (ADI) to determine the degree to which communities can be categorized as informal, and intersected their ADI with a COVID-19 risk score to prioritize communities for outreach and support (REACH resource centre, 2020).

Another important use of the Domains of Deprivation Framework is to identify missing data, and focus innovation on data collection and analysis methods, and policy/advocacy efforts to fill these data gaps. This review revealed a dearth of data about Physical Hazards & Assets, Contamination, Infrastructure, and Governance which are all key to identify and respond to deprived areas. Early work on this framework, for example, inspired the Slumap Project to identify and map large waste piles using high resolution data (SLUMAP, 2020) to fill the need for waste management data in the domain of contamination (Thomson et al., 2019). We strongly encourage readers to think of innovative proxies such as Ron Mahabir's team (2018) to map indicators such as street lighting or sewage treatment (Infrastructure), or civic participation or zoning/land use boundaries (Governance). We encourage readers familiar with EO data to also consider ways to make data about flood zones (Physical Hazard) or air pollution (Contamination) more discoverable and usable by a broad audience, for example, by sharing on the Humanitarian Data Exchange (HDX, 2020) in common file formats (e.g., .shp, .tiff).

The framework additionally serves as an accountability and development planning tool by tracking household- and area-level indicators within domains that will already be familiar to policy-makers and planners (e.g., Infrastructure, Facilities & Services, Governance). We hope that this framework might prove to be a useful vehicle for collaboration and data sharing across local government departments and across disciplines who often deal with divergent data related to populations versus the environment. Additional applications of the Domains of Deprivation Framework could include community-based profiling and enumerations, such as those conducted by Shack and Slum Dwellers International (SDI) Federations. SDI teams survey slum areas in terms of household- as well as community-level needs, but may benefit from an additional tool to integrate data and understand related issues of pollution or security, which may not currently be profiled using SDI methods (SDI, 2020). The UN-Habitat Participatory Slum Upgrading Programme who works with local governments and other partners to profile cities might also find this framework helpful. Their flagship programs, such as RISE-UP, supports the urban poor to create resilient settlements and Inclusive Cities to promote social cohesion, improved transport and sanitation as well as infrastructure links with migrant communities and informal settlements (UN-Habitat, 2020a).

Limitations

By nature of being a literature review, our framework is limited by what other researchers have written and measured, and may include blind-spots that render our framework incomplete. For example, few researchers explicitly measured and discussed how women and men experience indicators differently in cities. Additionally, few frameworks included a domain like contamination or pollution, despite solid waste management often constituting the largest budget line in municipal budgets (Hoornweg & Bhada-Tata, 2012), and air pollution being a leading environmental risk factor for premature death globally (Babatola, 2018). We attempted to distill conceptually unique domains of deprivation from the existing literature without regard, necessarily, of frequency of measurement to ensure that under-measured, but important, domains and indicators were represented. Although we attempted to draw on a broad literature from across social and physical sciences, it is possible this review missed relevant urban deprivation articles, for example, in the refugee and humanitarian studies literature (Deola & Patel, 2014).

We believe that all, or at least most, of the domains in the Domains of Deprivation Framework are important to characterize deprived areas, and thus we advise researchers to not only use domains which are convenient to measure. We recognize that the use of EO and spatial data to measure area-level outcomes might present technical barriers for social scientists and practitioners, and the limited availability of pre-processed spatially-referenced social data may frustrate physical data scientists; however, robust mapping and measurement of deprived areas calls for interdisciplinary collaboration. We believe this framework can be operationalized.

As a global framework, there will be challenges to localizing its application. Who decides which indicators best represent each domain in a particular setting? Data availability will always play a role in these discussions. Indicator decisions should be taken through an inclusive, multi-stakeholder process which ensures that people living in deprived areas are part of the conversation about how they are mapped and measured. Not only is this the right thing to do, applications of the Domains of Deprivation Framework will benefit from the unique insights of people who experience deprivation locally. Furthermore, many community-based groups have profiled their own community already, and are likely to have existing data that could be used in collaborations.

CONCLUSION

The IDEAMAPS Domains of Deprivation Framework aim to conceive the major domains of deprivations significant in LMICs, and understand the types of indicators that represent these domains across contexts following a scoping review of the literature and stakeholder engagement. This was achieved with our framework, conceptualizing nine domains of deprivation with 67 relevant indicator groups. This generalized framework combines household data and area-level data which can be applied locally, used for comparison between cities and used by different stakeholders for different purposes whether for research, policies or by communities to hold the Government accountable. This framework also brings to the fore the need for more research and data production in relation to area-level indicators, specifically on physical and social hazards, contamination, infrastructure, and city-level governance. The combination of both household-level and area-level data helps to determine the degree to which any community can be described as being "deprived," and brings us closer to leaving no one behind.

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DECLARATION OF INTEREST

The authors declare no conflicts of interest.

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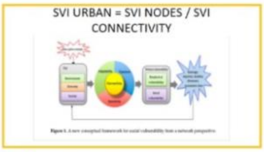
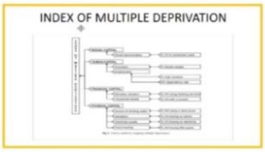
APPENDIX A. Figure of Key Framework Visuals



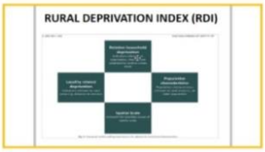
1 Author - Ge et al (2017)



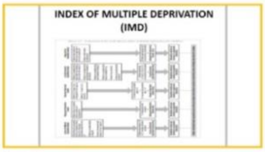
2 Author- Exeter et al (2017)

3 Author- Barnes et al (2007)

4 Author- Akter and Rahman (2016)

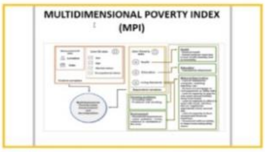


5 Author- Burke and Jones (2018)

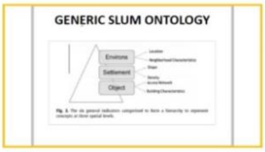


6 Author - Baud et al (2009)

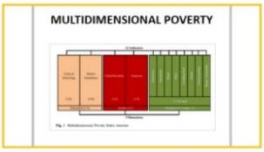
7 Author- Exeter et al (2017)



8 Author- Deinne and Ajayi (2019)

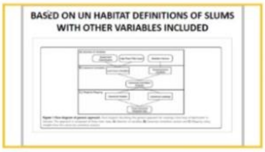


9 Author- Kohli et al (2012)



10 Author- Altamirano et al (2016)

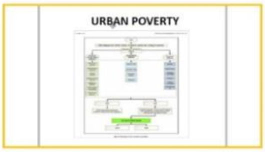
11 Author- Oxford Poverty and Human Development Initiative (OPHI) 2018



12 Author- Hacker et al (2013)

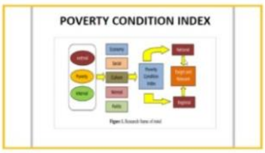
13 Author- Wan et al (2017)

14 Author- Ajami et al (2019)



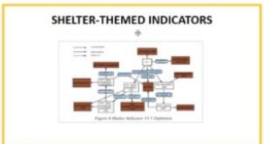
15 Author- Rahman (2019)

16 Author - Cáceres and Ahumada (2018)



17 Author- Pairan (2018)

18 Author- Taubenbock et al (2018)



19 Author- Wan and Fox (2016)

20 Author - The Sphere (2011)

APPENDIX B. Summary of Literature Included in this Review [Excel file]