

Review

“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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ARTICLE INFO

Keywords:

Global south

Indicators

Urban

City

Poverty

Neighborhood-level

ABSTRACT

The majority of urban inhabitants in low- and middle-income country (LMIC) cities live in deprived urban areas. However, policy efforts and the monitoring of global goals and agendas such as the United Nation's Sustainable Development Goals (SDGs) and UN-Habitat New Urban Agenda are hindered by the unavailability of statistical and spatial data at metropolitan, city and sub-city scales. Deprivation is a complex and multidimensional concept, and presently, there is a strong focus within the existing literature on household-level (including individual) deprivation and less on area-level deprivation and this is problematic because deprivation at the area and household-level are known to interrelate and result in multiple challenges for individuals and communities. Within this scoping review, we build on existing literature that focuses on household- or area-level deprivation to arrive at a combined understanding of how urban deprivation is defined in relation to LMIC cities. The scoping review of existing literature was used in conjunction with local stakeholder workshops to produce a framework titled “Domains of Deprivation Framework”. The Domains of Deprivation Framework conceptualizes urban deprivation at three different scales, including at the household scale, within the area scale and at the area connect scale. It includes nine domains, (1) Socio-Economic Status and (2) Housing Domains (Household scale); (3) Social Hazards & Assets, (4) Physical Hazards & Assets, (5) Unplanned Urbanization and (6) Contamination (Within Area scale); and (7) Infrastructure, (8) Facilities & Services and (9) City Governance (Area Connect scale). The Domains of Deprivation Framework is designed to support diverse urban, health, poverty, and development initiatives globally to characterize and address deprivation in LMIC cities from a holistic perspective, combining traditional data sources (e.g., surveys or census data) with new data sources (e.g., Earth Observation data).

1. Introduction

More than half of the world's population (55%) live in cities – with a projected increase to 68% by 2050 (UNDESA, 2018). The rate and scale of growth present 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, Bhatt, Duerto, & Uteng, 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

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<https://doi.org/10.1016/j.compenvurbysys.2022.101770>

Received 10 July 2021; Received in revised form 8 January 2022; Accepted 21 January 2022

Available online 4 February 2022

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870,000 people per year through 2035 (UNDESA, 2018). Increasing urbanization exacerbates the 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 ecosystem that not only characterizes deprivation, but also helps a diverse range of stakeholders respond to it.

In response, an Integrated Deprived Area Mapping System (IDEA-MAPS) of deprived areas is pursued, aiming to provide open-access information on the location and diversity of deprived areas across and within LMIC cities (Thomson et al., 2020). The production of routine, accurate maps of deprived areas across cities in LMICs requires the combination of different mapping traditions, including machine learning with Earth Observations (EO), census and survey aggregation, and community mapping (IDEAMAPS, 2021). A user-centred approach is required for the data ecosystem production, i.e., an approach that is designed for users in national/local governments, community-based organizations, NGOs, universities, and elsewhere to exchange and integrate geographic data (Kuffer et al., 2021). For the development of such a data ecosystem, it is fundamental to conceptualize key domains of deprivations to guide which data are needed to characterize deprived areas. To avoid a common trap of using data simply because it has been used before (precedent) or it is available (convenience) (Radford & Joseph, 2020), it is urgent to develop a global framework, maintaining a focus on data user applications, data requirements, and conceptualizations of deprivation from a multidimensional perspective.

Deprivation can be manifested at different levels within urban areas. Although ‘deprivation’ may refer to the lack of basic necessities at an individual/household- or area-level, deprivation levels (poverty levels) are mostly conceptualized at the individual/household-level (e.g., “slum” definition by the UN is only referring to individual/household-level characteristics). Individual/household-level deprivation refers to issues or factors of deprivation occurring within the house, i.e., the socio-economic characteristics of the household’s residents, as well as the structure and adequacy of the house itself. Instead, area-level deprivation refers to the characterization of the surroundings of the house (i.e., households located within a deprived area are exposed to area-level deprivation such as social, environmental, economic and ecological risks; this adds to the household-level deprivation). The area-level characteristics add to the individual/ household-level deprivation and play a part in residents’ exposure to deprivation. Few studies, however, seek to understand the interplay between individual/household-level deprivations and deprivation occurring at the area-level (Lilford et al., 2019; Thomson et al., 2019). The combination of both perspectives with a focus on LMICs is hardly existent. We use a scoping review to respond to this gap.

The scoping review analyses academic and grey literature on household-level (including individual level), as well as area-level deprivation, to develop a framework that can be used to conceptualize and collect data on these issues. We recognize that individual-level deprivation can be disaggregated to look at intra-household disparities and inequalities (e.g., women might be more deprived as the household on average) but have chosen to combine individual and household level issues so we can better conceptualize deprivations that occur and intersect between the area level and individual/household-level (hereafter called household-level). The focus is on reviewing the literature on urban deprivation within LMICs as urbanization is occurring more rapidly in LMICs, resulting in a range of challenges (as well as opportunities) for the urban poor. Furthermore, updated understanding - data - is therefore urgently required in urban areas to track urban issues. For the classification of LMICs versus HICs, we use the World Bank classification, which is based on economic factors and allows flexibility for countries to change between 4 classes (i.e., low, lower-middle, upper-middle, and high-income countries) (World Bank, 2022).

Deprivation frameworks and concepts have been influenced by

actors as well as research based in High Income Countries (HICs). Deprivation indexes and frameworks first emerged in countries such as the United Kingdom and the USA before proliferating to LMICs. As such, we use section 1 to provide context to the evolution of deprivation literature, starting with HICs before shifting to the LMICs context. Section 2 includes the methodology for the scoping review that shows how we arrived at the Domains of Deprivation framework. Results are included in section 3, which respond to the research questions below and show frequency and geography of deprivation issues that emerge from the scoping review while highlighting seminal articles and authors. In section 4, we present our Domains of Deprivation framework, and section 5 offers a discussion of thematic issues and recommended next steps in terms of research, as well as for policy/practice.

This section has indicated that the overall aim of the scoping review is to assess existing literature on deprivation with a view to producing a deprivation framework that can be used to respond to urban deprivation issues within LMICs contexts. To respond to this goal, we address the research questions below:

- How is urban deprivation conceptualized within the academic and grey literature focusing on cities/urban areas globally? (Addressed as part of the introduction in section 1)
- How can these conceptualizations be translated into domains of deprivation and related indicators that measure aspects of deprivation within LMIC cities? (Addressed within the methodology, section 2)
- Which domains are particularly relevant to urban stakeholders in LMICs, and how can they be presented in a framework to facilitate response to urban inequities? (Addressed within the results, section 3, as well as the presentation of the Domains of Deprivation Framework, in section 4)

1.1. Contextual backdrop to the evolution of deprivation literature

Initially published conceptualizations of deprivation were mainly focused on HICs with attention to indexes and frameworks concentrating predominantly on deprivation occurring at the household-level. Over the last half-century, these frameworks have expanded to include theories and concepts 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 (Fig. 1). The shift from a focus on HICs to LMICs and urban issues within LMICs is detailed in sections 1.2–1.4. In addition, Fig. 1 below represents this shift and highlights key actors and research that has helped to guide deprivation frameworks within HICs, and later within LMICs and urban contexts.

1.2. Multiple-deprivation indices in HICs

Fig. 1 shows that deprivation frameworks have existed in HICs since the 1980 s. The UK indices of multiple deprivations (IMD), e.g., the English deprivation index (McLennan et al., 2019), are seminal in attempting to capture the range of ways that individuals and households experiences are impacted by deprivation. The IMD was designed to collect data on a range of themes/topics, rather than focusing on single measures such as income. In the last two decades, the focus on creating a more holistic picture of deprivation has been influencing the development of deprivation studies in both HICs (Singh, 2003; Matheson, Dunn, Smith, Moineddin, & Glazier, 2012; Hugo Centre for Population and Housing, 2020) and LMICs (e.g., Arribas-Bel, Patino, & Duque, 2017; Baud, Pfeffer, Sridharan, & Nainan, 2009). Deprivation studies in HICs have commonly better access to rich data on different domains of deprivation as compared to LMICs.

At first, deprivation indices, such as IMD, mainly used national censuses and surveys to collect data at the household-level but

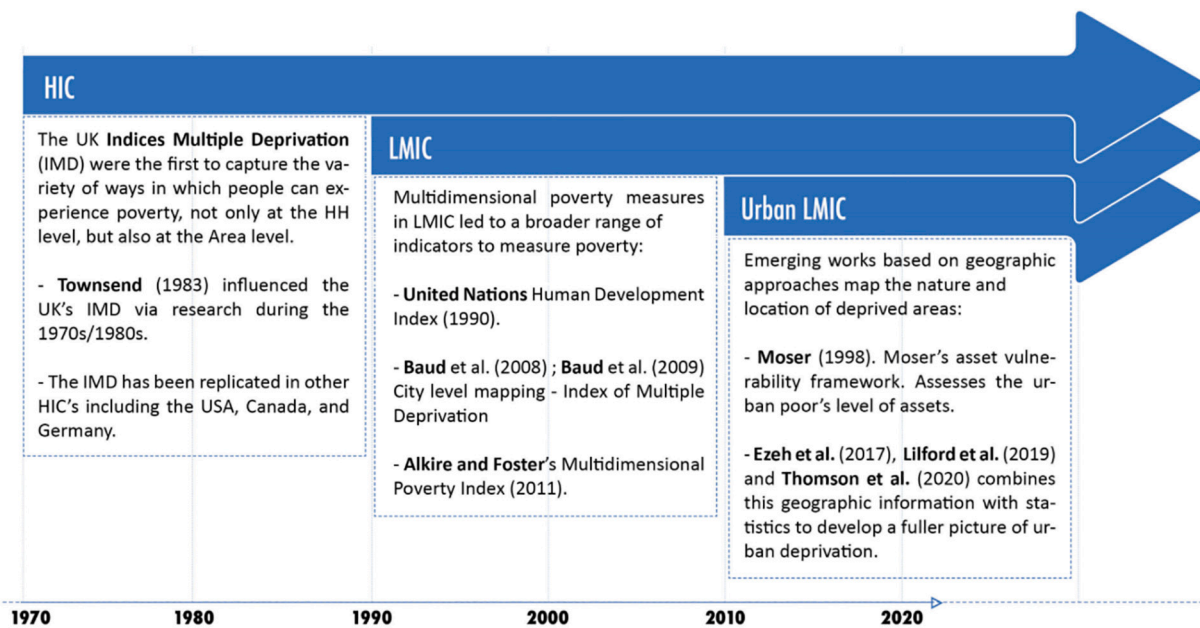


Fig. 1. Evolution of key deprivation frameworks from an initial focus on HICs to more recent frameworks based on multiple deprivations in LMIC urban settings.

aggregated household responses to relevant administrative units, which represented geographic areas of a town/city/village. Over time area-level indicators were introduced to indices such as measuring levels of outdoor air pollution or numbers of road-traffic accidents, which are more representative of issues impacting area-level deprivation. Currently, 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 (Dymond-Green, 2020). The living environment domain collects data on area-level issues, whereas the other mentioned domains provide household-level responses.

Other UK-focused indices measured household deprivation within small areas but with fewer indicators and/or domains. For example, Sally Holtermann (1975) 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, Philimore, & Beattie, 1988), Jarman Underprivileged Area Score (B. Jarman, 1984), and Carstairs Index (Richardson, 2009) were 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 US: Area Deprivation Index (Singh, 2003); Canada: 2006 Canadian Marginalization Index (Matheson et al., 2012), Germany: Indices of multiple deprivations (Maier, 2017); and Australia: Accessibility/Remoteness Index of Australia (ARIA) (Hugo Centre for Population and Housing, 2020).

1.3. Multiple-deprivation indices in LMICs

During the 1990s, quantitative measures of multiple deprivations were applied and tailored to LMIC settings and were shaped by thought leaders such as Amartya Sen (1992, 2009) as well as the development of the United Nations Development Programmes (UNDP) and Human Development Index, both of which intended to go beyond single measures focused on monetary indicators such as income and GDP. Sen's Capability approach, for example, conceptualizes development as the removal of 'unfreedoms' to enable people to fulfil their potential or 'capabilities' Sen (1999). For a girl living in India 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; for example, Martha Nussbaum developed a model that suggested ten central capabilities or traits to lead human dignity (Nussbaum, 2000, 2011).

While conceptual models for deprivation were being devised, improvements in the quantification/measurement of deprivation occurred as donor countries and agencies supported LMIC governments to invest in routine national household survey programs (Fabic, Choi, & Bird, 2012). Survey programs and resulting household-level data on aspects including population health and wellbeing fed into the monitoring of global goals such as the 2000–2015 Millennium Development Goals (MDGs), and the current United Nations (UN) Sustainable Development Goals (SDGs) (Alkire, 2014). As the SDGs were kicking off, Sabine Alkire (2015) pioneered the Multidimensional Poverty Index (MPI), including a broad range of indicators to define poverty beyond income and money-focused approaches. The MPI (mainly building on household-level data) has gone on to influence poverty and deprivation studies in LMICs, including articles featured in this scoping review (e.g., Altamirano Montoya & Teixeira, 2016; Zakaria, Hassan, Othman, & Asmuni, 2017). Despite some investments by donors in household-level survey programs in LMIC, a lack of administrative resources and capacity have hindered other ways to analyze deprivation within LMICs (Setel et al., 2007). For example, spatial data about infrastructure and environmental deprivations are often missing, or data are incomplete and fragmented across organizations (Dotse-Gborgbortsi, Wardrop, Adewole, Thomas, & Wright, 2018; Mahabir, Crooks, Croitoru, & Agouris, 2016). In addition, household surveys 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 a fine geographic scale (Perez-Heydrich, Warren, Burgert, and Michael Emch, 2015).

Given that household census and survey data have been essentially the dominant source of comparable data across LMIC 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 MDG 7 and SDG 11 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, 2016). In practice, tenure status is rarely measured in censuses or surveys, leaving four household assets (i.e., water, sanitation, crowding and durable housing) to define the complex concept of “slums” across diverse, dynamic cities (e.g., Fink, Günther, & Hill, 2014). Not only is the exclusion of tenure status problematic, this approach implicitly - and incorrectly - assumes that “slum households” are concentrated in 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 (Elseiy et al., 2016). The creators of the “slum household” definition acknowledged its limitations and advocated for more representative area-level measures (UN-Habitat, 2002).

One further shortcoming of urban indices, as well as surveys and censuses, is that they frequently fall short in terms of mainstreaming experiences of different groups, for example, by understanding deprivation issues in terms of gender, age, ethnicity, ability, and sexual orientation. To take gender as an example, the 1975 Beijing Conference for Women recommended the collection of sex-disaggregated data, i.e., data collected on men, women, girls and boys. 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, as part of this scoping review, we seek to understand if, at a minimum, sex-disaggregation is included in urban deprivation indices, and we isolate which gender issues are counted.

1.4. 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 dynamic advancement of new technologies, computing power, and spatially detailed data cannot be understated: in the last twenty years, openly available very high-resolution satellite imagery and sensor data, the ubiquitous use of mobile phones and Global Positioning System (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). Despite the development, conceptualizations of deprivation by physical data scientists have predominantly focused on the form and morphology (physical arrangement) of features such as buildings and roads (Duque, Patino, & Betancourt, 2017; Leonita, Kuffer, Sliuzas, & Persello, 2018; Taubenböck, Kraff, & Wurm, 2018; Wurm & Taubenböck, 2018; J. Wang, Kuffer, Roy, & Pfeffer, 2019). Divyani Kohli and colleagues, for example, published a seminal “ontology of slums” that defined whether an area is 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, Sliuzas, Kerle, & Stein, 2012). This framework and others like it (e.g., Kuffer, Barros, & Sliuzas, 2014; Mahabir, Croitoru, Crooks, Agouris, & Stefanidis, 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, Pfeffer, and Sliuzas (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 the 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 (using the five slum indicators) widely used today and discussed above (UN-Habitat, 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 (Ezeh et al., 2017; R. J. Lilford et al., 2017). The workshop in Bellagio (henceforth called the Bellagio workshop) resulted in the proposal of five domains for measuring deprived areas, reflecting social and physical science perspectives: 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 deprived areas. Negative perceptions lead to resettlement and eviction policies, while positive measures lead to the 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 (Moser, 1998, 2007; Moser & Dani, 2008).

1.5. State of the field and research gaps

We identified the research gap as the inexistence of an operational framework that combines household- and area-level deprivation supporting the mapping of the complexity of deprivation in LMIC cities. The most established poverty and deprivation frameworks are rooted in a period when government census, survey, and administrative data (mainly in HICs) were chief sources of information about poverty, and measurement of area-level deprivation depended on the aggregation of household data to either small neighborhood-sized areas (HICs) or across all urban areas in a country (LMIC) (Lucci, Bhatkal, & Khan, 2016). 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. This calls for an integrated framework to measure the multiple dimensions of deprivation faced by the poorest in LMIC cities using a multitude of datasets produced by diverse stakeholders.

2. Methodology

The overall objective of the scoping review is to develop an operational and multidimensional deprivation framework, relevant for LMIC cities (Fig. 2). To achieve this, we reviewed a large body of academic and grey literature (section 2.1), with guiding questions and standardized coding categories (section 2.2) to establish what had been conceptualized and measured in terms of deprivation (section 2.3) and used these findings to establish a ‘Domains of Deprivation Framework’, which was subsequently validated in workshops with diverse stakeholders in different LMIC cities. This section describes the employed methodology to arrive at the ‘Domains of Deprivation Framework’.

2.1. Scoping review of academic and grey literature

We performed a scoping review on the extent and nature of urban

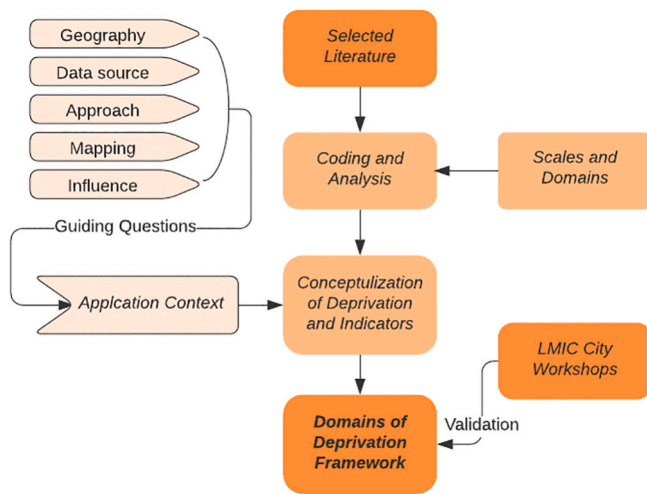


Fig. 2. Overall workflow of the scoping review.

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. The scoping review suitable to identify key concepts, definitions and operationalizations (Munn et al., 2018) allowed to identify key domains and indicators used to measure household as well as area-level deprivation. 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 a 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 ($N = 101$), which were excluded. The search did not result in any African language publications. This resulted in 2447 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 2475 publication titles and abstracts were screened, and 350 publications were reviewed for a proposed and/or applied deprivation framework. After reviewing full texts, 115 publications were retained for analysis (Fig. 3).

2.2. Analysis of articles

First, we used a list of questions to extract standardized information from each of the 115 articles into Excel. The questions belonging to categories helped to structure the analysis of the reviewed frameworks (115 articles). The first category allowed us to identify the geographic context of the deprivation frameworks, including the regions and the analytical units (e.g., grids, neighborhoods). The second category on data source provided an understanding of the type of input data, which links to the operationalization of the frameworks. The third and fourth categories provide insights into the application of the framework (e.g., in the form of a composite index) and whether/how results are mapped. The fifth category on influence supports a general understanding on the importance of the reviewed frameworks. The questions coded for each article were:

(1) Geography:

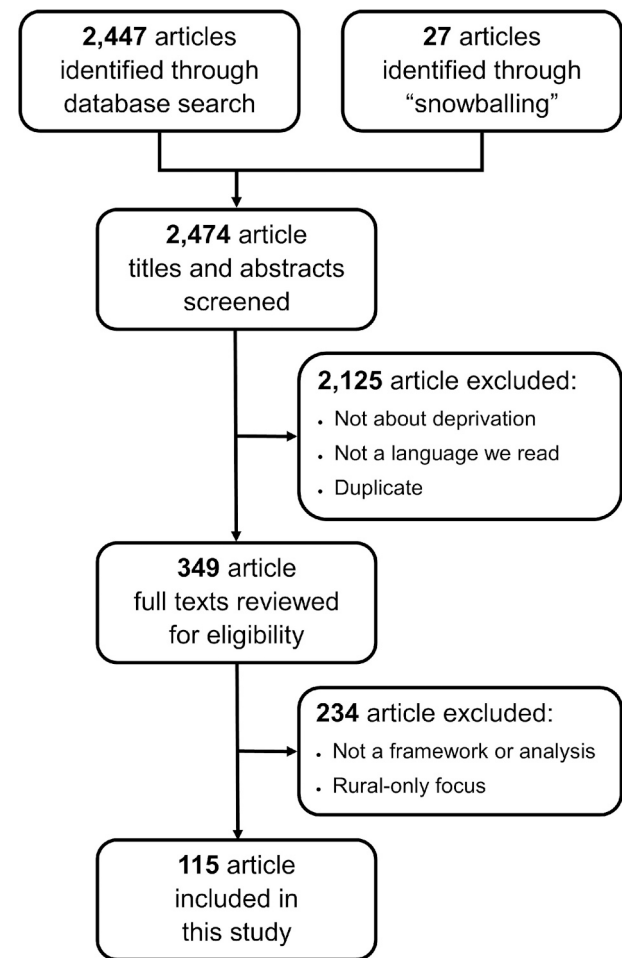


Fig. 3. Diagram of systematic literature review criteria.

- a. What is the finest geographic scale used for analyzing the indicators of deprivation (e.g., household census enumeration area, neighborhood, homogeneous grid)?
- b. Which countries or regions are covered by the included papers?
- (2) Data source:
 - a. Is 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 EO data (e.g., satellite images) used?
- (3) Approach:
 - a. Is the result also providing a composite output (e.g., in the 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: $\text{Number Citations} / (2020 - \text{Publication Year})$

2.3. Coding of indicators, and development and validation of the framework

Each indicator and domain mentioned in the 115 articles were coded 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 (Fig. 3) (Thomson et al., 2019). We chose this framework as a starting point because the Bellagio Framework has 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 LMICs urban deprivation. Through three iterations of this process, Social/Environment was split into three different domains (Socio-Economic Status (SES), Social Hazards & Assets, Physical Hazards & Assets), Lack of facilities/Infrastructures was separated into two domains (Infrastructure, Facilities & Services), and one domain was added (Governance) (Fig. 4).

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 1877 indicators from the 115 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, Heath, Cameron, Rashid, & Redwood, 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 1877 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. The aim of the workshop was to identify and address any gaps in the framework domains and indicators and improve its layout. 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 in semi-structured discussions to provide suggestions to improve the framework, and report 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, Lak, & Timothy, 2019; J. Jarman, 2001; Pairan & Tjendani, 2019; 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

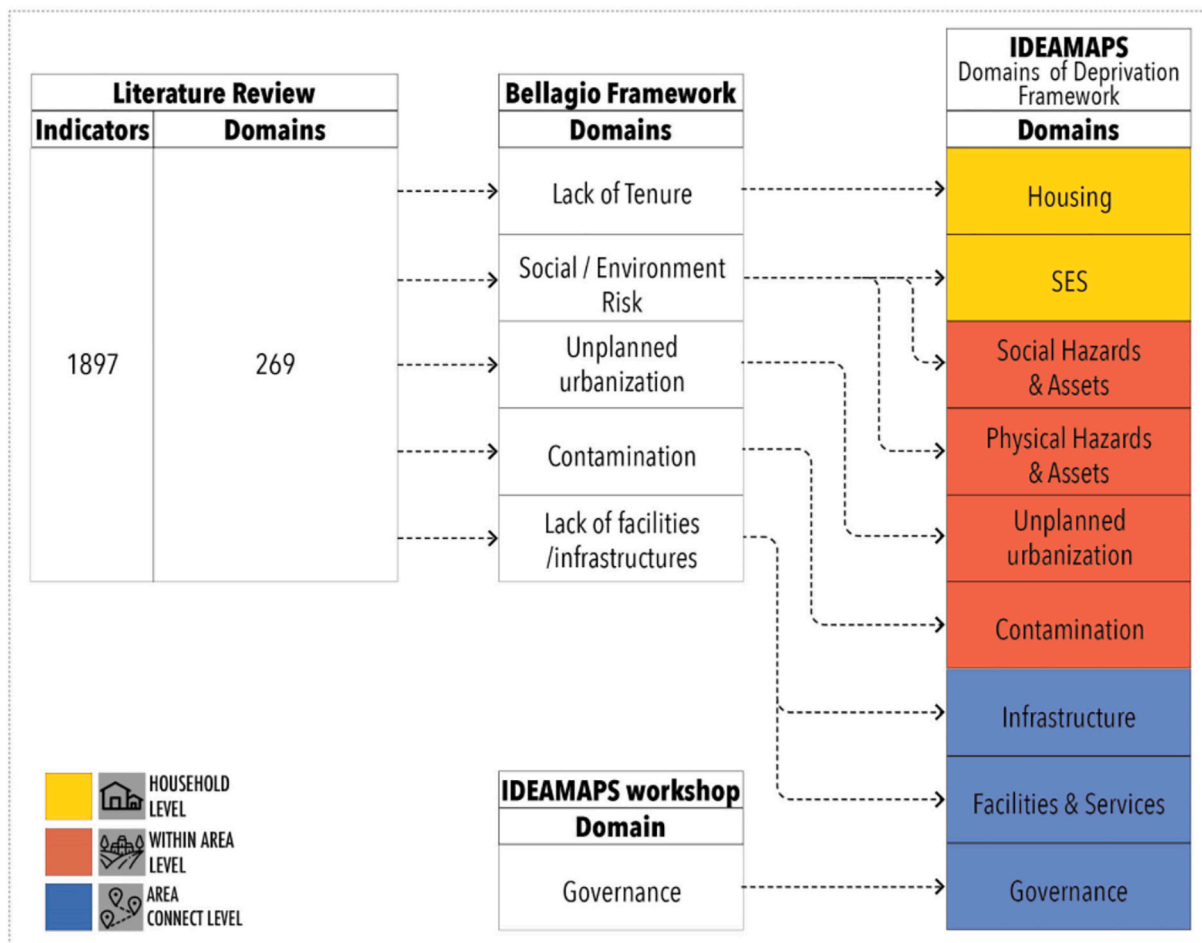


Fig. 4. Diagram of the design process for the Domains of Deprivation Framework.

mentioned street lighting, the need for functioning drainage systems in addition to water and sewage systems, and the measurement of ecological diversity. Based on workshop feedback, we revised our coding framework a final time (Fig. 5), reapplied it to the indicators, and revised our Domains of Deprivation Framework.

3. Results

The results section is split into two sections. First, we provide an overview of the findings guided by the questions. Second, we analyze the frequency of domains and indicator groups in the literature to allow for an overall grouping of indicators.

3.1. Findings to guiding questions of the coding framework

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

3.1.1. Geography

A large number of the existing deprivation frameworks were developed for use in the UK and countries historically linked to the UK,

including the US, India, South Africa, and Australia (Fig. 6, Table 1). More than half of the articles were developed in, or applied to, LMICs (Table 2). The regional distribution of these studies shows that Europe and Asia received the bulk of attention (28.7% and 20.9%, respectively), with Africa, the Middle East and Latin America lagging behind in terms of the number of studies (Table 2). Few frameworks have been developed for application in a Global or Global South context.

3.1.2. Data source

From the articles we reviewed, 47.8% utilized or made available open-source data, and only 7.8% of the studies definitely did not. There were, however, 44.4% of the articles in which it was hard to discern if the data was openly available (Table 2). Out of the 115 articles reviewed, 85.2% applied concepts and/or measurements of deprivation to specific case studies (Table 2), for example, to a specific geographic context (e.g., Caicedo & Jones, 2014; Mishra, Kuffer, Martinez, & Pfeffer, 2018). The majority of frameworks were based on a single country (84.3%), reflecting the importance of geographic context when measuring and addressing deprivation (Table 2). Of those studies which applied a framework to measure deprivation, census data were used in 61.2% of articles, and survey data in 59.2% (Table 2).

IDEAMAPS Domains of Deprivation Framework		
Household SES	Social Hazards & Assets	Infrastructure
<ul style="list-style-type: none"> - Assets (e.g. car, bike, TV, fridge, phone) - Crowding - Demographics - Education, literacy, & training - Employment & occupation - Ethnicity and migration - Healthcare utilisation - Health, nutrition, & disability status - Income, expenditures (except housing), debt, credit, & savings - Insurance - Public social services recipient - Sense of freedom, security, & support - Sense of fulfilment, self-esteem, concentration - Subjective poverty - Urbanicity (urban/rural) - Non-specific / multiple 	<ul style="list-style-type: none"> - Crime, safety, conflict (reported) - Security (perceived) - Food security, distribution, & nutrition - Livelihood opportunities - Mobility - SES inequality - Savings & loan initiatives - Social capital & identity - Stigma 	<ul style="list-style-type: none"> - Drainage - Roads & walkways - Street lighting - Transportation & traffic - Waste management - Water, sewer - Non-specific / multiple
	Physical Hazards & Assets	Facilities & Services
	<ul style="list-style-type: none"> - Ecological diversity - Natural hazards (e.g. slope, flood zone) - Natural assets (e.g. biodiversity) - Non-specific/multiple 	<ul style="list-style-type: none"> - Access -financial, social - Availability/distance -commercial - Availability/distance -municipal - Availability/distance -recreation/culture - Availability/distance -worship - Availability/distance & quality -health - Availability/distance & quality -schools - Availability/distance -all or other
Housing	Unplanned Urbanization	Governance
<ul style="list-style-type: none"> - Energy for lighting, heating, cooking - Property type, ownership, affordability - Sanitation - Structure quality & attributes - Tenure - Water 	<ul style="list-style-type: none"> - Building or population density - Building morphology (area, shape, arrangement, height) - Building quality (roof materials) - Building uses or functions - Coverage or area of green space - Land cover - Land use - Plot size 	<ul style="list-style-type: none"> - Access to information - Civic participation & inclusion & fairness - Corruption & accountability - Finance & bureaucracy - Integrated planning - Legal & policy frameworks
	Contamination	
	<ul style="list-style-type: none"> - Air pollution - Garbage accumulation - Industrial pollution (incl. toxic waste) - Noise or smell pollution - Water pollution - Non-specific 	

Fig. 5. Final coding framework.

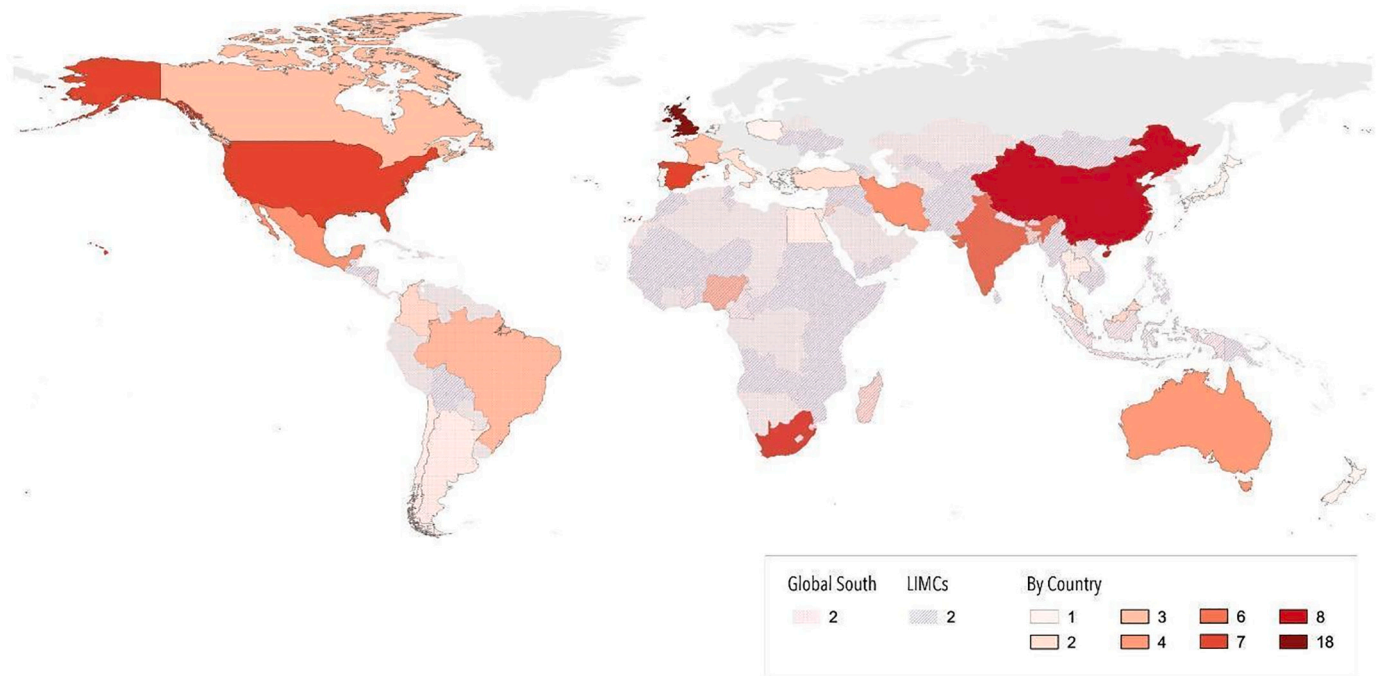


Fig. 6. Number of deprivation framework publications by country.

Furthermore, 46.9% of authors consulted with stakeholders such as local communities, or those involved with the government (Table 2). 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 8.2% of the articles which applied a framework used EO data (Table 2). 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 (Ajami et al., 2019; Hacker et al., 2013; Roy et al., 2020).

3.1.3. Approach

A majority (67.8%) of the articles that applied a framework 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., 2009, 2008; D. Exeter, Zhao, Browne, & Lee, 2016; McLennan et al., 2019) (Table 2). 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 and data-driven methods that allow the generation of clusters (Krishnan, 2015; Mari-Dell'Olmo et al., 2011; Roy et al., 2020) (Fig. 7). In recent years, advancements in methods such as artificial intelligence (AI) have enabled additional analyses of multiple deprivations (Ajami et al., 2019), as well as the development of deprivation measures in relation to the fuzziness of concepts (Gao & Sun, 2020). Developments such as these are designed to address the limitations of simple summative indices that obfuscate the complexity of deprivation.

3.1.4. Mapping

Few articles (14.3%) that applied a deprivation framework mapped deprived areas at fine-scale such as settlement or census enumeration areas (Table 2). 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 (Ajami et al., 2019; Harris & Longley, 2004; Taubenböck, Kraff, & Wurm, 2018).

3.1.5. 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 (Fig. 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 (Fig. 8). Along the vertical axis of Fig. 8 are the data sources mentioned to apply the framework (e.g., census, EO). Influential articles that recommend the use of EO data to measure deprivation have only emerged in the last decade (Fig. 8). In particular, EO allows to capturing area-level deprivation, including environmental deprivation.

The most influential framework was developed by David McLennan and colleagues, with 206 citations per year, as indicated by the darkest blue shade (Fig. 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 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 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 (Fig. 8).

Table 1
Percentage of total ($n = 115$) deprivation framework publications by region

Regions	Percent	Citations
Central & South America	7.8	Altamirano Montoya & Teixeira, 2016; Alves, 2013; Builes-Jaramillo & Lotero, 2020; Caicedo & Jones, 2014; D'Ambrosio & Rodrigues, 2008; Del Carmen Rojas, Meichtry, Ciuffolini, Vázquez, & Castillo, 2008; Feres & Mancero, 2001; Hacker et al., 2013; Seguel & Villaroel, 2018
Eastern & Southern Asia	20.9	Ajami, Kuffer, Persello, & Pfeffer, 2019; Akter & Rahman, 2017; Bag & Seth, 2018; Baud et al., 2009; Baud, Sridharan, & Pfeffer, 2008; Chen, Leu, & Wang, 2019; Chen & Wang, 2015; Chowdhury & Mukhopadhyaya, 2016; Ensor et al., 2020; Fukuda, Nakamura, & Takano, 2007; Gao & Sun, 2020; Ge, Dou, & Zhang, 2017; Ling, 2009; Mahadevan & Hoang, 2016; Manap, Zakaria, & Hassan, 2017; Mitra & Nagar, 2018; Pairan & Tjendani, 2019; Saif-Ur-Rahman et al., 2018; Tipayamongkhogul, Podang, & Siri, 2013; Wan & Su, 2017; Webster, Wu, Zhang, & Sarkar, 2016; Wu & Qi, 2017; Yuan, Xu, Cao, & Liu, 2018; Zakaria et al., 2017
Europe & Central Asia	28.7	Abarca-Alvarez, Reinoso-Bellido, & Campos-Sánchez, 2019; Alguacil & Camacho, 2014; Arribas-Bel et al., 2017; Bayram, Bilgel, & Bilgel, 2012; Bocquier et al., 2013; Bradshaw & Finch, 2003; Cornado, Garcia-Almirall, Vima, Busqued, & Uzqueda, 2017; Coromaldi & Zoli, 2012; Eroğlu, 2007; Eskandrani, 2007; European Commission, 2010; Guillaume et al., 2016; Harris & Longley, 2004; Havard et al., 2008; Jacobsen, 2016; B. Jarman, 1983; J. Jarman, 2001; Jordan, Roderick, & Martin, 2004; Kearns, Gibb, & Mackay, 2000; Mari-Dell'Olmo et al., 2011; Martínez & Lechuga, 2012; McLennan et al., 2019; Ministerio Ministerio de Fomento & De, 2018; Niggebrugge, Haynes, Jones, Lovett, & Harvey, 2005; Noble, Wright, Smith, & Dibben, 2006; Page, Langford, & Higgs, 2019; Panori, Kakderi, & Tsarhopoulos, 2019; Payne & Abel, 2012; Scottish Executive, 2004, 2006; Smith et al., 2015; Swiader, Szebrański, & Kazak, 2017; Venerandi, Quattrone, & Capra, 2018
Middle East & North Africa	5.2	Abu-kharmeh, 2009; Asadi-Lari et al., 2013; Bérenger, 2017; Borzooie et al., 2019; Najjary, Saremi, Biglarbegian, & Najari, 2016; Zandi, Zanganeh, & Akbari, 2019
North America	10.4	Bell, Schuurman, & Hayes, 2007; Casas, Horner, & Weber, 2009; CONEVAL, 2010; Fuentes, Peña, & Hernández, 2018; Jenerette, 2018; Johnson, 2007; Krishnan, 2015; Medina Perez, Bass Zavala, & Fuentes Flores, 2019; Messer et al., 2006; Reckien, 2018; Roy, Bernal, & Lees, 2020; Y. Wang & Fox, 2017
Oceania	4.3	Baum, 2006; Exeter, Zhao, Crengle, Lee, & Browne, 2017; Hulse, Pawson, Reynolds, & Herath, 2014; Pawson, Davison, Wiesel, Australian Housing, & UNSW-UWS Research Centre, 2012; Saunders, Naidoo, & Griffiths, 2008
Sub-Saharan Africa	11.3	Ajakaiye, Jerome, Olaniyan, Mahrt, & Alaba, 2014; Barnes, Wright, Noble, & Dawes, 2007; Beck, Hahn, & Lepenies, 2020; Deinne, Ajayi, & Dare., 2019; Duclos, Sahn, & Younger, 2006; Günther & Harttgen, 2009; Mpenya, Baye, & Epo, 2020; Noble et al., 2009; Noble, Barnes, Wright, & Roberts, 2010; Noble & Wright, 2013; Oldewage-Theron & Slabbert, 2008; Steinert, Cluver, Melendez-Torres, & Vollmer, 2016; Yakubu, Mobolaji, Ijaiya, Kilishi, & Yaru, 2014
Global	8.6	Anindito, Maula, & Akbar, 2018; Davis, 2003; Moser, 1998; Ompad, Galea, Caiaffa, & Vlahov, 2007; Oxford Poverty and Human Development Initiative, 2020; Sphere., 2018; Taubenböck, Kraff, & Wurm, 2018; UN-Habitat, 2003; UNDP, 2009; WHO, 2012
Global South	2.6	Alkire & Santos, 2010; Kohli et al., 2012; Wilkinson et al., 2020

Table 2
Summary of literature review results in terms of geography, data source, approach, and use of maps

Indicator	Percent
Finest Geographic Scale ($N = 115$)	
National	47.8
Sub-national	47.8
Not applicable	4.3
Coverage, extent ($N = 115$)	
Single country	84.3
Multiple countries	15.7
Coverage, World Bank 2020 designation ($N = 115$)	
Low Income Country	1.7
Lower-Middle Income Country	15.7
Upper-Middle Income Country	34.8
High Income Country	40.9
Not applicable (Global coverage)	7.0
Indicator data are open/available ($N = 115$)	
Yes	47.8
No	7.8
Unclear	44.4
Composite Index ($N = 115$)	
Yes	67.8
No	30.4
Unclear	1.7
Framework is presented with applied example ($N = 115$)	
Yes	85.2
No	14.8
If applied example, data from stakeholder engagements used ($N = 98$)	
Yes	46.9
No	53.1
If applied example, census data used ($N = 98$)	
Yes	61.2
No	38.8
If applied example, survey data used ($N = 98$)	
Yes	59.2
No	40.8
If applied example, EO data used ($N = 98$)	
Yes	8.2
No	91.8
If applied example, local (settlement-level) map presented ($N = 98$)	
Yes	14.3
No	85.7

3.2. Frequency of domains and indicator groups in the literature

Existing deprivation frameworks overwhelmingly emphasize indicators of household-level Socio-Economic Status (SES) (58.4%) and Housing (15.1%) deprivation, which can be easily measured in census and survey data (Table 3). The next three most commonly measured domains in the literature were Facilities & Services (7.2%), 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 3). 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 3), then this review highlights major gaps in the literature to measure, and therefore, label and address these challenges and assets.

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 the sense of freedom or fulfilment were rarely measured (Fig. 9). In the less common domain of Facilities & Services, distance to (or a number of nearby) health facilities was most commonly measured, whereas the distance to (or a number of nearby) schools was rarely used as a measure (Fig. 9). In the uncommon domain of Contamination, air and noise pollution were most often measured, but water pollution and garbage accumulation

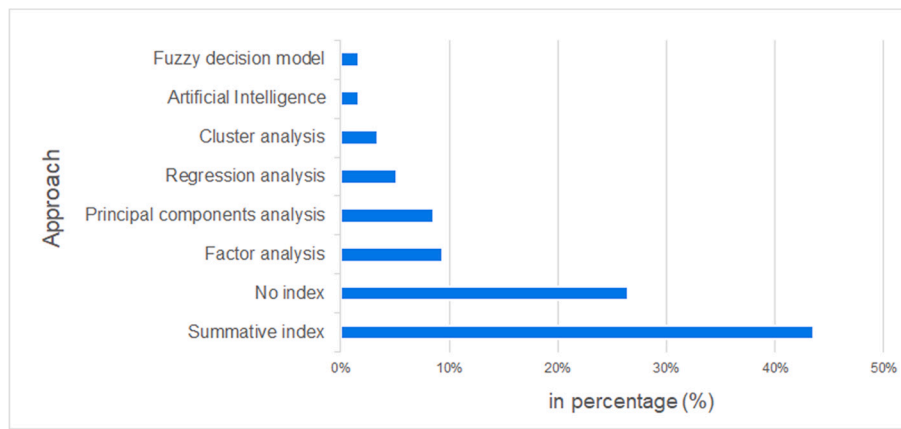


Fig. 7. Approaches used in studies to calculate a multiple deprivation index (N = 115).

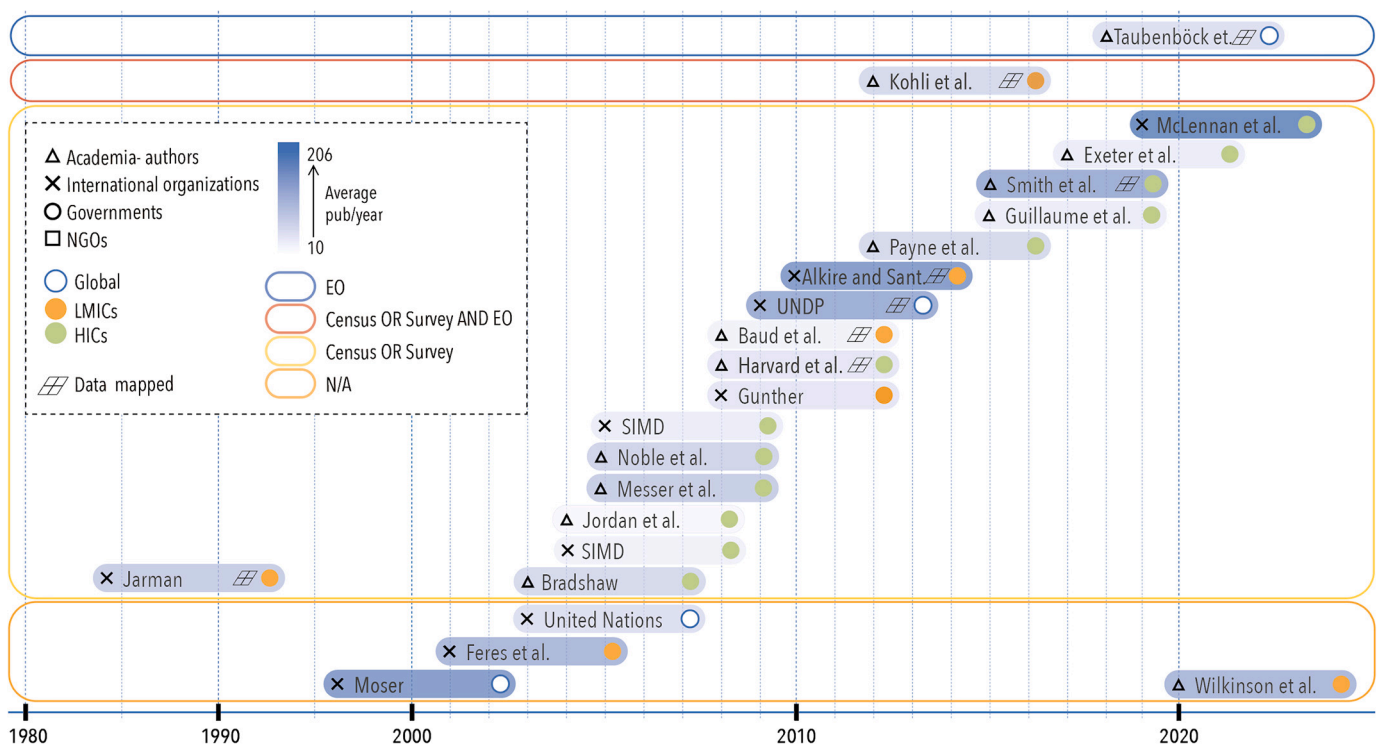


Fig. 8. Timeline of the most representative frameworks.

Table 3
Frequency of indicators by domain

Scale	Domain of deprivation	Indicator	
		Frequency	Percent
Household-level	SES	1097	58.4
	Housing	283	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	7.2
	Governance	29	1.5
	Total	1877	100.0

were rarely measured (Fig. 9).

Out of the 1877 indicators, only 51 (2.7%) had a sex-disaggregated component (Table 4). Sex indicators tended to focus on whether the house was led by a female, or disaggregated education and employment by male/female (Table 4).

4. IDEAMAPS domains of deprivation framework

The development of IDEAMAPS Domains of Deprivation Framework has been guided by the articles of the scoping review. This was done by iteratively coding domains and indicator groups with several rounds of refinements. The main purpose is to provide interdisciplinary support to future deprivation characterization studies and to support the operationalization of deprivation mapping. The framework contains 70 indicator groups in nine domains across three scales of measurement: household (including individual issues), within area, and “connecting” or area-connect scales (Fig. 10). For all domains, example indicator

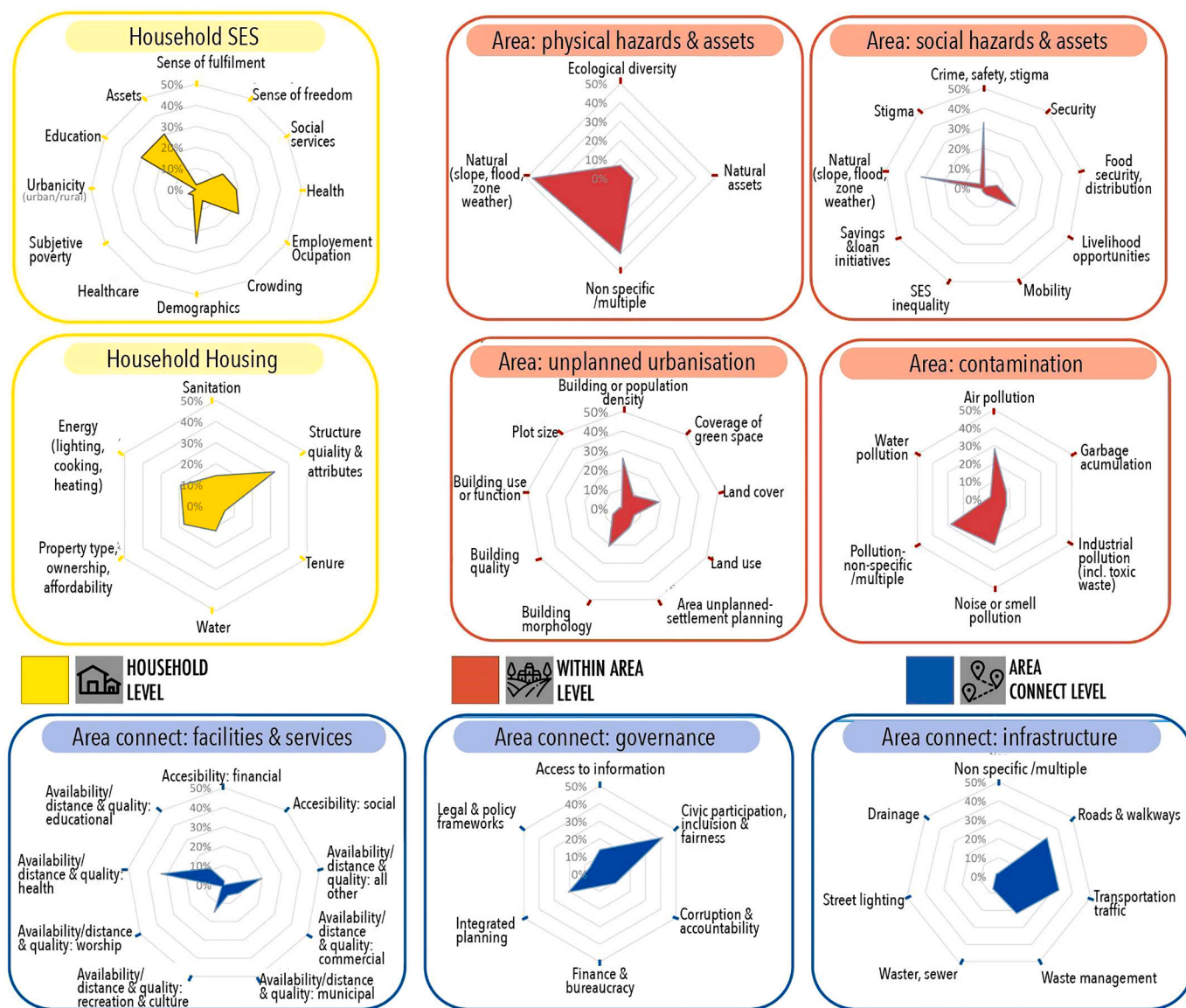


Fig. 9. Percentage of indicators group contributions within domains.

Table 4
Sex disaggregated indicators

Domain - Indicator group	Frequency	Percent
SES - Household demographics	16	0.9
SES - Health, nutrition and disability status	10	0.5
SES - Employment and occupation	9	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 - Assets (e.g., car, bike, TV, fridge, phone)	1	0.1
SES - General	1	0.1
All gendered indicators	51	2.7
All non-gendered indicators	1826	97.3
Total	1877	100.0

groups are listed. This is intended to guide the operationalization of the framework. Local adequate indicators can be developed within each domain, e.g., building on open spatial datasets (for details on how to operationalize the framework refer to IDEAMAPS (2021)). At this stage, the main goal of the review is to set out the deprivation framework,

which can provide interdisciplinary support for those researching or responding to urban deprivation.

Household-level domains of deprivation reflect indicators measured at the individual- or household-level, often by census or survey. The first domain, *SES*, is measured with indicators that reflect individual education rates, health status, employment, and household ownership of assets. A separate *Housing* domain is included within the domain *SES* 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 & Assets*, *Physical Hazards & 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 a 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 the presence of trees and plants to maintain cooler temperatures and cleaner air. Indicators within the *Unplanned Urbanization* domain are associated

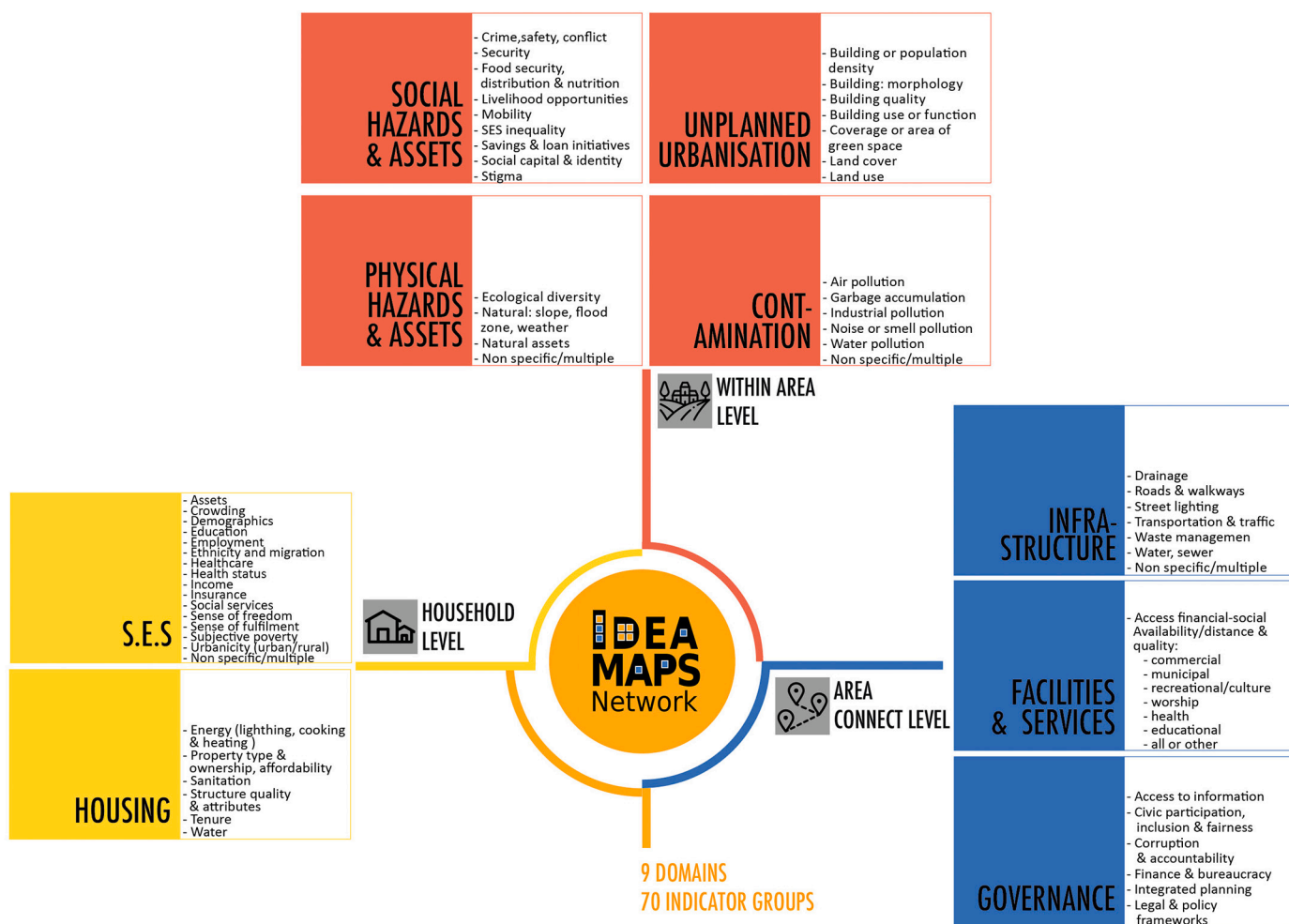


Fig. 10. Diagram of IDEAMAPS Domains of Deprivation Framework.

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 the accumulation of garbage, water pollution, air pollution, or high levels of constant noise that affect the well-being of residents.

Area Connect domains refer 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 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.

5. Discussion

This paper reviewed conceptualizations of urban deprivation in LMIC cities, integrated key concepts from social and physical sciences, and developed 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 household-to-city-level, and this is reflected in the classification of domains within a simple spatial hierarchy (i.e., household- area- area connect level). We also, importantly, link dozens of indicator groups to

each domain based on the literature review and local workshops. Therefore, our novel IDEAMAPS Domains of Deprivation Framework departs from existing frameworks that are not holistic enough to reflect household and area-level domains of deprivation in LMIC cities. Our proposed 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. The discussion is framed in terms of new research directions recommended building on our framework, highlighting scale, data integration, data aggregation, policy and practice relevance, as well as limitations of the review approach.

5.1. Scale – Towards a scalable framework

Within this scoping review, 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 2). As with several UK indices highlighted in the introduction, e.g., the Scottish Index of Multiple Deprivation 2006 (Scottish Executive, 2006), or 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, the percentage of households

using a flush toilet (household-level) is not necessarily related to the percentage 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 EO linked to field work (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 vary 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 ten 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).

To deal with these problems, when defining the Domains of Deprivation Framework, the scale approach was important. This led to the differentiation of three scales (levels), i.e., the household-, area- and area-connect-level. The multi-scale approach allows to capture deprivation domains and related indicators at their appropriate scale and avoids, e.g., the association of area-level indicators to households. This multi-scale approach stresses that households face deprivation because of household-level characteristics (e.g., assets), but also face on top area-level deprivation (e.g., access to open spaces) and deprivation due to the connectivity with the entire city (e.g., infrastructure provision).

5.2. Data integration and need for new data for routine mapping of deprivation

The Domains of Deprivation Framework allows the flexibility to be integrated with existing geo-statistical models. To support this 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, Tatem, Bird, & Burgert Brucker, 2015) are already disaggregated in this way, though models are subject to error (Leyk, Boesch, & Weibel, 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 EO data alongside newly emerging data sources, e.g., social media data (Taubenböck, Staab, et al., 2018), Street View images (Aravena Pelizari et al., 2021), the extraction of data focusing on specific aspects of deprived areas from available repositories, e.g., lack of physical accessibility extracted from OpenStreetMap (Soman, Molina-Solana, & Whyte, 2020) or the use of AI and EO data to capture environmental characteristics contributing to deprivation, e.g., accumulation of waste piles (Georganos et al., 2021; 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 the unavailability of data. To bridge this data gap, Ron Mahabir et al. (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 of the economic pyramid resulting in a segment of rental and owned property transitions taking place offline (Birch, Chattaraj, & Wachter, 2016). 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, de Díaz-Torres, Gradilla-Hernández, & de la Torre-Castro, 2019). Data cubes provide new solutions in terms of data access, spatially disaggregated data and capturing the complexity of spatial phenomena such as deprivation.

5.3. Data disaggregation – Moving towards an intersectional understanding of deprivation

Another gap is the lack of data disaggregated by important sub-groups such as including age, sex, disability, income, migratory, social groups, etc. (UN-Habitat, 2016). 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 exist in numerous areas of daily life, including limited access to decent work opportunities, unbalanced workloads between paid and unpaid work activities, barriers to access financial assets and housing security, unfair tenure rights, limited access to services, unbalanced asset accumulation, limited participation in public governance structures, and problems with personal security (Chant & McIlwaine, 2016; IWPR, 2015; C. Moser, 2016; Tacoli, 2012; Tacoli & Satterthwaite, 2013). 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).

Within our Domains of Deprivation Framework, we stress the importance of data disaggregation by sex and gender. Data disaggregation can also unmask challenges that affect men (as well as women) 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), while men might instead be more likely to experience mugging, and gang-related or street crime (Meth, 2017). As mentioned in the introduction, disaggregation of data and deprivation measures by sex is not enough. Nowatzki & Grant (2011) recommend firstly undertaking gender analysis to understand the differing needs of women and men in order to establish which issues need to be measured. Gender analysis should ideally reveal how different groups of women, men, and those who identify as non-binary, experience opportunities and challenges in relation to urban deprivation. This would be taken further by an intersectional gender analysis, which would demonstrate how gender intersects with age, disability, class, religion, sexuality, and ethnicity and thus create a fuller picture of urban deprivation within cities in LMICs.

5.4. Operationalizing the domains of deprivation framework in support of policy

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 & Assets, will vary by location (e.g., Tirana versus Timbuktu) and coverage (e.g., city-wide versus continent-wide). Krakowka, Malcomb, and Ringle (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 pre-published version of the framework (Shonowo et al., 2021), 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). Similarly, the National Institute of Statistics and Geography (INEGI, Mexico) is presently implementing the framework as a pilot to complement their census data on deprivation. This shows the potential of the framework and will allow us to further develop existing domains, and how these can be contextualized to various settings. In the process of operationalization, ethics and privacy need to be reflected. For example, the use of gridded maps and the aggregation of indicators to gridded units (e.g., 100 m by 100 m) obfuscates the exact boundaries and reduces the risk of stigmatization (Owusu et al., 2021).

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 et al. (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 policymakers 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 that 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, support 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).

5.5. Future research directions

By nature of being a scoping review of existing literature, our framework is limited by what other researchers and practitioners 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 distil 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) as well as possible studies in the Chinese language per the exclusion criteria in the review process.

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 that 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. This framework is already being operationalized, and we welcome further research and critically reflect on the framework and its impact.

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, as well as a fair exchange of data (e.g., it is not ethical to collect data from communities without returning information to communities). Indicator decisions should be taken through an inclusive, multi-stakeholder process that ensures that people of different backgrounds (e.g., genders, age groups, abilities, ethnicities, sexual orientations, etc.) 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 (e.g., SDI, 2020).

6. Conclusion

The IDEAMAPS Domains of Deprivation Framework aims to present the major domains of deprivations significant in LMIC cities, 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 70 relevant indicator groups. This generalized framework combines household (including individual) 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 co-production in relation to area-level indicators, specifically on physical and social hazards, contamination, infrastructure, and city-level governance. An area-level deprivation benefits from recent advances of Earth Observation technologies, increasing availability of geo-spatial data, and new data (e.g., social media data) and computing power. Such data allow capturing area-level deprivation, including building morphology (e.g., density, size, shape, proximity, and orientation), environmental quality and pollution (e.g., flood, landslides, air pollution, extreme temperatures). However, new data (e.g., social media data) can support the mapping of social issues (e.g., stigmatization); here, more work is needed to integrate such data within area-level domains of deprivation.

The combination of both household-level, area- and area-connect-

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. The Domains of Deprivation Framework supports multiple stakeholders’ interaction in the definition of indicators and local adaptations. Key stakeholders include residents, local community groups, NGOs, government officials, academics, and practitioners. The framework supports the development of a data and modelling ecosystem that can be continuously populated with spatial data coming from surveys, EO and other spatial data. The data ecosystem will allow local stakeholders to combine and validate data, specify definitions of deprivation, which they prefer to use and train their own models of deprivation. This will support democratization in access to data, in particular for local stakeholders such as community groups, and allow an evidence-based dialogue between local groups and government officials on development issues.

Funding

This work was supported by the UK Economic and Social Research Council (ESRC), Global Challenges Research Fund (GCRF) focused on Digital Innovation and Development in Africa (DIDA) [EP/T029900/1].

Author contributions

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Declaration of Competing Interest

The authors declare no conflicts of interest.

Acknowledgements

We would like to thank Dr. Adelina Mensah and her team at University of Ghana for organizing an IDEAMAPS stakeholder workshop in Accra, and the 20 participants who provided critical and helpful feedback on our Domains of Deprivation Framework. We would also like to thank our colleagues on the IDEAMAPS pilot study, PI Dr. Caroline Kabaria, Mr. Francis Onyambu, and Ms. Ivy Chumo from the African Population and Health Research Center, Dr. João Porto de Albuquerque from the University of Warwick, Dr. Ryan Engstrom from George Washington University, and Dr. Luis Bettancourt from University of Chicago. NWO (Dutch Research Council) grant number VI. Veni. 194.025.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compenvurbysys.2022.101770>.

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