Chapter 1
Data and Urban Poverty: Detecting and Characterising Slums and Deprived Urban Areas in Low- and Middle-Income Countries

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Abstract A multidimensional characterisation of urban areas is essential to provide relevant data for monitoring deprived urban areas (urban poverty) beyond the dollar threshold (World Bank) or household characterisation (UN-Habitat). We present a holistic characterisation of deprivation through a framework composed of domains

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and indicators for measuring urban poverty. It includes socio-economic and household characterisation (household-level) as well as the characterisation of physical and environmental conditions (area-level). In this chapter, we showcase the use of Earth Observation techniques to extract area-level data. The combination of Earth Observation and open geospatial data allows routine mapping and characterising essential aspects of urban deprivation related to the urban environment (e.g., contamination such as waste accumulations), urban morphology (e.g., unplanned urbanisation defined by built-up densities, street geometry, open/green spaces), and connectivity (e.g., the presence of infrastructures such as streetlights or road access). Such a mapping system provides meaningful information for classifying deprivation levels and discovering differences between and within deprived areas. Results are provided as an online tool for users to access information at the city and settlement scale in sub-Saharan African cities. The tool allows users to tailor information to support the improvement of living conditions for the rapidly growing number of urban inhabitants.

Keywords Cities · Slums · Earth observation · Spatial analysis · Deep learning

1.1 Introduction

A balanced housing demand–supply and access to employment, basic infrastructure, and services are often unattainable in urban areas, leading to the emergence and proliferation of "slums" or "informal settlements", referred to as deprived urban areas (DUAs) in this chapter. Consequently, the majority of the sub-Saharan African urban population lives in DUAs. Policy responses to support DUA upgrading have been inadequate (UN-Habitat 2016), leaving out the poorest citizens residing in substandard housing, commonly located in areas that lack urban facilities, services, and infrastructure, and are often unplanned and located in hazardous and contaminated zones. These areas are frequently considered urban "anomalies" and are not included in city planning (Beukes 2015; Sliuzas et al. 2008). However, there is insufficient data on urban conditions to identify and characterise the poorest areas, and therefore there is a lack of data monitoring programs. Local actors, including local and national governments, non-governmental organisations (NGOs), and community groups, require up-to-date data to guide and monitor pro-poor policies and upgrading programs (Owusu et al. 2021) (Fig. 1.1).

Generally, consistent and city-level data are urgently required to monitor the progress of the urban Sustainable Development Goal 11 (SDG 11), in particular SDG 11.1.1. on the "proportion of the urban population living in slums, informal settlements or inadequate housing" (UN-Habitat 2020a). However, data supporting its monitoring is not readily available. Available datasets on the SDG 11.1.1 indicator are country-level estimates that do not provide localised data (Kuffer et al. 2018; Kavvada et al. 2020). Thus, available data do not provide information about city-scale spatial patterns of DUAs and their dynamics. Geospatial and Earth Observation (EO)

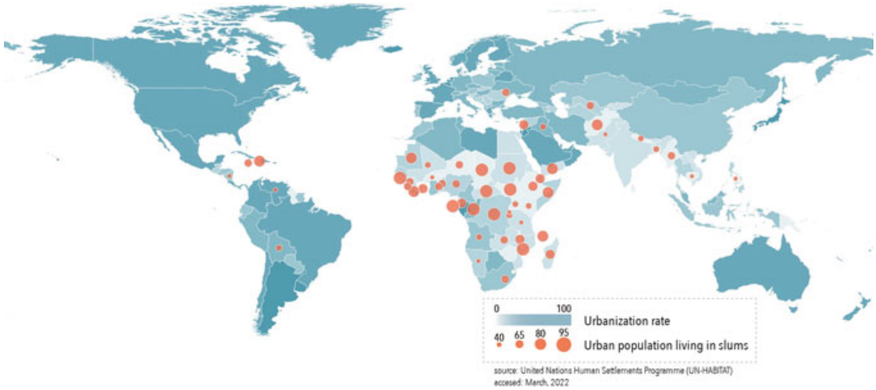

Fig. 1.1 Percentage of urbanisation rates (coloured by country) and the urban population living in slums (shown only for countries with >40% of the urban population living in slums) (Abascal et al. 2022a)

data have demonstrated their capabilities to map and monitor DUAs (Kuffer et al. 2020, 2021a; Liu et al. 2019). Data are increasingly available and accessible, and algorithm developments, big data, and cloud-based computation have been bridging the bottleneck to providing city-to-global mapping products. However, most EO-based mapping studies on DUAs work at a city scale or below (Ajami et al. 2019; Badmos et al. 2018; Wurm et al. 2019) and do not deal with the main challenges of scalable, transferable, and low-cost solutions (Kuffer 2020). To date, EO data have not shown their capabilities to provide adequate monitoring instruments supporting knowledge on the location, characterisation, and dynamics of DUAs (Kuffer et al. 2021b), e.g., supporting local SDG 11.1.1 reviews. A recently published needs assessment of different user groups that require such data (Fig. 1.2) has shown that data are needed for a fine-grained spatial scale (e.g., gridded data at 100 m) with an update cycle of 1–2 years (Kuffer et al. 2021b). Generally, urban development questions require city-scale information and detailed neighbourhood analysis (Kuffer et al. 2018; Merodio Gómez et al. 2021).

Two interrelated developments aim to produce city-scale and settlement-scale data on DUAs. The Integrated Deprived Area Mapping System (IDEAMAPS) network (IDEAMAPS 2022) leverages the strengths of current poverty geodata sources, i.e., census, field-based survey, and EO-based mapping, the latter through research carried out in the SLUMAP project (SLUMAP 2022). The combination of different mapping approaches aims at overcoming the limitations of individual approaches to DUA mapping, e.g., the deep knowledge of community-based mapping combined with the capacity to cover large areas with EO-based mapping. However, until recently, most EO-based studies (e.g., Wang et al. 2019; Williams et al. 2020) relied on very-high-resolution (VHR) satellite image acquisition (high-cost imagery and processing demands).

To support routine and accurate mapping and characterisation of deprived urban areas, the IDEAMAPS network developed the Domain of Deprivation Framework to

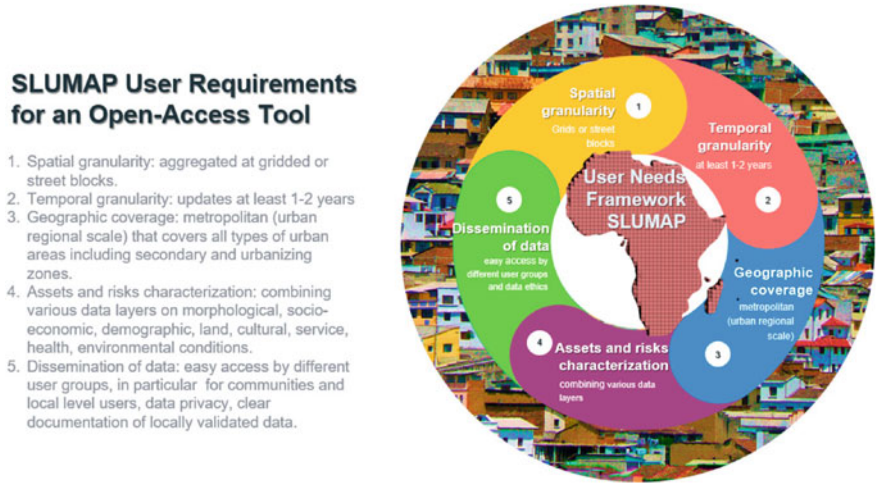

Fig. 1.2 User requirements of deprived (slum) related spatial information (Kuffer et al. 2021)

identify relevant geospatial and EO data for urban deprivation mapping and analysis (Abascal et al. 2022b). This framework builds on existing deprivation frameworks (e.g., the English Deprivation Index and the Bellagio Framework (McLennan et al. 2019; Gale et al. 2013)). The primary rationale for modelling deprivation not as a binary phenomenon but as a continuous layer is the high level of uncertainties of slum versus non-slum maps, as even local experts have difficulties agreeing on boundaries (Kohli et al. 2016). Existing deprivation mapping frameworks typically use census data, with availability issues and low temporal granularities, which quickly go out of date in fast-growing and transforming LMIC cities (Thomson et al. 2021). The IDEAMAPS Domains of Deprivation Framework groups locally meaningful DUA indicators into nine domains at three scales. Two domains reflect household deprivation (socio-economic status and housing characterisation). Four domains reflect area-level deprivations (social hazards and assets, physical hazards and assets, unplanned urbanisation, and contamination). Three domains reflect aspects of deprivation that relate to the connectivity to the city (i.e., infrastructure, facilities and services, and governance). A guide for authorities and users (IDEAMAPS 2021) has been developed to support the operationalisation of all domains building on openly available geospatial data (e.g., night-time lights (see Kuffer et al. 2018) or sub-air pollution) and contextual image features (e.g., using Sentinel-2 imagery) (Fig. 1.3).

The SLUMAP project that focused on sub-Saharan African cities investigated the potential of EO for mapping and characterising DUAs, aiming for cost efficiency. Experiments involving machine learning algorithms and satellite imagery with different spatial resolutions showed that city-level deprivation mapping could be achieved with open, cost-free Sentinel-1/2 images, while very-high-resolution images were requested to produce detailed settlement-level characterisation (Abascal et al. 2022; Georganos et al. 2021; Vanhuysse et al. 2021). At the city scale, the

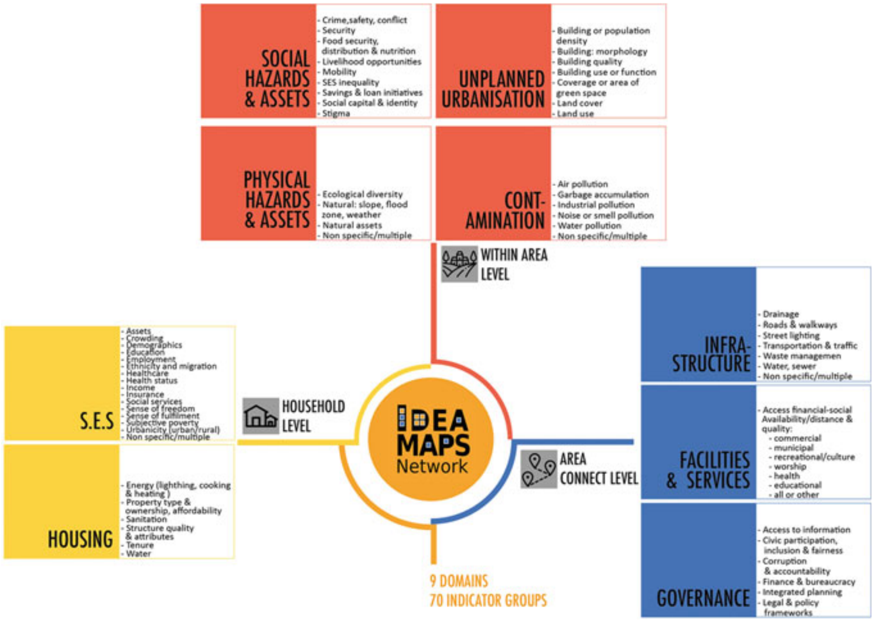

Fig. 1.3 IDEAMAPS domain of deprivation framework for LMIC cities (Abascal et al. 2022b)

location and extent of slums within a city were modelled, while detailed characteristics of the physical environment within slums were extracted at the settlement scale. The methodological objectives included scalability and transferability of the developments.

IDEAMAPS and SLUMAP work on DUA models that utilise open geospatial and EO data. In particular, EO processes have advantages over traditional methods, such as cost-effectiveness, fine grain coverage, and high temporality. Thus, EO data allow for routine mapping of DUAs and characterising aspects related to the physical urban environment observed from space, connected to area-level domains. Such area-level information includes the urban environment (e.g., contamination and infrastructure to detect waste accumulations or other environmental hazards), unplanned urbanisation defined by the urban morphology (e.g., built-up densities, street width, and availability of open/green spaces), and urban facilities, services, and infrastructure (e.g., availability of streetlights, health services, and road access).

EO approaches are commonly top-down, with no or limited user interactions. In contrast, our framework combines EO data with user engagement and includes data from local communities, acknowledging the importance of citizen science. Thus, the information needs and requirements of different user groups are the guiding principles for developing a flexible DUA mapping system. The deprivation data is also frequently analysed and disseminated in academic formats not easily accessible to local users (e.g., DUA communities, NGOs, or governments). To develop strategies for shortening the gap between inconsistent and non-available datasets in DUAs, the first step needs to develop an adequate understanding of user requirements at different scales (i.e., from the local community level to the national government and international organisations).

1.2 Methodology

1.2.1 Operationalising IDEAMAPS Domains of Deprivation Framework Through Semi-automated SLUMAP Processes

The IDEAMAPS "domains of deprivation framework" allows the flexibility of integrating existing geostatistical models with innovative spatial-data cubes. The availability of geospatial data differs between locations, particularly in sub-Saharan African countries where available data are often outdated or have a low spatial resolution (coarse data). To mitigate the data scarcity issue, we use EO data to show their capacity to partially align with the IDEAMAPS framework by extracting relevant indicators. We use the city of Nairobi (Kenya) to explore the potential of high-resolution (HR) and very-high-resolution (VHR) sensors (i.e., Sentinel-1/2, SPOT6/7, WorldView-3, and Google Earth images) to produce deprivation indicators. We employ Sentinel-1/2 images to reduce the costs of city-scale mapping, responding to user requirements for a low-cost mapping system. Working with publicly available satellite imagery allows for the development of standardised, transferable, and scalable mapping methods, i.e., supporting routine mapping of DUAs. We use a gridded mapping system of 100 by 100 m grid cells to avoid showing exact settlement boundaries that might contribute to stigmatisation.

Furthermore, at the city scale, the overall probability of an area being deprived is displayed, which avoids binary labels (i.e., slums vs. non-slum areas). At the city scale, indicators can exhibit built-up densities, which is often a good proxy of deprivation levels. The local characterisation relies on the potential of VHR images to describe aspects of the urban morphology that constitute environmental and health issues (e.g., waste/garbage piles) and automate building mapping and detection (in support of local planning needs). Results are made available through a user-friendly WebGIS interface that provides information on the city- and settlement scale to address the accessibility requirements of users identified in earlier work (Kuffer et al. 2021) (Fig. 1.4).

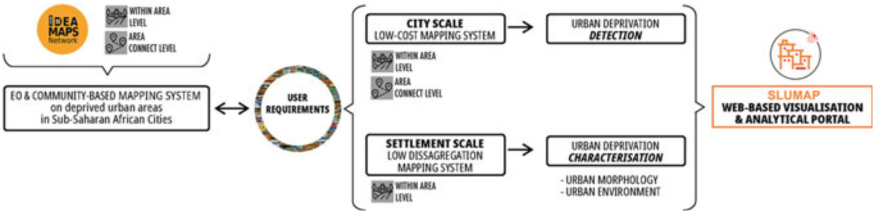

Fig. 1.4 IDEAMAPS/SLUMAP solution to address user requirements for spatial data on DUAs

1.2.2 *Urban Deprivation Detection Using Open Software and Low-Cost Imagery at City Scale*

We assessed the potential of cost-free Sentinel-1/2 versus low-cost SPOT-7 for mapping the gridded probability of deprivation at the city scale (Vanhuysse et al. 2021). For this purpose, we implemented a machine learning workflow using Free and Open-Source Software (FOSS). This was done with GRASS GIS and R functions, employing Jupyter Notebook for automation. A morphological deprivation probability was computed, reflecting the probability for a grid cell to be part of a DUA (which is different from a degree of deprivation severity) based on morphological characteristics captured by EO. We opted for gridded mapping as this approach was successfully used in previous studies, although with very-high-resolution imagery (e.g., Duque et al. 2017). Besides, gridded layers can easily be combined with the rapidly increasing number of other open gridded mapping products (e.g., Facebook's High-Resolution Population Layer, WorldPop, Global Human Settlement Layers (GHSL), and World Settlement Footprint (WSF)).

We developed our workflow in the pilot study area of Nairobi, Kenya. Nairobi was selected because of data availability and the large number of inhabitants living in DUAs (around 60% of Nairobi's population live in DUAs). Our study area covers the entire Nairobi metropolitan area, including continuous built-up areas extending outside the city boundaries but excluding the Nairobi National Park (the total area is 652 km^2). We used Sentinel-1/2 and SPOT-7, i.e., publicly available images from Copernicus and low-cost commercial imagery (Fig. 1.5) and compared the results. The mapping approach also includes ancillary open global datasets (i.e., SRTM, Open Street Map (OSM), WSF 2019; Marconcini et al. 2020).

In the first step, a vast number of image features were extracted (over 2000 spectral, spatial, and ancillary features). For optical imagery (S2 and SPOT7), these features included various vegetation indices, water or moisture indices, built-up indices, image transforms, texture metrics (e.g., Grey Level Co-occurrence Matrix (GLCM), Structural Feature Set), and a few metrics calculated on an unsupervised classification output (such as the Mean Patch Size). The image features of the SAR imagery (S-1) included intensity, coherence, textures, and filtered bands. The list of ancillary features covered geomorphometric features, built-up, and street density. Statistics were calculated at the grid-cell level. Feature selection was used to reduce the high

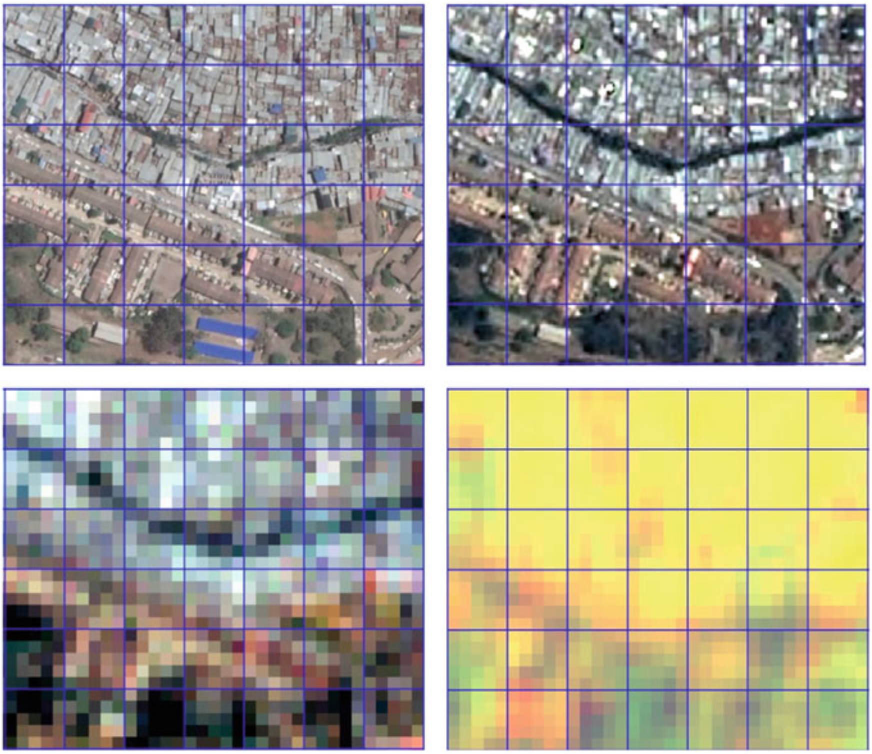

Fig. 1.5 The interface between deprived and non-deprived urban areas. Top left: GE imagery. Top right: SPOT7 (RGB). Bottom left: S2 (RGB). Bottom right: S1intensity (VV, VH, VV/VH) (Kuffer et al. 2021a)

feature dimensionality. We employed the Variable Selection Using Random Forest (VSURF) algorithm (Genuer et al. 2015). For classification, we used a classical machine learning approach (Random Forest) that allows working with a limited amount of labelled training data (as compared to deep learning). The classification scheme includes the following eight land-use/cover classes: (1) High to mid-density-built area, (2) Low density-built area, (3) Industry/large structures, (4) Paved ground/Bare ground, (5) Vegetation, (6) Water, (7) Deprived urban areas (typical), and (8) DUAs (atypical). For the class "deprived urban areas", we used two sub-types that have relevantly different morphological characteristics, based on the following definition of the deprived classes:

- (7) Very high built-up densities in the form of compact arrangement of low-rise buildings that form "organic" patterns. The area has no structured street layout except for a few main streets (often at the boundary). Little or no vegetation.
- (8) Areas shows variations in densities (high- to mid-densities) with compact arrangements of buildings that are more regular than in class 7.

For training and testing, 3962 manually labelled samples (i.e., grid cells) were prepared for the target classes. We compared the performance of several feature combinations using standard accuracy metrics (i.e., precision, recall, and F1 score) for optimising the process.

1.2.3 Urban Deprivation Characterization: At Settlement-Scale

On top of a city-scale analysis, we also characterise settlement-scale intra-deprived area environments (Georganos et al. 2021). This analysis included four main topics, (1) the accumulation of waste (i.e., garbage piles), (2) the built-up densities, (3) built-up morphology (i.e., morphological features of the built-up patterns), and (4) a bottom-up population estimate. For this level of analysis, we use VHR images. For the extraction of land cover/use information, we used superspectral image data acquired by the WorldView-3 satellite (8 multispectral and 8 SWIR bands). The main target classes are buildings, ground cover (bare soil and asphalt), vehicles, vegetation (tall and low vegetation), water, garbage, and shadow (residual class). For the image classification, a state-of-the-art processing framework utilising machine learning classifiers combined with Geographic Object-Based Image Analysis is deployed (Georganos et al. 2018a, c). Moreover, we analyse the produced land use/land cover models for deprived areas. The results are assessed, considering, besides quantitative assessment (i.e., overall accuracy), an analysis of interpretability and transferability (Georganos et al. 2018b). This assessment included, e.g., an analysis of a suitable grid size to reflect the urban morphological patterns in DUAs. Consequently, we compared indicators at different grid sizes (e.g., 25, 50, and 100 m). For example, we analysed a suitable grid size for analysing and visualising the density of garbage/waste piles in settlements, one of the most severe environmental issues in deprived urban areas (Fig. 1.7a). A similar effort is presently ongoing in local communities collecting geodata about garbage piles in several deprived urban Nairobi regions (Fig. 1.6).

Besides land cover/use information, we also extracted morphological information. This analysis builds on building footprints extracted from the baseline band set (red, green, and blue) of very-high-resolution imagery, as displayed on platforms such as Google Earth. We analysed whether morphological features differentiate DUAs from other parts of the city. This analysis entails two significant steps: (1) extracting building footprints using deep learning (a modified U-Net architecture) and (2) calculating morphological features based on the building patterns using the open-source Python library MOMEPY (2022). For the building footprint extraction training, we use a global training dataset provided by Wuhan University that contains labelled building footprints of a worldwide sample (Wuhan University 2020). The morphological analysis output provides a clustering result optimised in terms of cluster number. Building footprint extraction is required as an input to morphological

Fig. 1.6 The living environment issues in deprived urban areas Community-based waste data collection ongoing work (*Source* https://slumap.ulb.be/news/trash_survey_foss4g/)

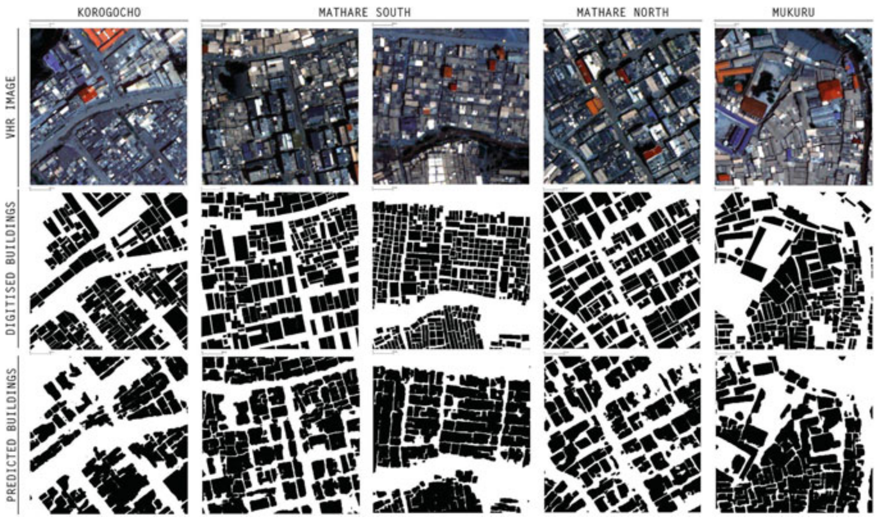

Fig. 1.7 Selection of image chips (top row) and corresponding building footprints, manually digitised (middle row) and predicted by CNN (bottom row), illustrating the challenges faced by automated methods in very densely built DUAs (Abascal et al. 2022c)

analysis, which is challenging in DUAs. Challenges are caused by the high densities and limited or no set-back between buildings, which causes clumps of buildings to be extracted (e.g., Fig. 1.7). Global or continental data layers of building footprints (e.g., Open Buildings by Google or Building Footprints by Microsoft) have significant omissions and large clumps in DUAs.

1.2.4 SLUMAP Web-Based Portal: Towards Dissemination That Reaches Out to Local Users

We developed a web portal that allows easy visualisation to optimise the user interaction with the mapping outputs. The data are packaged at city- and settlement scales, allowing for interactive visualisation. The city of Nairobi is used as a pilot, while other cities are presently processed (e.g., Accra, Dakar, Kampala, Kisumu, Ouagadougou, and Khartoum). The website allows users to switch between city scale to settlement scale information. Besides visualisation, users can make simple printouts of maps. Furthermore, comparing cities after implementing different cities will also be possible.

1.3 Results

1.3.1 Detecting Deprived Areas at City Scale

Dimensionality reduction resulted in a dramatic decrease in the number of features required to achieve optimal accuracy and minimise the complexity of the application. Indeed, this allowed us to reduce processing time and supported the scalability of the method. The results were validated with an independent test set generated through visual interpretation. The validation focused on the two deprived classes (see deprivation definition of subclasses 7 and 8). Generally, the highest accuracy was obtained using SPOT7 and ancillary features. However, it did not differ substantially from the best combination of Sentinel 1/2 and ancillary features (Table 1.1). Consequently, the preference was given to using Sentinel-1/2 and ancillary features to support a low-cost mapping system.

The morphological deprivation probability is the combined probability of the two classes of deprived areas (i.e., classes 7 and 8) (Fig. 1.8). The values show low

Table 1.1 Precision, recall, and F1 scores of the best feature combinations employing Sentinel-1 (S1), Sentinel-2 (S2), SPOT7, and ancillary global features

Class	Metric	S2 S1	S2 S1 Ancillary	SPOT7	SPOT7 Ancillary
Class 7	Precision	0.94	0.96	0.86	0.94
	Recall	0.89	0.89	0.89	0.93
	F1	0.91	0.92	0.87	0.94
Class 7	Precision	0.79	0.84	0.79	0.88
	Recall	0.82	0.89	0.78	0.89
	F1	0.80	0.86	0.79	0.89

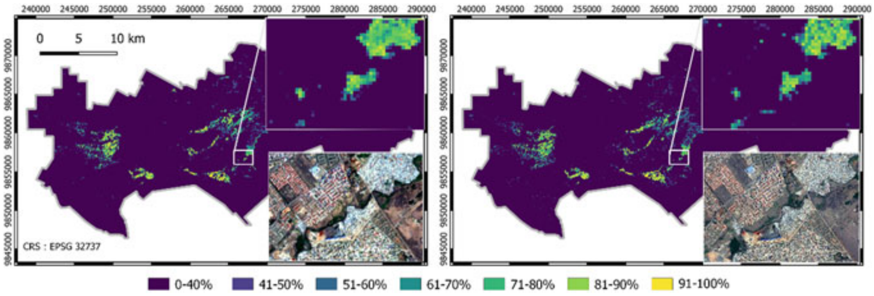

Fig. 1.8 Gridded deprivation probability (Nairobi, Kenya). Left: From S1-2 and ancillary open geodata. Right: From SPOT7 and ancillary geodata (Adapted from Kuffer et al. 2021a)

probability values for areas that are commonly understood as non-deprived areas (e.g., planned urban areas with regular road patterns and vegetation cover) and high probability values for the well-known deprived urban areas (locally known as slums or informal areas—such as Kibera/Kibra), which are characterised by high built-up density and limited or no green spaces.

1.3.2 Intra- and Inter-urban Deprivation Characterisation Through Land Use and Land Cover Indicators

The example of the Mathare settlement in Nairobi (Fig. 1.9) shows the spatial patterns of land use/cover. This base map allows the extraction of information (indicators) about the urban environment that links to the domains of deprivation. The environmental conditions of DUAs are dominated by overcrowding and the absence of green and open space. Indicators that can be extracted from land cover/use information, e.g., relating to built-up densities, availability of roads that can be accessed by vehicles (for instance, cars cannot access high-density built-up areas, causing problems for infrastructure supply and in case of emergencies such as fires). Furthermore, environmental degradation is highlighted by the massive accumulation of waste (Fig. 1.9). Several indicators can also serve as socio-economic proxies (Engstrom et al. 2017), e.g., the presence of vehicles (Fig. 1.9) relates to accessibility and socio-economic activity. Concerning the classified maps, the overall accuracy (OA) using all WV-3 bands (multispectral + shortwave infrared) surpassed 87%, exhibiting a strong potential to capture fine details of the urban environment. The produced indicators have been summarised at a coarser grid level to provide aggregated information on different aspects of the urban environment (Fig. 1.9). The gridded map shows the spatial patterns of waste concentration in Mathare. The patterns mostly follow the area's drainage system, i.e., in case of rain, garbage flows into the central drainage

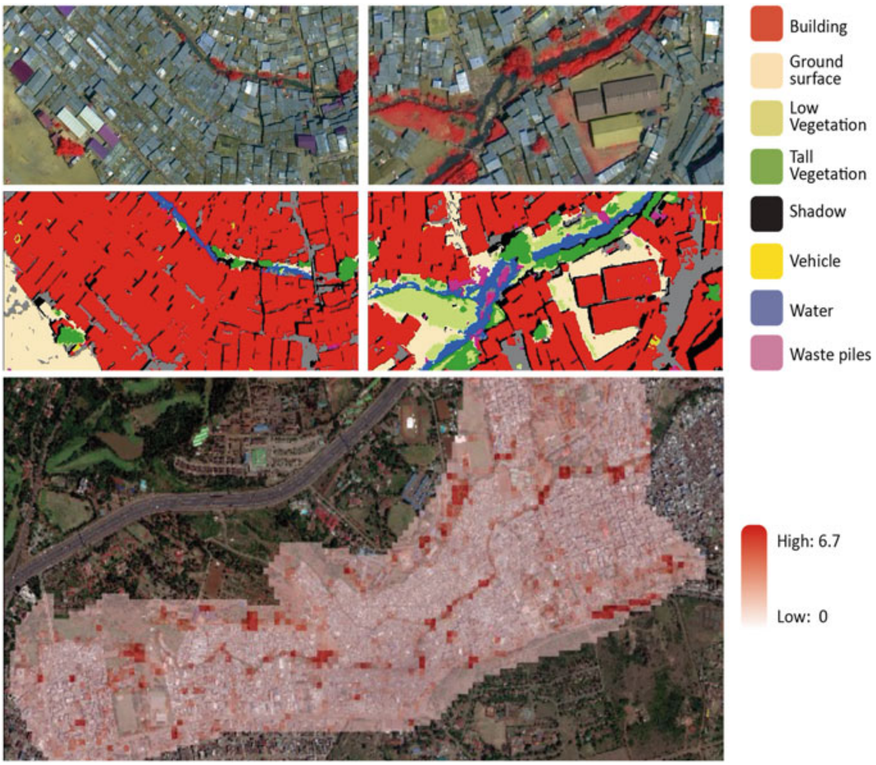

Fig. 1.9 Land use/cover mapping in deprived areas in Mathare, Nairobi, highlights garbage piles, lack of openness, detection of vehicles, and gridded garbage density (%) (Adapted from Georganos et al. 2021; Kuffer et al. 2021)

systems, polluting the water and causing obstructions to the drainage. These obstructions increase the flood severity, often causing a massive loss of properties of an already very vulnerable population.

1.3.3 Intra-urban Deprivation Characterisation Through Morphology Indicators

The morphological analysis provides a consistent method to extract similar morphological clusters. This can be done across cities, as shown in Fig. 1.10, to understand the comparability of morphologies of deprived urban areas across SSA cities.

Figure 1.11 shows morphological diversity within Nairobi city with two samples of building footprints from a slum/deprived urban area and a planned/non-deprived urban area. The building configurations and shapes show significant differences

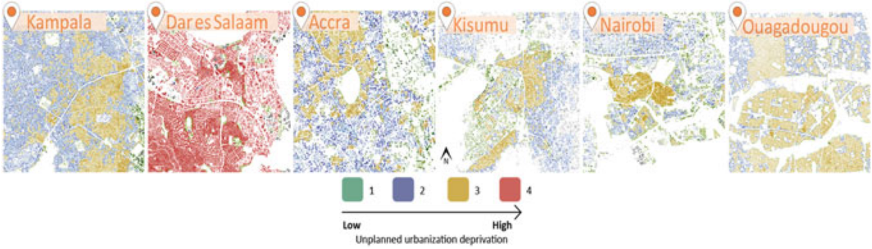

Fig. 1.10 Urban deprivation clusters based on building morphology indicators

across the city. These differences can be measured with morphological metrics and are captured by different morphological clusters.

Once the morphological building patterns are explicitly measured, clusters of similar building patterns are classified. The result is morphological clusters that show similar built-up morphologies. The morphological group highlighted in red

Fig. 1.11 **a** Building footprints extracted in recognised local slums. **b** Building footprints extracted in non-slums. **c** Clusters based on morphological metrics (Nairobi)

(Fig. 1.11b) reflects the distribution of deprivation areas delineated by local actors (locally known as slums).

1.3.4 SLUMAP Web-Based Data Portal

While users do not necessarily have access to and knowledge of working with EO data, GIS software is commonly used across diverse local actors. To make the geodata accessible, we package them in a web-based visualisation tool (Roca and SLUMAP 2022). The tool provides easy access to data processed at different levels. Gridded information about the deprivation probability and built-up densities at the city scale is combined with the highest resolution gridded population data (Facebook; see Fig. 1.12). We enable users to obtain estimates of the most deprived population from a specific area.

At the settlement scale, for several DUAs, more detailed data is provided about the land use/cover, i.e., the built-up environment and aspects of environmental conditions (e.g., vegetation presence and garbage pile locations; see Fig. 1.13b). To further develop deprivation indicators, the land use/cover information has been developed into gridded indicators to develop deprivation indicators (Fig. 1.13a) further. These indicators include the density of vegetation cover, garbage piles, and build-up for each grid cell. This is combined with a bottom population estimate using local population data from DUAs in Nairobi.

The web application allows users to change class boundaries in the case of continuous values, thus generating different maps, legends, and statistics. In addition, the user can activate/deactivate various categories of the legend and filter data by a defined range of values.

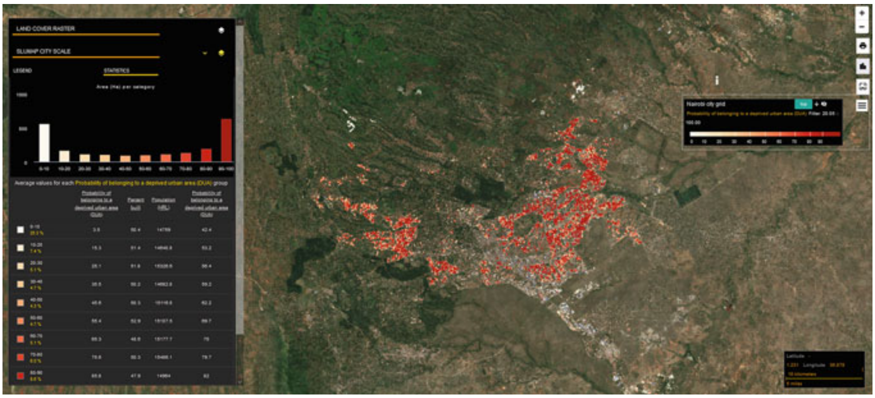

Fig. 1.12 SLUMAP web visualisation of morphological deprivation probability at city scale

Fig. 1.13 **a** Mathare settlement build-up percentage, **b** Mathare zoom-in land cover classes

1.4 Discussion

1.4.1 The Importance of Open-Access Data that Deals with Data Ethics and Privacy

The results of DUA mapping done within SLUMAP allow concluding that Sentinel images, which are cost-free datasets with wide temporal availability, are a valuable option for mapping some aspects of multidimensional deprivation at the city scale, e.g., the morphological deprivation probability. When well-trained and paired with additional features from available global datasets (e.g., WSF (Marconcini et al. 2020)), models using Sentinel-1/2 can reach accuracy levels close to models based on commercial HR imagery. The main advantages of Sentinel images are that they allow for frequent updates, are widely available and accessible, and can be processed with limited computational resources (compared to VHR images), thereby meeting users' requirements (Kuffer et al. 2021).

Geo-ethics and the potential implication of mapping vulnerable groups are significant when mapping poverty. In this respect, aggregating metrics at the grid level could be preferable to using disaggregated building metrics that expose citizens to personal identification, or administrative divisions, which can potentially cause the well-known modifiable areal unit problem (MAUP) (Openshaw 1984; Grippa et al. 2019). We aim to link our data environment with other platforms that provide deprivation data at a grid level, such as WUDAPT or WorldPop (Chi et al. 2021; Stewart and Oke 2012; Bondarenko 2020). Combining datasets that highlight deprivation aspects in a data-poor environment can shed light on topics that have been systematically omitted and allow to visualise the scale of the required solutions. For example, sanitation and water solutions (besides the main other infrastructure solutions) are urgently needed. The absence of improved sanitation and safe water is a major factor that reduces the life expectancy in such areas by 10–20 years. For designing locally relevant—low-cost solutions, besides co-designing such solutions, data that guide decision-making about technical requirements are crucial (Friesen et al. 2018).

1.4.2 Departing from Binary Slum Versus Non-slum Maps Towards Characterising Living Conditions

Urban deprivation is very diverse (multidimensional) and cannot be simplified into binaries of slum and non-slum conditions (Baud et al. 2008, 2009; Georganos et al. 2021). Even in field experience (Fig. 1.14), mapping often experiences challenges in drawing the exact boundaries between slum and non-slum areas (Kohli et al. 2016; Pratomo et al. 2016). Furthermore, details on the variation in living conditions, local needs, and priorities are essential to use local resources to improve living conditions economically.

1.4.3 Understanding Intra- and Inter-urban Deprivation Diversity in Support of Pro-poor Policies

Efforts to classify intra-slum variability according to its characteristics highlight the existence of spatially observable urban physical differences (Georganos et al. 2021; Kuffer et al. 2021; Noble and Wright 2013). The differences related to building density, absence or presence of vegetation, vehicles, and waste piles are the first step to better understanding the internal structure of deprived areas and provide meaningful indicators to support pro-poor policies and evidence-based policymaking for sustainable cities. Such differences have a locational-geographic dimension (Kuffer et al. 2017). For example, inner-city DUAs often have very high built-up and population densities, e.g., structures might have several floors, while peri-urban DUAs have more commonly lower built-up densities but are much more deprived in terms of access to infrastructure and services. However, densities also differ between cities, e.g., DUAs in Kisumu (Kenya) have much lower densities (on average) than DUAs in

Fig. 1.14 Satellite and ground photos from diverse deprived urban areas in Nairobi City

Nairobi (Kenya; Karanja 2010; SLUMAP 2022). Upgrading infrastructure requires understanding and related data (Friesen et al. 2018). For example, the provision of infrastructure (e.g., sanitation) is more accessible in lower density DUAs, while in very-high-density DUAs, many public services (e.g., waste collection trucks or fire brigades) cannot enter, and local solutions (e.g., the use of handcars) need to be developed (Corburn et al. 2020; Wanjiru 2021). It is essential to understand that local solutions that are co-designed and locally owned are generally more successful and scalable than top-down interventions that are not considering the needs of communities (Kotadiya et al. 2018; Patel et al. 2015).

1.5 Conclusion

DUAs emerge with the rapid urbanisation occurring in LMICs, ineffective planning, and a lack of affordable housing options (among other factors; see Cities Alliance 2021 and UN-Habitat 2020b). The proposed Integrated Deprived Area Mapping System framework (IDEAMAPS 2022) provides a flexible gridded mapping system to be operationalised in LMIC cities to uncover urban deprivation. SLUMAP showcases the potential of EO data for, on the one hand, producing city-scale maps that localise the diversity of deprivation and, on the other hand, unravel their characteristics across and within DUAs. A user-friendly web was created to provide relevant urban data to local actors. The proposed approach has the advantage of being scalable and transferable and allows for local adaptations in the form of a user-centred mapping approach. Results support cross-disciplinary information needs on DUAs and show EO data's potential to be combined with geospatial data for local SDG monitoring.

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