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In-Between the Lines and Pixels: Cartography's Transition from Tool of the State to Humanitarian Mapping of Deprived Urban Areas

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Abstract

Cartography has been, in its pre-modern and modern production of maps, influential in determining how space and territory is experienced and defined. But advancements in telecommunications and geovisualization software, along with geoinformation systems and geoinformation science (GIS), have transformed cartographic practice from a tool of dominantly state apparatus to a scientific, commercial, and humanitarian enterprise. This is exemplified in the use of remote sensing (RS) techniques to acquire, process, and visualize images of the Earth. In the last decade, RS techniques have increasingly incorporated Artificial Intelligence (e.g., Convolutional Neural Networks) to improve the speed and accuracy of feature extraction and classification in remotely sensed images. This paper will investigate the use of CNNs in the classification of deprived urban areas referred to as "slums" and "informal settlements" in the Global South. Using a postphenomenological methodology, this paper shall analyze the role of classification and use of geoinformation in shaping how deprived urban areas are algorithmically classified. This analysis will reveal that besides the technical opportunities and challenges, attention needs to be given to three ethical areas of concern: how deprived area mapping using AI impacts the agency of communities, how there is a potential lack in the democratization of these RS technologies, and how the privacy and data protection of communities being mapped is endangered.

Keywords CNN · Remote sensing · Global South · Postphenomenology

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1 Introduction

As cities in the low-middle-income countries (LMICs) have become increasingly urbanized, many of these cities face rising proportions of people living in deprived urban areas commonly referred to as "slums" or "informal settlements" (Ajami et al., 2019; Thomson et al., 2020). These areas are hosting increased populations facing difficulties in meeting basic needs such as affordable housing, access to water, and sanitation, along with public health and economic stability. As a result, international organizations such as UN-Habitat and UNICEF along with educational institutions and non-governmental organizations (NGOs) have partnered in collaborations to assist these areas. But a vital component of improving the living situation of these peoples is acquiring much needed information on the exact numbers and conditions of those living in these areas. Information is required to accomplish urban redevelopment initiatives such as meeting the Sustainable Development Goals (SDGs). But what is becoming increasingly clear when looking at the mapping of deprived areas in LMICs is the development of new technologies to acquire, store, and display spatial information to supplement state censuses that are often inconsistent and outdated. And over the past decade, there are increasing studies that explore the opportunities (and challenges) involved in using Artificial Intelligence (AI)-based technologies in the classification and representation of deprived areas in LMICs. This paper shall be investigating the use of such technologies, analyzing the use of AI-assisted classification using deep learning algorithms, such as Convolutional Neural Networks (CNNs) in the mapping of deprived urban areas in the field of remote sensing (RS).

In Sect. 2, the power of geographic information in improving the legibility of cities for the purposes of extending the state's control will be explored, beginning with a brief genealogy of cartography as a discipline, to highlight the role and function of maps specifically as a tool of expressing state power. This genealogy will illustrate that the production of maps helped in extending the power of the state by shaping how the body of the state was to be understood and represented (Edney, 2019; Winichakul, 1997). Maps were therefore important tools in making the space which the state wished to claim as its territory more legible (Scott, 1998) and therefore controllable. This ability to make claims over territory reflects what geographer Wood and Krygier (2010) refers to as the map's discourse function, i.e., the ontological authority that maps have in making claims over what exists in a given space. Making sense of space will be revealed to be a product of making space readable. This readability will be explored from the perspective of postphenomenology's analysis of hermeneutic relations between humans, technology, and the world (Ihde, 1990, 2009; Tinnell, 2014). This perspective will inform the way in which maps not only mediate between map producers/users and the world being mapped, but also make manifest a particular way of interpreting and experiencing the world, shaping not only how the world becomes experienced, but also changing the subject producing and using maps. The genealogy presented will therefore tie together the role of classification and legibility in the consolidation of the state's power, as revealed in the hermeneutic relations involved in the mediation of maps.

In Sect. 3, the transition from traditional cartography to the development of digital technologies and methods in map production and the use of these technologies in humanitarian interventions will be explored. In this transition, it will be demonstrated that one of the important areas in the use of Geographic Information Systems (GIS) and the discipline of RS is the mapping of deprived urban areas for humanitarian intervention. The use of GIS and more specifically the field of RS deals with improving the legibility of deprived areas for the sake of meeting international agendas such as the SDGs. And the field of RS is increasingly developing AI-assisted methods, ranging from classical machine learning methods (e.g., Support Vector Machine and Random Forest), to the emerging mainstream use of deep learning algorithms. The use of CNNs in mapping deprived areas in Mumbai (Verma et al, 2019) will provide an instance of AI-assisted mapping, to elaborate the challenges as well as opportunities offered by CNNs.

And in Sect. 3, this case example will also provide an opportunity to analyze the novel hermeneutic role that CNNs play in the mediation of maps, inspired by Hongladarom's (2020) notion of machine hermeneutics. This novel role is reflected in the way CNNs, based on the geospatial training data they are fed, play an active interpretive role in the identification and classification of deprived areas. Since the input they are given (i.e., ground truth data) heavily influences the generated maps produced, CNNs perform an algorithmic discourse function in shaping how deprived areas are made manifest. But this function relies on several factors, including the quality of training data, access to ground truth, uncertainty in the accuracy of the finished mapping product, uncertainty in datasets used, as well as accessibility to non-experts. At the same time, however, an area which does not get enough attention in the RS literature is the ethical dimension of being mapped by these RS technologies. This dimension entails considering the subjectivity of those mapped (i.e., how they feel about the presence of these technologies): how being mapped affects the agency of communities in deprived areas, the potential challenge of democratization of these technologies given their technicality, as well as the importance of privacy and data protection in the domain of mapping groups rather than just individuals.

2 Section 1—What Is a Map and What Do Maps Do?

An entire history of the discipline of cartography would be outside the scope of this paper. Instead, in this section, a brief genealogy of cartography's role as an instrument of the state from the seventeenth century to late twentieth century will be presented, focusing on its development specifically in Europe.

2.1 Cartography and Legibility

The need to understand space and what exists within that space (including natural resources, individuals/groups, neighboring groups, and built structures) was an important concern in matters of statehood. As Winichakul (1997) points out, "Space itself has no meaning if human beings have not encountered and mediated it by certain concepts and mediators" (Winichakul, 1997, pp. 35–36). When it comes to

defining space that the state occupies, or in other words what is referred to as the state's territory, this is a contestable issue. But such definitions rely on systems of classification. Winichakul states that modern geography provided not just new data but "another *kind* of knowledge of space with its own classificatory systems, concepts, and mediating signs" (Winichakul, 1997, p. 36), knowledge that competed against pre-modern ways of understanding and representing space, for instance, more cosmological mappings or dividing space between sacred and profane areas (Biggs, 1999, p. 377). Thus, an important concern for early modern states was how to represent and make sense of space within what it considered its domain. Edney (2019) asserts that Europe's *ancient régime* depended on both "nonterritorial structures of authority, whether patrimonial, feudal, or jurisdictional" and direct control, which resulted in a "proliferation of spaces whose political and territorial status were often ambiguous" (Edney, 2019, p. 110). And as a result "different parts were governed according to fundamentally different rules" (Biggs, 1999, p. 386). This ambiguity meant that the space of the state was not always in complete control of the state authorities. And this ambiguity was a problem that was to be resolved, in part, through the establishment of a common, universal measurement and classification system.

Scott (1998) argues that for the early European monarchies, such as in France, the administration of the state was problematized by the plurality of practices of measurement. These practices were important for ensuring fair trade (e.g., in terms of the weight of products) as well as taxes owed to the crown. Due to this plurality of measurement systems, "It was as if each district spoke its own dialect," and so "the state risked making large and potentially damaging miscalculations about local conditions, or it relied heavily on the advice of local trackers" who would easily take advantage of the state's lack of knowledge (Scott, 1998, p. 29). Consequently, for the European states attempting to gain a better understanding of the space they wished to control, they had to render that space legible in a singular language, which would lead to the abandonment of the plurality of measurement practices. The need for legibility is therefore tied to how well the body of the state can be administrated over, as "the relative illegibility to outsiders of some urban neighborhoods" provided "political safety from control by outside elites" (Scott, 1998, p. 54), which remained outside the purview of the state needed to be consolidated under the state. And this need was met by the initiatives of states and city planners in the creation of gridded city scapes (e.g., Fig. 1) along with the discipline of cartography.

Resultingly, from the eighteenth century, there came greater "state centralization and industrialization [that] gave a further bureaucratic and statistical edge to the movement to systematically survey Europe" as well as "boundary commissions consistently [seeking] to delimit precise lines in the landscape" (Edney, 2019, p. 110). This systematic survey of Europe, that combined the mapping of urban morphology, landscapes, and ocean coastlines, gave rise to what is today understood as cartography. Cartography became a tool for improving the legibility of the body of the state, as well as a tool that came to distinguish European state power and knowledge in contrast to their non-European colonies. "Westerners used cartography's geometrical essence to distinguish themselves from the Asians and Africans whom they colonized," and this geometrical essence "marked Westerners as innately rational, while

Fig. 1 Gridded planned urban space (Mexico City, left) and medieval organically developed space (Lisbon, right) Source: Google images

apparently non-geometrical maps of colonized peoples marked them as innately irrational and therefore properly subject to Western rule" (Edney, 2019, p. 5).

With this preliminary genealogy of cartography, that is in no way completely exhaustive but for the sake of brevity should suffice, it is clear the function of mapping out the space which the state occupied (physically and politically) was instrumental in improving the legibility of the body of the state and extending the state's power. At the same time, it should be noted that maps as a medium for representing space were also important in the domains of navigation (at sea and on land), astronomical study, urban planning, and for the disciplines of history and geography. The focus on the map as a vehicle for state dominance is merely to show the close relationship between understanding of space and the place of the individual as well as boundary of the state, in political discourse.

2.2 Classification and the Hermeneutic Relations of User-Map-World

This improvement in legibility as well as the role of the "totalizing classification" and squaring off regions of the Earth into "measured boxes" (Anderson, 2006, p. 173) can be explored in terms of human-technology relations conceptualized by Don Ihde (Ihde, 1990). Using this approach enables analyzing how the world is experienced and phenomena made manifest through tools that are used by humans. At the same time, it also allows looking at how the subject (using a particular tool) is also constituted in a distinct manner. In the case of cartography and map use, there is a hermeneutic relation through which maps allow the world to be read or interpreted (Ihde, 2009, p. 43) through a technologically mediated interpretive process. Maps therefore mediate between the surveyor, explorer or state, and the territory in the world that needs to be made legible. But as mentioned in the shift from the plurality of measurements to a singular measurement system, making a city or entire body of the state (and beyond) more readable was tied to enabling greater extension of the state's control. Consequently, the means of making the world more readable transforms those that are read on the map to no longer be free from the potential control of those doing the reading. The use of maps transformed the territory as well as those who were mapped—as well as transforming the user of the map, instilling what Pickles (2004) refers to as the cartographic gaze. This gaze "privileged a particular form of seeing (distanced, objective and penetrating),

predicated on an epistemology and politics of mastery and control of earth, nature and subjects" (Pickles, 2004, p. 83). Using a map reshapes the subjectivity of the map user, as they gain a God's-eye perspective that expands their perspective as well as their ability to make claims over what they survey on the map. In the hands of the state, the map therefore functions not as a neutral mirror of the world but instead as an active component of extending state authority during the emergence of European cartographic practice. This is a result of what Dennis Wood refers to as the map's discourse function, as he considers maps to be "systems of propositions" that are "unrivalled as vehicles for the creation and conveyance of authority about and over territory" (Wood et al., 2010, p. 52).

As maps make the world legible, they do so by *making it legible in a particular way* in relation to who is producing them. Maps therefore project a functional perspective (Kiran, 2015) on what they map. It is this projection that becomes a "totalizing classification," as the map stamps what can be considered to be somewhere or not to be somewhere, gaining this totalizing character based on who authorizes the map. Consequently, as maps make statements about what does or does not exist and how they exist, as these statements become repeated and reaffirmed, they "solidify rapidly into facts" (Wood and Krygier, 2010), p. 52). There are a number of examples of this where the drawing of arbitrary boundaries or magnification of certain areas has far reaching consequences. For instance, one example of this is the Mercator map projection. Regions "near the equator tend to be smaller than those near the poles" making "the continent of Africa looks smaller in size to Greenland although the former is 14 times larger" (Wellner, 2020, p. 4). Such a discrepancy between spatial representations and the territory being represented can be said to reflect efforts of minimizing "the importance of Africa in global politics and enlarge Europe and its Northern territories" (ibid), or again in the Berlin Conference of 1884–1885, where the borders of African countries were not drawn up by members of these countries but by European states to support their colonial expansion (Pickles, 2004, p. 108).

The power and discourse function of the map is therefore to make things manifest that formerly were not, and the validity of this power reflects who is responsible for producing this manifestation. Since the "factuality of a map is a function of the social assent granted to the map's propositions" (Wood and Krygier, 2010, p. 52). This illustrates how the hermeneutic relation constituted through maps between map users and those in the areas mapped has epistemological (shaping the knowledge of what is mapped) as well as political (potentially expanding the power of those with the knowledge of what is mapped) impact.

3 Section 2—GIS and Deprived Area Mapping

From the late twentieth century, map production moved out of the state's exclusive hands, along with out of the hands of only professional cartographers (Crampton, 2001; Crampton & Krygier, 2018; Pickles, 2004). Advances in computing technology enabled moving from traditional cartographic methods that relied on surveyors, towards the capturing of digital data through RS (e.g., with satellites), specialized geovisualization software, and methods of analyzing spatial as well as temporal

relationships of geographic phenomena. These powerful tools known collectively as Geographic Information Systems (GIS), access to the Internet, improved graphical user interfaces, "coupled with easy access to large quantities of spatial data, [made] it possible for individuals to undertake many mapping and spatial analysis activities that would previously have been out of their reach" (Marble, 2015, p. 491). Although this shift in who can produce maps has also meant that there is no longer a strict need to follow cartographic rules on the way maps are presented, meaning that issues of misinterpretation, accuracy, and validation are also important to be aware of. These developments have led to maps being made and used in a variety of fields and purposes, including being produced by researchers, private companies, and NGOs for supporting humanitarian interventions.

3.1 Defining and "Capturing" Deprived Areas

Over the past two decades, there has been increasing attention given to LMICs regarding the use of geographic information to support urban (re)development. This attention has been part of long-running initiatives from the United Nations (UN) to increase the development in earth observation technologies and GIS, dating back to 2002 World Summit of Sustainable Development and further emphasized in the 2012 *The Future We Want* report and 2015 formulation of the *2030 Agenda for Sustainable Development*. These initiatives highlight the growing importance of improving the legibility of cities in LMICs, in light of the rapid urbanization that outpaces the ability of many countries to keep track of and adequately support the rising number of city dwellers (Kuffer et al., 2018). While censuses are often the traditional means of monitoring and keeping population counts, the developments in digital mapping has allowed researchers, non-governmental organizations (NGOs), and geographic information producing companies (e.g., Esri) to assist in improving the legibility of these cities. The importance of geoinformation in making these cities more legible reflects a different kind of cartographic gaze than one that is "predicated on mastery of the earth, nature and subjects" as Pickles frames it in Sect. 2. The cartographic gaze utilizing geoinformation technologies is predicated on mastery of spatial data for humanitarian aid, which begs the question—what responsibility do those who control the spatial data have over those who are represented in the data? This question shall be returned to in Sect. 4.

Despite the inclusion of new actors in the production of maps, states (local and national governments) are still key actors in map-making. The greater availability of computational tools for map production has meant that a wider range of actors can make use of the map's discourse function to make their own spatial and territorial claims. But these claims are either made in contestation against the state's spatial and territorial claims (a situation commonly experienced by communities in deprived areas[1]) or are only given sanction if approved by the state. More so, it is

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[1] Many deprived areas are excluded from official state maps or underrepresented for a variety of reasons, which leads to their very existence being something that maps can epistemically and ontologically erase or make visible.

also the case that many humanitarian initiatives from private companies as well as NGOs rely on collaboration with the state. Therefore, while the exclusivity of map production is no longer solely tied to the state's hands (or state approved hands), this does not mean that the state is not also invested in the digital cartographic landscape. Thus, as citizens, communities, NGOs, and private companies take control of map production and dissemination for research, commercial, and recreational purposes, it should be noted that this democratization of the power and discourse function of the map is not completely divorced from the potential involvement of the state.

As a result of the growing demand of geographic data on cities in LMICs, areas and communities that would have been unacknowledged become visible and part of a growing trend of data-driven urban planning and management. Involving stakeholders both within and outside of the state where the mapping is done. The developments in digital mapping technologies and initiatives show that through "digitization qua geo-information, territories become a constitutive element in the essential technicity of perception, memory and decision-making" (Tinnell, 2014, p. 73), which is to say, the cities of the Global South are being read and interpreted in terms of these (re)development agendas, classified according to metrics reflecting how close or how far off they are from reaching the SDGs. The legibility of these cities relies on utilizing geoinformation technologies for the collection of geoinformation to understand urban morphology, the demographics of specific communities, and their exposure to environmental risks.

And such geoinformation is especially scarce in areas commonly referred to as "slums" or informal settlements. Following the work of Kuffer et al. (2020) and Thomson et al. (2020), the term deprived area will be adopted throughout the paper in place of "slum" or informal settlement where deprivation is looked at as a value (from highly deprived to not deprived) rather than a binary division (i.e., slum and non-slum/formal and informal). The information on deprived areas has been a problem that warrants increased international attention due to the rate at which these areas are growing. Deprived urban areas are a global phenomenon (Verma et al, 2019, p. 1), and "are the most visible, distinct manifestation of poverty" (Wurm et al., 2019, p. 59). Their growth is often in response to high rates of rural–urban migration that outpaces the planning as well as capacity management of many local governments (Ajami et al., 2019; Kuffer et al., 2017; Wang et al., 2019). Although they are a global phenomenon, deprived urban areas are heterogeneous in form and character (Taubenböck & Kraff, 2014, p. 42). At the same time, many studies use the operational definition of what counts as a "slum household" based on five aspects: lack of security of tenure, water and sanitation, overcrowding, and inadequate structural quality of housing (UN-Habitat, 2018), measured according to the criteria in Table 1. Though it should be noted that the measures below define a slum "household," while the shift to measures of deprivation combine the situation faced by communities at the household level and area level (e.g., assessing the deprivation of an entire neighborhood).

While the growth of deprived urban areas is being given more attention, this growth is not being documented in a consistent manner (Kuffer et al., 2018) which has contributed to those living in these areas being underrepresented in official state statistics. This lack of consistency is due to a number of reasons. Firstly, traditional

Table 1 Indicators used by UN-Habitat in categorizing "slums" (UN-Habitat, 2018)

INDICATOR	MEASUREMENT
SECURITY OF TENURE	• Proportion of households with formal title deeds or tenure arrangement to either land and/or residence
ADEQUATE WATER	• Settlements are considered to have an inadequate water supply if less than 50% of households have a household connection, public stand pipe, or less than 20 L/person/day available
ACCESS TO SANITATION	• Settlements are considered to have inadequate sanitation if less than 50% of households have public sewers, septic tanks, pour-flush latrine, or ventilated improved pit latrines
STRUCTURAL QUALITY OF HOUSING AND LOCATION	• Settlements are considered lacking adequate location if they are located next to geological hazardous zones, around high-industrial pollution areas, or other unprotected high-risk zones (e.g., railroads and energy transmission lines) •Settlements are considered lacking in structural quality of housing based on the quality of construction materials and compliance with local building codes, standards, and bylaws
OVERCROWDING	• Settlements are considered overcrowded if households have more than two persons allocated in a room

censuses are generally outdated (with data often being 2–3 years old) and fail to account for the rapid growth of these areas. Secondly, deprived areas are defined differently throughout the world and even within the same city experts and communities differ in categorizing what counts as a deprived area (despite the operational definition from UN-Habitat) (Kuffer et al., 2017, p. 3). Without one universal term to use, identifying these areas will always be a local rather than global classification, which also presents a technological issue, since depending on the semantic classification, geoinformation technologies will either be able to identify and represent these areas in satellite or drone imagery or fail to do so (leading to continued underrepresentation). Thirdly, boundaries that distinguish where these areas start and stop are not always clear or agreed upon (Verma et al., 2019, p. 1). Lastly, the data on these areas is either inadequate due to the lack of ability to access certain deprived areas due to their morphology or the data shows signs of political manipulation as some governments do not acknowledge these areas (Wurm & Taubenböck, 2018, p. 42). Thus, these issues contribute to challenges in measuring the composition, rate of growth, and exact locations of deprived urban areas.

Due to these challenges, there are geoinformation gaps regarding the exact location, composition (i.e., morphological, population, and socioeconomic status), as well as environmental risk exposure of deprived urban areas. These gaps make it difficult to properly meet the SDGs, notably SDG 3 (promoting good health), 6 (access to clean water and sanitation), 11 (access to affordable housing), and 13 (climate change adaptation). To close these geoinformation gaps, there is an increasing turn towards computational methods to supplement the identification of deprived areas. And in the turn to computational methods, as already mentioned, new actors including private organizations (e.g., Google's Open Building data), researchers, NGOs, and the communities living in deprived areas themselves can take on the role of

mapping as well as distribution of maps themselves. But it should not be assumed that there is now a complete divorce between the state and these mapping projects and technologies. Rather, digital mapping methods have grown to supplement the state's epistemic gaps, with the crucial difference being these gaps are reduced for reasons other than simply state expansionism.

3.2 AI-Assisted Deprived Area Mapping

The use of computational tools to identify deprived urban areas falls under the discipline of Earth Observation (EO) and RS. RS has been used for decades to produce land cover maps using visual image interpretation or parametric classification methods of moderate resolution images (e.g., 30-m Landsat images). Since the availability of very high-resolution images (after 1999), urban mapping has been booming. Increasingly over the past decade, studies in RS deprived area mapping have utilized classical machine learning (e.g., using Support Vector Machine) and more advanced semi-automatic convolutional neural networks (CNNs). The choice of using ML methods in RS has become attractive for researchers due to the increased availability of open-source satellite datasets and open-source DL modules to make use of. These allow the transformation of geospatial data "into different layers of abstraction which are then used for prediction and data presentation tools" (Verma et al, 2019, p. 2). The significance of this increased reliance on machine learning (ML) for the identification and classification of deprived areas is taking the traditional role of reading and interpreting spatial data being done primarily humans, to the combined reading and interpreting of humans and algorithms. Looking at the use of CNNs will help make this point clearer.

CNNs are "artificial neural networks that learn spatial-contextual features in several hierarchical nonlinear layers" (Mboga et al., 2017, p. 2). CNNs are able to detect objects in images as each pixel of an image is assigned a semantic class (Wurm et al., 2019, p. 60), this class being either "vegetation," "urban," or "slum." The ability of CNNs to detect these features of images relies not only on the particular set up of the algorithms used, but also on the periphery technologies involved, which include the specific geo-location of images, what kind of sensor or satellites are used (which affect the angle of the images as well as quality), and the resolution of the images used (which depends on choosing higher cost and higher quality, versus free, and coarser quality). Additionally, CNNs require massive amounts of training data which is especially an issue given the geoinformation scarcity of deprived areas.

An illustrative example of a CNN-deprived area mapping workflow is given below (Fig. 2), using a RS study of Mumbai (Verma et al., 2019). The first step in the process is selecting input images, such as satellite imagery, of the deprived area. In the Mumbai study, satellite images and a reference map of labeled slums from the Mumbai Metropolitan Regional Development Authority were used. A training dataset is then created, which has specific urban classes labeled (e.g., slum, vegetation, water), and samples from the input images are selected that represent these urban classes—a portion of the samples are reserved as a testing dataset not fed into the CNN at this stage. These samples of the training dataset are then processed through
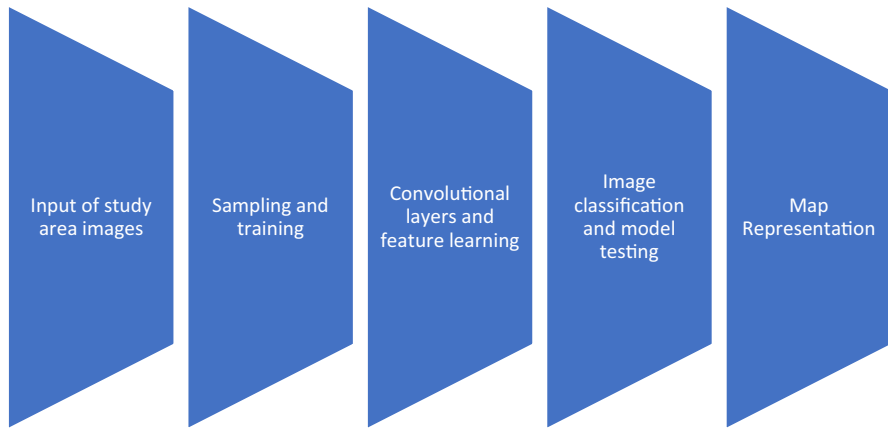
Fig. 2 CNN-deprived area mapping workflow

the convolutional layers to detect features of each class, learning these features as the layers go through several iterations of training. Once the CNN is trained, its ability to detect these features is tested by using the samples from the test dataset—this allows measuring the accuracy of the CNN's ability to predict where deprived areas can be found. These predictions are then output in the last stage as maps that are generated which highlight where deprived areas are predicted to be (as seen in Fig. 3). It needs to be highlighted that the performance of the CNN heavily depends on the availability, quality, and size of the training dataset, as this will influence the ability of capturing the necessary features of deprived areas. In addition, there is also the time that it takes to train CNN models, ranging from weeks to months.

The usability of the generated maps in supporting communities (e.g., by improving representation or in helping upgrading projects) depends on a number of factors. Firstly, how well these CNN-based maps can offer support relies on the levels of uncertainty they contain, meaning how well the generated maps overlap with the study area images and the errors that exist between the generated map and the area mapped. This is due from the beginning on the quality of the images used as input, as well as the training data that the model is trained with, which affects the accuracy of feature extraction and classification. Secondly, the scale of the maps (i.e., covering a small portion of a city or entire region) affects the level of support, which depends on the RS technology chosen, resolution of images, as well as validation of generated maps. Thirdly, while the CNN and algorithm used in one city may be effective in capturing the features of deprived areas in that particular city, the same CNN and algorithm may not be able to perform as well in other cities. This is due to the training of the algorithm as well as the heterogeneity of the morphology of deprived areas. As a result, the transferability of the CNN and algorithm is negatively affected, as the ability to classify and represent deprived areas in one city may be high, but in mapping other cities, the CNN may not perform as well. These technical challenges therefore limit how well CNNs or in general any other AI-assisted

Fig. 3 Prediction of slum areas in Mumbai by CNN using very high-resolution (left) and medium-resolution (right) imagery, with boundaries from reference map (Verma et al., 2019)
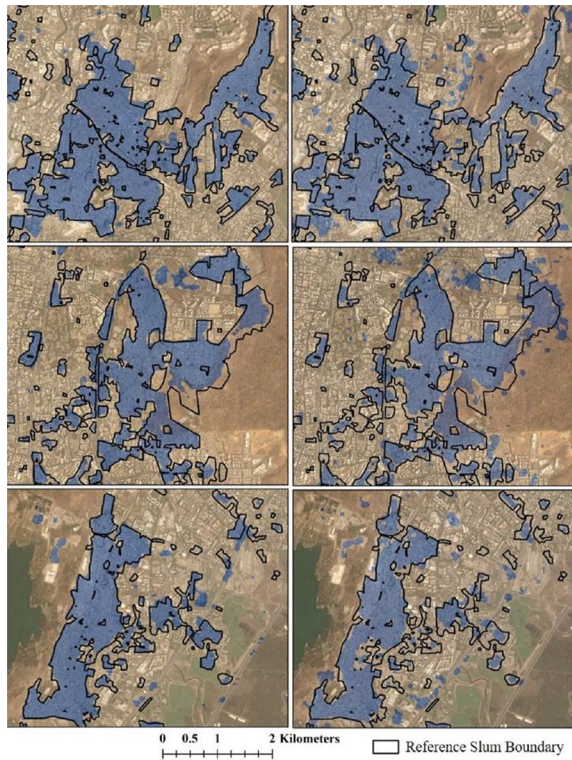
techniques of deprived area mapping can aid in national and international level support (e.g., monitoring SDGs or upgrading the infrastructure in deprived areas).

4 Section 3—Making the Unseen Seen

4.1 The Hermeneutic Mediation of Machine Learning

The use of CNNs points towards the opportunity of algorithmic assistance in improving the legibility of deprived areas, as well as offering an interesting instance for analyzing the hermeneutic mediation happening through ML-generated maps. In the deprived area mapping literature, it is worth taking note that a difference is made between the "slum"/deprived area as it exists and the "morphological slum" or "RS-based identification" (Wurm & Taubenböck, 2018, p. 46) of deprived areas that is captured by RS technologies. As the exploration in the previous section of the CNN-based workflow captures, this difference is reflective of a process of choices as well as interactions between geoinformation technologies and software mediating between the deprived area and the geoinformation scientists who produce these remotely sensed maps. In the traditional human-technology relation schema offered by Don Ihde (2009), this hermeneutic mediation would appear as follows:

Human (technology – world) or User (CNN-generated map – deprived area)

Given that deprived areas are often either left out of state censuses or under-represented due to their rapid growth, RS is involved in making the unseen seen, revealing what in many cases are the invisible within cities in LMICs. But the use of ML introduces a new element to the hermeneutic relation constituted by maps. Notably, "machines share the task of interpreting and analyzing the data" regarding deprived areas, as "the software performs its own interpretive tasks, categorizing and suggesting its own predictions" of the size, boundaries, and location of deprived areas (Hongladarom, 2020, p. 5). Hongladarom's assessment of the involvement of machines in the hermeneutic process, alongside humans, led him to create the following schema of human-technology relations:

I – technology – World2 – AI – World1

where World1 represents where the input for the AI comes from, in the case of deprived area mapping, the study area images, and training dataset (i.e., ground-truth data). The AI is the CNN that then works to extract and classify features from World1, producing World2 or the "morphological slum." This is what is interpreted by the CNN and is represented through the specific geoinformation software and hardware used by geo-information researchers as well as other stakeholders that would use the CNN-based deprived area map for community support. As deprived areas cannot be delineated directly in satellite imagery, AI/ML and other geoinformation techniques enable the revealing of these areas. The process of remotely sensing the deprived area is therefore a layered, technologically mediated process, and the CNN is actively involved in revealing the deprived area. The difference between the AI and the technology is that while the technology (e.g., satellite or visualization software) is relatively transparent (i.e., merely presenting images of the deprived area), the CNN makes the deprived area visible based on the training data and testing data used. The more automatically these algorithms perform the classification of these areas, the more involved they are in mediating and making claims over where deprived areas are and what form they take. Consequently, in line with what Wood and Krygier (2010) referred to as the traditional map's discourse function, this machine hermeneutics, as Hongladarom refers to it, calls to attention the algorithmic discourse function of AI-assisted map production.

And this algorithmic discourse function also presents several challenges that need to be addressed. Firstly, there is the role of bias in the selection of training data for CNNs, biases that may be present on the side of those responsible for acquiring and labeling this data. Such biases can lead to reducing the accuracy of predictions, given that if a model is trained with data in one region, city, or type of structure (e.g., roof material), the model may not be as able to classify objects in another region. The biases in the training data may not always be documented or communicated, which can therefore lower the efficacy of the finished map products—if these products are to be used for humanitarian interventions.[2] Secondly,

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[2] Many studies of the application of AI to deprived area mapping are published for researchers without necessarily being instrumental in policy decisions or NGO initiatives.

there is a gap between the promise of AI-assisted deprived mapping to improve the wellbeing of communities and the capability of the community to be part of the interpretation, critique, and access to the process of map production. As will be explored further below, the communities mapped are often left out of the dialogue on the value and outcome of mapping projects. This gap problematizes the accuracy of map products. The issue of accuracy becomes reflective of those living in or nearby communities (including NGOs and municipal authorities) disagreeing with the boundaries that are drawn by algorithms used by researchers on the extents of the deprived areas, showing that there is a definite need for input from those on the ground, despite promise of the higher-level and semi-automatic classification done by ML models. More so, this is coupled to the challenge of utilizing finished ML map products into policy decisions, as was the case in a study in Indonesia where municipality authorities did not see the usability of ML-based deprived area maps (Leonita et al., 2018, p. 21) due to how computationally intensive and technically demanding the methods are. This shows that the technical potential of ML-based deprived area maps is not all that matters to their efficacy— whether the authorities on the ground can give their endorsement of these tools is also highly relevant. Thus, these ML-based maps may have a lot of promise, but their efficacy to improve the wellbeing of those mapped depends on the accessibility and adoption of these tools.

4.2 The Subjectivity of Those Mapped

And another dimension that is often missing in the literature of RS and AI-assisted deprived area mapping is the ethical dimension of RS mapping practices, particularly what it is like to be mapped by remote technologies and remote mappers. One notable study that explores this ethical dimension is Gevaert et al (2016), assessing the use of UAVs (unmanned aerial vehicles) to provide community support through deprived area mapping in Kigali, Rwanda. Beyond the more technical concerns regarding the difficulty in using UAVs along with more administrative issues of regulations limiting UAV flight, the study focuses on the feelings of the inhabitants towards the presence of the UAV. While many "were curious, crowding around to watch the flights, taking pictures and asking questions," there were also "a number of people [who] were concerned… based on the fear that the UAV was being used to survey the area and plan for expropriation" (Gevaert et al., 2016, p. 13). This fear is shared in many deprived areas due to the fact that not all governments provide support for those living in these areas, and so to put them on the map would be to invite unwanted attention by those who would want to evict them. In the Kigali study, these fears were due to lacking insight into why the area was being mapped using a UAV and who would be making use of the information after the mapping was finished. Similarly, in an interview with Vice Versa, Nicera Wanjiruk, the founder of the Kenya-based Community Mappers, highlighted that in many instances, geoinformation researchers

failed to gain the trust of community members due to their lack of transparency on why and for whom the information they gathered was for (Mwaura, 2021, para. 9–10).

This illustrates the responsibility that researchers have to the people that are being mapped, a responsibility that is not always overtly stated. More so, it is not always clear the extent to which communities living in deprived areas can even give their consent to the production of these maps. Partially given that the images used to produce maps may be open source, the level of detail may not be able to identify individuals, but perhaps mostly because there is often a lack of direct contact between researchers and the communities they map, direct contact that would enable dialogue on the value and accessibility of these mapping tools, as well as training in reading data and using these technologies. The lack of direct contact is especially problematic given the fact that the way the spatial data is represented can have consequences on the lives of those mapped (e.g., leading to the eviction of those living in deprived areas). And lack of contact means those mapped cannot offer their critiques on how they end up being represented. There is therefore a gap that exists between the value of geoinformation that is expounded in the RS literature and the communication of this value to those who are being mapped.

And this gap has three important consequences for the utility of RS technologies in supporting these communities: the impact on the agency of communities, the potential lack of democratization of these technologies, and the lack of privacy and data protection of the spatial data collected on these communities. When these technologies are used by researchers who have no close communication with these communities, it leads to the members of these communities appearing as data subjects who provide information or in some cases who are ignored entirely (as the data is provided by municipal authorities). In such a situation, the growing demand for and gathering of geoinformation in LMICs may follow a similar trend as the demand and gathering of big data, whereby the legibility "created by the new data empires are not designed by states" which end up "making citizens better data subjects" or "better subjects of development interventions" (Taylor, 2016a, p. 5). This situation becomes more complicated when AI is used, given the opacity, uncertainty, and knowledge necessary to explain how the algorithms produce predictions of where deprived areas are to be found. As a result, this leads to an exclusive rather than inclusive process of mapping these areas, where the communities are left out of the conversation in how they are mapped.

Consequently, while the use of AI may improve the legibility of deprived areas, this gives rise "to a condition of ever-increasing legibility without better political representation" (Taylor, 2016a, p. 5). And this reveals the second consequence, the lack of democratization of these technologies. In many cases, the lack of communication between researchers and communities means that there is a lack of access to the data that is gathered or insight into where

the data is stored and by whom. In other cases, based on the way that the algorithms are trained, there will be biases in what fits the semantic class "slum"/deprived area. These biases will have the effect of capturing some deprived areas but leaving many underrepresented, contributing to further deepening the invisibility of these areas, and continued lack of support for the communities within them. This highlights the importance in not only how much data is needed in the training of these algorithms, but it also points out the importance of which stakeholders are involved in the validation of the data that is provided and maps produced.

More so, as these RS technologies can produce greater visibility in relation to the geospatial data that is gathered and used, an additional point of concern becomes privacy and data protection not just at the individual level but at the level of the communities that are mapped. While becoming made visible may, on the surface, be what communities living in deprived urban areas require to be able to give voice to their struggles, this visibility can also be detrimental. From a privacy and data protection standpoint, mapping deprived areas is epistemically concerned not with singular individuals but identifying classes (e.g., built-up or "slum") based on the geospatial data that is collected and fed through CNNs or other algorithmic techniques. But if this process of identification is done exclusively by geoinformation researchers and their algorithms, without contact with those being mapped or local experts close to the communities, those living in these areas become grouped and classified remotely without their input. As highlighted by Taylor (2016b), the notion of groups in this context is no longer "collections of individual rights" as the process of being grouped is done algorithmically, "and the aim of the grouping may not be to access or identify individuals" (Taylor, 2016b, p. 15).

However, this carries the danger that even though the geospatial data collected by RS technology may not be personally identifiable to individuals living in deprived areas, actionable decisions can still be made by state authorities and private organizations that affect the communities that are being mapped. These actionable decisions can include improving conditions for the communities living in these areas (e.g., upgrading of facilities and infrastructure) as well as further endangering these communities (e.g., being forcibly evicted after their location is identified by state authorities). Consequently, any discussions on the accuracy, utility, and potential of RS technologies used to map deprived areas should be coupled to the concern that as algorithms and digital maps are more relied on in making communities legible, more attention should be paid to the privacy and data protection of these communities, something that presents not only an ethical but also legislative concern since while regulations such as GDPR focus on protection against harms through identification, algorithmic grouping bypasses this as "people may be acted upon in potentially harmful ways without their identity being exposed at all" (Taylor, 2016b, p. 19).

In sum, what the discussion so far has aimed to address is the fact that the transition to digital cartography for humanitarian purposes highlights that there are a range of technical, social, political, and ethical concerns that are worth being raised. While on the surface, it may appear as though humanitarian mapping projects downplay the role of the state (at local and international level), but this is not the case. The state is still invested in the role and importance of mapping, but under a different guise—the state is invested in digital cartography under the banner of urban development initiatives, rather than purely for state expansionism. But as new technologies and methods for mapping become available, spear headed by private companies and researchers, the role of ownership as well as production of maps has shifted from the state or state-appointed hands. What this has meant is that while there is a lot of promise, for instance with AI-assisted mapping, the efficacy of these new tools and methods relies on adequate skills and resources to operate them. At the same time, while private companies and research institutions may have these resources and skills, they cannot neglect the importance of ground truth data which is often difficult to acquire due to the epistemic gaps (e.g., census data being drastically outdated or reference maps not having consensus on boundaries) as well as socio-political factors (e.g., some states not wanting to make their data publicly accessible to researchers).

Without ground truth, the accuracy as well as level of uncertainty within AI-assisted mapping is something that needs to be well documented especially if one algorithm becomes used in multiple LMICs without getting the same results. More so, access to ground truth may be further problematized by the lack of contact that private companies and even research institutions have with NGOs and communities living in deprived areas. This may be due to the fact of physical remoteness, but also as highlighted above; this may be due to lack of trust and transparency between those mapping and those being mapped. Consequently, mobile phone and GPS-based mapping projects have been undertaken by NGOs (e.g., the land tenure recording tools of its4land[3]) and communities (e.g., initiatives supported by Slum Dwellers International[4]) so they may lead the mapping themselves rather than rely on private companies or research institutions (an area of the deprived mapping literature which it is outside the scope of this paper to be addressed). Thus, what is revealed is that there are a range of incentives as well as obstacles that exist between those who wish to deploy digital mapping methods for humanitarian intervention and those who are mapped by these methods. An overview of which can be seen in Table 2. This range of incentives and obstacles shows that the promise of digital humanitarian mapping, especially if assisted by AI, reflects a dynamic where geoinformation is a necessary tool to advance the interests of all actors involved, a tool that has a lot of promise, but the efficacy of which is not univocal.

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[3] https://its4land.com/

[4] https://sdinet.org/

Table 2 Incentives and obstacles for digital humanitarian mapping

Actor	Incentive	Obstacle
State (local and international) E.g., UN-Habitat	Reduce epistemic gaps for improving urban development strategies	Lacking the necessary skills and resources to make use of geoinformation tools (e.g., ML-based mapping)
Private companies E.g., Google Open Building and Microsoft Building Footprints	Producing geoinformation tools for commercial and humanitarian use	Lack of ground truth data to improve the scalability and transferability of certain algorithms and tools
Research institutions E.g., Integrated Deprived Area Mapping System[a]	Using geoinformation tools for humanitarian and research purposes	Lack of ground truth data to improve the scalability and transferability of certain algorithms and tools
Non-governmental organizations E.g., Slum Dweller International	Supporting deprived area communities	Lacking the resources to coordinate projects or contact with state municipalities for collaboration
Deprived area communities E.g., Community Mappers based in Nairobi, Kenya	Using geoinformation tools to improve their wellbeing through community-driven mapping	Lacking technical skills and ownership of data captured and in other cases trust in municipal/private/research actors

[a]https://ideamapsnetwork.org/

5 Conclusion

As cartography and map production has shifted from the exclusive hands of the state and professional cartographers, to a wider user group that includes researchers working towards humanitarian goals, the role of maps has also shifted. As outlined in Sect. 1, in the hands of the state, the map was an important tool that improved the legibility of cities, enabling greater control of the infrastructure as well as inhabitants of these cities. The legibility of cities is therefore closely tied to how space becomes classified and bounded, which has epistemic, social, and political consequences. But in the transition of map production being predominantly to further state expansionism to the international humanitarian demand for greater geoinformation on cities in LMICs, improving the legibility of these cities becomes part of supporting the communities of deprived areas. A key part of this transition is the development of computational methods in the classification, storage, and representation of geoinformation in the field of RS. Over the past decade, ML has increasingly been relied on to help in the semi-automatic classification of deprived areas, which warrants the need to pay attention to the role of algorithms in identifying and representing these areas. As expressed in Sects. 2 and 3, the use of CNNs demonstrates the technical potential as well as challenges involved in deprived area mapping. But the detrimental impact on the agency of those mapped, lack of access to data by more than just geoinformation scientists along with poor communication with communities on the value of gathered geoinformation that impedes the democratization of these technologies, and concern over privacy and data protection are all ethical aspects that need to be brought into greater consideration in the RS literature and mapping practice. These aspects are especially important to ensure that those in deprived areas are not seen as data subjects but instead become more integral to the gathering and validation of the geospatial data that is used to produce deprived area maps. Furthermore, the dynamic configuration of actors involved in the digital humanitarian mapping landscape reflects the incentives as well as obstacles that affect the demand and efficacy of geoinformation as a vital component for each of these actors, incentives and obstacles that highlight the need for collaboration and dialogue, if the promise of geoinformation especially as a means to improve the wellbeing of communities in deprived areas is to be actualized.

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Declarations

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