A Survey on Mapping Informal Settlements with AI

Arvin Hariri, Chelsea Baker, Daniela Shuman, Fabrizio Serafini, Moritz Pail, Palis Pisuttisarun
Harvard University
Cambridge, MA
{arvinhariri, cpbaker, dshuman, fserafini, mpail, ppisuttisarun} @college.harvard.edu

Abstract

This survey paper explores the use of AI in mapping informal settlements around the world. In particular, we illustrate which methods have been implemented by researchers over the last four years (CNN, classic ML, other), as well as where those methods have been implemented geographically, and to what degree of success. Finally, we discuss the ethical considerations of these research advancements and what they mean for the communities being mapped at increasing autonomous efficiency. We found that, while drawing boundaries between informal settlement buildings (building segmentation) proves the biggest and most variable challenge to current research, AI analysis of satellite image data has proved incredibly effective in the mapping process—across all researched geographies. Still, many of the models underlying this research were paper-specific, focusing on a few heterogeneous areas at once, ultimately reducing the generalizability of models across this field of research. Additionally, the more technical AI papers covered in this survey do not discuss any interactions or inclusion of mapped stakeholders, suggesting a new type of hermeneutic injustice when it comes to the automated representation of the voiceless.

Introduction

Over 1 billion people live in illegal living communities, or informal settlements,[1] across the world (UN, 2024). This number is expected to grow to 3 billion by 2050 as people are expected to move to urban environments. However, informal settlements are technically invisible in the eyes of the government. Despite being the most common form of urbanization on the planet, informal settlements are chronically understudied (Samper, Shelby, and Behary 2020). The lack of information within these communities results in a chronic lack of services and support from private organizations, private companies and public agencies. These communities face perpetual cycles of poverty and have little support in order to escape. An important step in providing the necessary support to open these communities up to the rest of the world is to close the information divide between these communities and the government, private companies, and non-profits.

> *"Billions of people are excluded from the rule of law, as the lack of a legal identity often prevents them from enjoying their rights as citizens. Setting up an* ***addressing system*** *is the first step towards tackling that issue."*[2]

Mapping informal settlements invites well-meaning stakeholders to provide services more efficiently and effectively. Further, mapping is the first step to formalizing these communities in the eyes of the government. As soon as a map exists, then an addressing system can be created, allowing residents to engage with the fruits of the formal economy and services from the government.

Existing efforts to address the *data darkness* in these kinds of communities have relied primarily on analyzing satellite imagery by hand. Since these communities can be 1) very large, and 2) often changing, hand-analyzed satellite-based methodologies have proven to be ineffective for cities, which require a deeper level of granularity to offer public or private services. Artificial Intelligence could offer a solution by offering quicker, more accurate, and more granular analyses. This is a survey of papers that used AI or Machine Learning technologies to map informal settlements across the world.

Objective of Study

This comprehensive review of related literature aims to achieve the following goals:

- Map the landscape of AI used in informal settlement mapping in the past 5 years
- Explore the social, political, or economic impact of these projects.
- Categorize existing methods for AI in informal settlements based on impact type, technology, evaluation method, and community engagement type.
- Document the conditions that are necessary for AI technologies to result in tangible impact in informal settlements

[1]Informal settlements are defined as communities developed without formal land rights, typically are illegal or fall out of control of the government. Slums, Favelas, ShantyTowns, Villas are other words for such communities

[2]Commission on Legal Empowerment of the Poor, United Nations Development Programme

We believe that such an exercise is useful because of the following reasons:

- Generate practical guidelines and examples for both communities that want to address their information invisibility and for AI researchers
- Encourage communication and collaboration amongst technologists and stakeholders. Particularly, to disseminate information about how leveraging AI in informal settlements may generate meaningful outcomes in these communities to encourage collaboration.
- Inform technologists and stakeholders on methodologies that can effectively apply AI technologies in informal communities to yield measurable impact.

Figure 1: Satellite Image of Dharavi, Mumbai, India

Problem Statement

Data darkness is defined as the state in which there is little information about an individual or community that makes it difficult for other stakeholders to engage. One way to tackle *data darkness* in informal settlements is to map these communities. Mapping these communities requires three components:

1. Identify the existing building structures
2. Identify the existing road systems
3. Identify the boundaries of the community, including differentiating what is already mapped and what still needs to be mapped.

Mapping these settlements using satellite data is difficult for a few reasons:

- Imagery is not always high quality, as it often based on only satellite imagery and not paired with aerial imagery (as many developed countries have).
- Depending on the environment, many buildings can be stacked on top of each other.
- Streets and alleys can be visually difficult to identify using satellite imagery given the density of the environments.
- These environments can rapidly grow, up to doubling in number of people per year (Samper, Shelby, and Behary 2020). Any system needs to be quickly deployable.
- Existing data is sparse or non-existent, so unsupervised methods are necessary.

Overview of Types of Papers Discussed

The papers relevant for this survey are those that address one of the above three components of informal settlement mapping. The survey will explore how these technologies address the difficulties in mapping informal settlements using AI or ML technologies.

Background on pre-AI models

Several papers have mapped informal settlements across the world without using AI models.

Samper et. al. (2020) mapped the boundaries of 215 settlements from manual from satellite imagery and self-reported community data. The growth of the settlements was mapped from 2000 to 2014. This was the first database of informal settlement growth of it's size and has been used by scholars to explore the changing nature of informal settlements.

While mapping informal settlements by hand has proven useful, the process is slow and subject to bias. A slow methodology is difficult to generalize to other communities or to document changes in the community. Thus, such by-hand efforts are sparse (documenting at most 215 informal settlements across the world). Further, by-hand efforts to map settlements can only occur on a yearly, or multi-year cadence. This is problematic because some settlements double within a year (Samper, Shelby, and Behary 2020). AI methods offer a faster mapping solution, allowing for a more scalable solution, as well as a solution that can track changes in these communities temporally.

Methodology

In selecting the papers to include in our review, we aimed to be comprehensive of the larger literature as well as sensitive to the nuances addressed by each paper. We used search tools such as Google Scholar and Harvard Hollis to select papers by the following criteria:

- The paper was published in the year 2020 or later. This ensured that we surveyed the most relevant recent efforts and familiarized ourselves with the most recent technologies. We made a few exceptions if the paper was very highly referenced, since we decided this would allow us to understand foundational influential works in the field.
- The method explored in the paper uses satellite imagery or aerial imagery, such as Sentinel 2A/B satellite imagery and Worldview-2 satellite imagery.
- The problem the paper aims to address relates either to the task of building segmentation or the impact of informal settlement identification:
  - The paper relates to building segmentation (task related). This may specifically be in the context of slum buildings or more generally in the context of other buildings. This pertains to the task of identifying and delineating the boundaries of buildings within an image or a scene.

– The paper relates to informal settlement identification (impact related). This pertains to the task of identifying whether a certain area or structure is an informal settlement—thus mapping areas where unplanned and housing developments exist within an image or scene.

- The paper methodology uses big data, whether supervised or unsupervised, to accomplish its goal. That is, the method utilizes large and diverse datasets to develop its ML model, such as in training or feature extraction.
- The paper methodology takes a machine learning approach, such as a convolutional neural network, random forest, linear regression, other methods, or a combination of ML methods.
- The paper contributes to technical understanding of the field or highlights important socio-technical or ethical considerations.
- The papers collectively highlight diverse geography and local contexts of informal settlements around the world. Given the diversity of informal settlements around the globe, an effort was made to include informal settlement efforts from around the world in order to provide a comprehensive picture of how these efforts look in different geographies and cultures.

Methods: Machine Learning with Big Data Multi-Layer Neural Network

Findings

Summary

We analyzed 32 papers that used advanced computational methods to identify informal settlements, identify buildings, or explore spatial or temporal characteristics of informal settlements. Here are some summary statistics:

- 32 papers that used advanced computational methods to identify informal settlements, identify buildings, or explore spatial or temporal characteristics of informal settlements
- 3 papers used street-level data (images or LiDAR) to identify whether a community was informal or to map the settlement (Ibrahim, Haworth, and Cheng 2021) (Miranda et al. 2021) (Najmi et al. 2022)
- 11 papers used some form of Convolutional Neural Network

We also read 4 papers that mapped slums by hand. These typically involved some combination of satellite imagery and local knowledge (Samper, Shelby, and Behary 2020), (Falco, Zambrano-Verratti, and Kleinhans 2019), (Kuffer et al. 2020), (Wurm et al. 2019).

Summary of Methods

Of the papers published since 2019, Table 1 demonstrates the breakdown of the papers.

We grouped all papers that used regression, random forests, or support vector machines for classification under Classical ML methods.

Overall, regression and machine learning techniques have been useful in this space consistently for the past 7 years for slum identification projects. Many of the largest slums have already been identified by hand. Many of these papers used a hand-made dataset in order to run a supervised approach. The shortcomings of this approach are two-fold. First, hand-made datasets represent informal settlements that have been studied enough to be able to create a dataset. However, many of the informal settlements where it is most beneficial to map, do not have a lot of data. Further, it is unclear that these classification methods, trained on higher data context settlements, would generalize to low-data context settlements. Second, these datasets require many person-hours to update. Given the nature of informal settlements, growth is very common, as well as changing structure of the built environment. These classification methods are useful within a couple years, but quickly become obsolete as the environment changes.

Table 1: Methodology Used since 2019

Method	Count
By Hand	3
CNN	11
Other	3
Classical ML	8

CNN technologies have become more useful as the model can be more generalizable. Further, CNNs can use a combination of supervised and unsupervised approaches in order to learn. Most CNN-based papers used satellite imagery to identify slums or go further and identify individual buildings. Given the low-data context, a teacher-student learning approach was effective for identifying individual buildings (Quinn 2021) and roads (Sirko et al. 2023) within informal settlements. This approach used a small subset of labelled data - either through hand labelling or from the Open Buildings Dataset - to train the ”encoder”. The student (’decoder’) learned from the teachers training process to classify more buildings. Together, the decoder and encoder learn to identify buildings, even in low-data contexts.

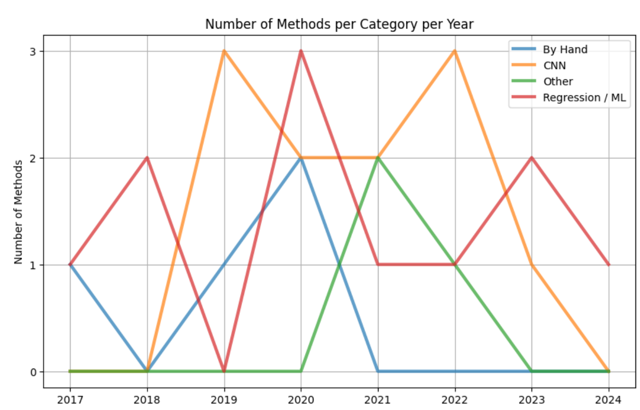

Figure 2: Categories of Methods Used by Year

Slum-Mapping Approaches

The recent advancements in slum-mapping techniques showcase a variety of approaches that utilize different data sources and methodologies. These methods can be broadly classified into three main categories:

Spectral and Object-Based Analysis Mudau et al. (Mudau and Mhangara 2021) and Fallatah et al. (Fallatah et al. 2022) represent the use of high-resolution satellite images and Landsat time-series data to identify informal settlements through spectral indices, textural features, and object-based machine learning analysis. This approach is beneficial for its detail and accuracy, particularly in differentiating between formal and informal settlements based on physical characteristics. Williams et al. (Williams, Wei, and Zhu 2020) employ a hierarchical object-based method that combines very high-resolution imagery with land boundary data to segregate slum from non-slum areas accurately.

Deep Learning and Semantic Segmentation Fan et al. (Fan et al. 2022) introduce UisNet, leveraging transformer-based blocks for semantic segmentation, significantly enhancing the mapping accuracy of urban informal settlements by integrating high-resolution images with building polygon data. Rehman et al. (Rehman et al. 2022) develop a semi-supervised learning approach for detecting temporary slums, combining deep learning segmentation with a scoring module for iterative improvement. Stark et al. (Stark et al. 2020) demonstrate the use of convolutional networks trained across varied geographies, indicating the importance of considering different morphological features of slums for effective mapping.

Transfer Learning and Scalability Owusu et al. (Owusu et al. 2024) focus on creating scalable and transferable models using Sentinel-2 data, highlighting the importance of adaptable models across different urban environments. Wurm et al. (Wurm et al. 2019) and Verma et al. (Verma, Jana, and Ramamritham 2019) explore transfer learning techniques to enhance the performance of models when applied to different resolution datasets or varied geographic locations, showing improvement in detecting slum areas accurately.

Accuracy Levels

The effectiveness of slum mapping approaches can significantly vary based on the methodologies employed and the data sources used. In evaluating the accuracy levels of these methods, we refer to specific metrics such as overall accuracy, mean intersection over union (mIoU), precision, recall, and F1 scores.

Spectral and Object-Based Analysis Fallatah et al. (Fallatah et al. 2022) report a high mapping accuracy of 95% using an object-based machine learning approach combined with time-series analysis. This demonstrates the effectiveness of combining spatial and temporal data for slum identification. Williams et al. (Williams, Wei, and Zhu 2020), through their hierarchical object-based method, achieve an impressive accuracy rate of 93.5% on satellite images from the Kingston Metropolitan Area, Jamaica.

Deep Learning and Semantic Segmentation Fan et al. (Fan et al. 2022) show outstanding performance with their UisNet model, achieving an overall accuracy of 94.80% and an mIoU of 85.51%, significantly outperforming existing semantic segmentation models on the UIS-Shenzhen dataset.

Transfer Learning and Scalability Owusu et al. (Owusu et al. 2024) present varied performance across cities with their Sentinel-2 data-based model; while a specific overall accuracy rate is not mentioned, they highlight a deprived F1 score of 0.81 when a model trained on Accra, and then a score of 0.68 for Lagos , indicating challenges in scaling. Wurm et al. (Wurm et al. 2019) show improved performance when transferring models to Sentinel-2 data, with an increase from 38 to 55% in positive prediction value and from 79 to 85% in sensitivity, showing the potential of transfer learning in varying contexts. Verma et al. (Verma, Jana, and Ramamritham 2019) achieve an overall accuracy of 94.2% and 90.2% for VHR and medium-resolution imagery, respectively, with Kappa scores of 0.70 and 0.55, demonstrating the effectiveness of pre-trained neural networks in slum detection.

Comparing these approaches, deep learning and semantic segmentation methods, particularly the UisNet model (Fan et al. 2022), stand out for their high accuracy and mIoU rates, marking them as highly effective for fine-scale slum mapping. Spectral and object-based analyses also demonstrate significant accuracy, especially when integrating spatial and temporal data (Fallatah et al. 2022; Williams, Wei, and Zhu 2020). Transfer learning methods show variable success; however, they hold potential for scalability and application across different geographical settings (Owusu et al. 2024; Wurm et al. 2019; Verma, Jana, and Ramamritham 2019).

Geographies

We find a significant geographical diversity in the study of informal settlements and urban slums. While the majority of the informal settlements explored in the analysis are concentrated in the Global south, but range from South America, to Africa, to South and East Asia. A visual overview of the geographies that are covered in the surveyed papers can be found in Figure 4.

In Table 2 we aggregate papers on a geographic level, where we group studies that focus on the same country together. Note, however, that even when papers focus on the same country, they often explore different urban areas within that country. The table shows that scholars predominately focus on a singular national context. (Matarira, Mutanga, and Naidu 2022; Prabhu, Parvathavarthini, and Alagu Raja 2021; Mahabir et al. 2020; Sirko et al. 2021; Fallatah et al. 2022; Falco, Zambrano-Verratti, and Kleinhans 2019; Lorraine Trento Oliveira and Pedrassoli 2023; Alrasheedi, Dewan, and el Mowafy 2023; Rehman et al. 2022; Miranda et al. 2021; Wurm et al. 2019; Williams, Wei, and Zhu 2020; Mast, Wei, and Wurm 2020; Mudau and Mhangara 2021; Verma, Jana, and Ramamritham 2019; Fan et al. 2022; Tingzon et al. 2020; Najmi et al. 2022; Owusu et al. 2021b).

Country	Count	Author(s)
India	5	(Prabhu and Parvathavarthini 2022; Prabhu, Parvathavarthini, and Alagu Raja 2021; Ansari, Malhotra, and Buddhiraju 2020; Wurm et al. 2019; Verma, Jana, and Ramamritham 2019)
Brazil	4	(Lorraine Trento Oliveira and Pedrassoli 2023; Miranda et al. 2021; Arndt and Lunga 2021; Wurm et al. 2019)
South Africa	3	(Matarira, Mutanga, and Naidu 2022; Arndt and Lunga 2021; Mudau and Mhangara 2021)
Kenya	3	(Arndt and Lunga 2021; Prabhu and Parvathavarthini 2022; Mahabir et al. 2020; Owusu et al. 2024)
Saudi Arabia	2	(Fallatah et al. 2022; Alrasheedi, Dewan, and el Mowafy 2023)
China	2	(Mast, Wei, and Wurm 2020; Fan et al. 2022)
Venezuela	2	(Falco, Zambrano-Verratti, and Kleinhans 2019; Arndt and Lunga 2021)
Ethiopia	2	(Sirko et al. 2021; Arndt and Lunga 2021)
Tanzania	1	(Arndt and Lunga 2021)
Senegal	1	(Arndt and Lunga 2021)
Thailand	1	(Arndt and Lunga 2021)
Indonesia	1	(Najmi et al. 2022)
Ghana	1	(Owusu et al. 2021b, 2024)
Jamaica	1	(Williams, Wei, and Zhu 2020)
Pakistan	1	(Rehman et al. 2022)
Nigeria	1	(Owusu et al. 2024)

Table 2: Countries by count and author: The table shows a break-down of geographies by country found in the surveyed papers.

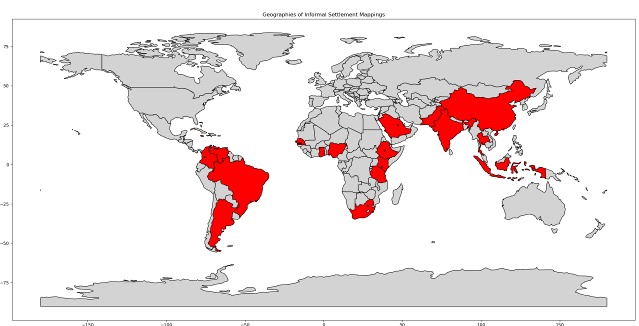

Figure 3: Locations of informal settlements that came up in literature. Countries that have come up are shaded in red. Specific cities that were mentioned are indicated with a black pin.

This reflects the reality that the mapping of informal settlements often necessitates local expertise, but also poses challenges and limits on the scope for broader generalization of these studies. However, there does exist a small set of studies that adopt a cross-country approach with the aim to develop methods to map informal settlements from different geographic and cultural contexts. (Stark et al. 2020; Arndt and Lunga 2021; Prabhu and Parvathavarthini 2022; Owusu et al. 2024)

Overall, our analysis highlight a research landscape that is widely fragmented by geography. While the focus on specific urban or national settings is crucial for capturing cultural, and morphological context that is associated with informal settlements in the region, it limits the potential for generalization across regions. Our analysis thus highlights a fundamental challenge in mapping informal settlements: achieving a balance between then need to capture local context and the need for methods that generalize across geographies.

Data Sources

Satellite imagery plays an important role for the analysis of informal settlements. Our survey finds that researchers are leveraging a variety of different datasets to suit their specific spatial requirements while adhering to limitations such as cost and availability. The majority of the surveyed papers use Sentinel-2A and Sentinel-2B data, which is usually classified as medium resolution (MR) satellite imagery data (Matarira, Mutanga, and Naidu 2022; Wurm et al. 2019; Verma, Jana, and Ramamritham 2019; Tingzon et al. 2020; Owusu et al. 2024; Sirko et al. 2021). Other data sources that are used in the literature include WorldView-2 (Prabhu, Parvathavarthini, and Alagu Raja 2021; Ansari, Malhotra, and Buddhiraju 2020; Prabhu and Parvathavarthini 2022; Mudau and Mhangara 2021), PlanetScope (Stark et al. 2020), GeoEye-1 (Fan et al. 2022), and SPOT-6 (Owusu et al. 2021b). Because VHR satellite imagery is expensive and not always readily available (Owusu et al. 2024), another trend that we found in our analysis, is using auxiliary data (e.g. OpenStreetMap, VHR imagery, etc.) in addition to MR imagery. (Fan et al. 2022; Fallatah et al. 2022; Verma, Jana, and Ramamritham 2019; Owusu et al. 2021b; Wurm et al. 2019)

Overall, we find that similar to the geographies of the studies, there's a big variation in what remote sensed datasets authors use in their studies. Since these datasets often form the foundation for the methods used in the papers, it makes it hard to compare model performance across studies. Further, we find that there is a lack of labeled data to test model performance. Instead, authors revert to creating manually labeled test datasets specific to their studies. Unfortunately, these datasets are often not made public, further complicating comparability and reproducibility.

Impact

The vast majority (92%) of the papers we explored in this analysis did not engage directly with the communities the projects were mapping.

The Google Open Buildings (Sirko et al. 2021) project that used a supervised CNN to identify the building footprints of buildings all across the globe, including informal settlements. Mapping the building footprints is disproportionately helpful for *data dark* communities, or communities that are not well studied, most likely to be informal settlements. Mapping these informal settlements is useful for a few reasons:

- Close the data gap between informal communities and the private market. Private companies need to have sufficient information to open business within these communities. For example, in order for a fast-food chain to open a franchise in the slum, the neighboring buildings need to be addressed. Additionally, providing addresses in the first place is useful for creating a useful system for the private market to engage with the community, i.e. through deliveries (Quinn 2021).
- Provide more accurate information for non-profits to offer poverty alleviation services. Sirko et. al. (2021) identified all the buildings in Ghana, even in the informal settlement (Sirko et al. 2021). After doing so, the team heard from UN agencies, non-profits, and academics who wanted to use the findings on the ground.
- Improve the logistical process for surveys to improve statistical indicators for national planning. Kuffer et. al. (2020) developed the IDeAMapS interface which contains deprived area mapping methods and slum area boundaries in urban areas across the world, identified by their methodology (Kuffer et al. 2020). The platform is open to any national or local governments, as well as community groups, NGOs, international agencies, or researchers. The platform is password protected for data privacy reasons, so only relevant stakeholders have access to the platform. The dataset is useful for these governments for reporting on more deprived regions.
- Governments and governmental organizations (i.e. UN or WHO) having access to more detailed and accurate information about the individuals living in informal conditions is directly useful for offering better humanitarian response in response to any emergency (United Nations 2019).

Gaps in Impact

None of the papers we looked at worked directly with the communities they were mapping. Of the mapping efforts that were used, the projects were impactful because third-party organizations found the resource and used the system after it was created (Kuffer et al. 2020) (Quinn 2021). This creates a divide between technologists and the stakeholders actually impacted by the system. This indirect form of engagement and value in the community needs to be improved upon in future AI for Informal Settlement papers.

While impact was hard to identify directly, it is important to mention that these papers did have an impact. Putting more information out there, even in paper form, is useful to address *data darkness*. The difficulty is the immeasurably of the impact. Because using the mapping tool requires additional involvement from other organization in order to bring in services to the community, the direct contribution of the mapping system is not easily identifiable.

Challenges

Although over 1 billion people worldwide live in informal settlements, research in mapping them is limited relative to the number of people affected by this work. The dearth of AI applications in this field can be attributed to several challenges that researchers face. In this section, we will highlight some of these factors that stakeholders in this area must address in order to support residents of these informal settlements.

Data Granularity

Mapping data is typically collected via satellite imagery taken hundreds kilometers above ground. Small buildings such as those contained in informal settlements only represent a few pixels within these images, even when they are high resolution (Quinn 2021). The deficiency of data on each of these buildings makes building segmentation, a key step in locating slum residents and connecting them with necessary resources, incredibly difficult. In light of this issue, researchers have proposed strategies to mitigate data granularity issues. (Miranda et al. 2021) observe a paucity of high-quality data mapping Rocinha, the largest informal settlement in Brazil. Urban research typically leverages aerial LiDAR data to gauge the morphology of informal settlements, but (Miranda et al. 2021) opt for LiDAR data collected on foot because many areas of Rocinha could only be accessed via foot traffic. This method also allowed these researchers to collect more granular data that may not have been high-resolution from an aerial perspective.

Building Segmentation

Building segmentation is a crucial step in mapping informal settlements, as it enables governments to provide addresses to residents and connect them with important public services. However, the nature of informal settlements can make this segmentation process particularly complex. Many of these limitations relate to the other challenges presented in this section. For example, lack of data granularity in informal settlements prevents algorithms from accurately classifying buildings. This phenomenon is described in (Quinn 2021):

> *"Because satellite imaging involves photographing the earth from several hundred kilometres above the ground, even at high resolution, a small building or tent shelter occupies only a few pixels. The task is even more difficult for informal settlements, or rural*

(a) Large buildings (b) Complex roof structure (c) Touching buildings (d) Ambiguous segmentation

(e) Tree occlusion (f) Confusing natural features (g) Round shapes vectorized to rectangles

Figure 4: Errors in building segmentation generated by the student-teacher classification model in (Sirko et al. 2021). Errors were sorted into 7 main categories, with (b), (c), (d), (e), and (f) most relevant to informal settlement mapping.

areas where buildings constructed with natural materials can visually blend into the surroundings."

The boundaries of each building may not be entirely clear, lowering the quality of training data and the resulting segmentation models. The quote above also touches upon the presence of natural materials, which both blur building boundaries and vary across geographies. Figure 4 provides some visual examples that (Sirko et al. 2021) encountered when doing building segmentation. This necessitates building out more specific and thus less generalizable models.

Generalizability of Methodology

A common issue raised by technologists working in this area is the lack of scalability and generalizability across algorithms. Many of these algorithms are trained on data from a single urban area, making them incredibly valuable in that particular locale but less useful elsewhere. Heterogeneity across slums in their topology, road systems, building structures, and surrounding features inhibits the development of methods that are applicable for different geographies. (Arndt and Lunga 2021) address this issue by developing two CNNs and deploying them in 13 cities across 4 continents. They incorporated both high-level urban structural units (USU) that were largely the same across cities as well as USUs unique to particular cities. Similarly, (Stark et al. 2020) develop a CNN called XFCN that they train using slums from different geographies with a diversity of morphological features. Most of the papers included in this document focus on an individual city or multiple urban areas within a single country. In the future, we advise researchers to develop more generalizable models that can be tailored to identify informal settlements in multiple geographies.

Dynamic Nature of Slums

UN-Habitat defines slums as households in which inhabitants lack one or more of the following features ((**?**)):

1. access to clean water
2. access to sanitation facilities
3. sufficient living area
4. housing durability
5. security of tenure

Many slums violate items 4 and 5 because of their transitory nature, inhibiting Rehman et al. (2022) distinguish between ”normal” and ”temporary” slums, with the former containing more of the aforementioned features than the latter. While ”normal” slums are semi-formal with some local economic activity and access to some amenities, temporary slums have significantly less access to amenities and are more vulnerable to displacement. (Rehman et al. 2022) The unstable nature of temporary slums makes them harder for governments to keep track of and thus further marginalizes their inhabitants. Rehman et al. develop a semi-supervised segmentation approach to map temporary settlements, supplementing the existing literature that focuses on more permanent informal settlement structures.

Ethical Considerations

There are several important ethical considerations in the field of mapping research. First, is an observation that, historically, the maps created by the researchers are done quite far away from the actual sites of investigation. For this reason, contact between the mappers and the mapped is sparse. If, as a society, we value maps as a source of truth, then one issue this asymmetrical research leads to is that of hermeneutic injustice, wherein one group of humans is exerting epistemic control over another. One well-known example of this is the Mercator projection, wherein our commonly shared world map spatially enlarges countries in the global north relative to many of those in the global south (Lobo 2023). Although mapping informal settlements can be seen as giving those without any recognition at least some form of visibility (and thus power), the externally imposed map does so by embedding them into the global apparatus and turning their existence into a site of public knowledge production.

Separately, mapping can lead to problematic outcomes where the maps are not distributed or provided to the residents of informal settlements. When a real-world application to the map is not found, it may simply stay in the hands of the researcher. When a real-world application is found, the map often simply goes to some local governing body (municipality, regional government) that is distinct from the settlement and does little to interface with settlement residents otherwise. Moreover, many governments, who refuse previously refused to map the settlements may have done so to avoid stretching their already-thin resources even thinner. If these governments were suddenly given maps, who is to say they would necessarily change their minds and provide the necessary aid and infrastructure (which are necessary for the social impact element of the research to begin with)? As Lobo et al. illuminated, many gangs live in these settlements to hide away from the government, and many community members, who have seemingly been abandoned by their government, have reason to mistrust it. Who is to say that, rather than using the map as a tool to spread economic prosperity, the government won't simply use it as a tool of surveillance, coercion, and control? Although researchers may not be able to conclusively enter a government's decision-making apparatus, this observation simply brings to surface that with great power comes great responsibility in the form of some basic due diligence. Maps should seldom, for example, be handed over to brutal authoritarian regimes or military dictatorships.

In other cases, the maps are given to third-party agencies, such as the World Bank (Lobo 2023), which are demonstrably aligned with humanitarian values. However, these organizations suffer from a top-down, abstracted approach to governance. It does not change the fact of hermeneutic injustice—that in the whole process, communities are ”read” but otherwise left in the dark.

Additionally, the notion of an AI's ”accuracy” may lead to the obfuscation of procedures and ultimately results. Researchers saying an AI was supposed to be accurate for a certain amount of time need to explain why it wasn't accurate that other, inevitable percentage of the time—in which case explaining the design of one's research is of paramount importance. Furthermore, done irresponsibly, AI can become a scapegoat when policy decisions that have pronounced effects on people's well-being, are found to be misinformed. In these instances, researchers may be able to use AI to deflect accountability, as while they understand the macro-levels of the workings of a CNN, it becomes impossible to understand the reasoning (and thus delegate responsibility) for any single decision that may have been wrong. For example, a recent project titled ”Do No Harm” with 510 Global and Red Cross Data Science uses AI to find weak building structures that are highly susceptible to future floods. If faulty AI predictions result in the unnecessary displacement of individuals and families which wouldn't have otherwise, it is easy to fall into the trap of no or low accountability (Lobo 2023).

Furthermore, while the abstraction problem of AI widens the gap of understanding from researchers, that gap is even further widened on the part of the researched. Although researchers may be unfamiliar with the results of their work, the mapped communities completely lose sight of the process that led to the results. In many of the papers, we saw how researchers could simply take satellite data of varying quality and make maps of it. Although this indeed opens up the possibility of not having to engage with community stakeholders, it is not necessarily specific to AI. We have seen a swatch of pre-AI research on mapping informal settlements, some of which have taken a community-oriented approach. For example, Falco et al. mapped settlements in Venezuela by crowd-sourcing knowledge from communities and encouraging them to fill out locations they were familiar with on a blank map (Falco, Zambrano-Verratti, and Kleinhans 2019). If, as discussed earlier throughout this section, non-engaging mapping methods lead to hermeneutic injustice, then this injustice is ossified with AI, as the hermeneutic aspect of the research has been replaced by a machine, and the procedural understanding of this machine requires extensive educational training. In other words, the interpretive element of mapping can no longer be explained—and thus cannot meaningfully be engaged with—unless the prospective "mapper" has extensive knowledge of how the AI works. This is realistically not the case for the residents of informal settlements, where educational standards are generally low (Lobo 2023). Thus, it becomes even more important for researchers to bridge that gap, and work with communities to translate their knowledge and desires into algorithmic thought.

Although there have been hints of advice throughout this section and particularly in the last paragraph hints, it is important to emphasize that there are no simple solutions to these ethical considerations. Rather, researchers need to further acknowledge the ambiguity of the map as an ontological and epistemological device, and designate their function as one of illuminating "possibilities" (Lobo 2023) rather than certainties or positivist notions of truth.

Future Directions

Direct Engagement: As mentioned above, 92% of the papers we found were developed in a lab and published, but did not work directly with the communities that were mapped. As shown by the papers that were used by nonprofits and government agencies, (Owusu et al. 2021b) (Tingzon et al. 2020) AI in Informal Settlements is significantly more impactful when there is direct engagement from the intended beneficiaries of the mapping system.

Temporal Characteristics: While buildings were spatially mapped across the globe, understanding informal settlements temporally is critical in order to provide governments with effective planning mechanisms. AlexNet and other CNN models have been used in temporal pattern recognition tasks. It may be worthwhile to explore how transfer learning can be used to measure growth of these communities.

More Robust Impact Evaluation Process: Impact in this space is difficult to measure because it requires buy-in from many different kinds of stakeholders. For example, health agencies may use the maps produced for efficient vaccine deployment, but if no health agency is willing to invest the resources to do so, the map may not be useful (Samper, Shelby, and Behary 2020). Introducing a framework for evaluating impact can be more useful in order to encourage more work in this field. Samper et. al. (2020) makes the argument that impactful mapping work is useful in so far as there is buy-in from the local communities (Samper, Shelby, and Behary 2020).

Introduce Standardized Benchmarks: The field is still rather fragmented and does not yet have slum segmentation benchmarks. These benchmarks exist in the developed world (such as connectivity and coverage), particularly as it pertains to the developed addressment system. We should introduce more granular and generalizable benchmarks to standardize how informal settlements are mapped.

References

Alrasheedi, K. G.; Dewan, A.; and el Mowafy, A. 2023. Mapping Informal Settlements Using Machine Learning Techniques, Object-based Image Analysis and Local Knowledge. *IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium*, 7249–7252.

Ansari, R. A.; Malhotra, R.; and Buddhiraju, K. M. 2020. Identifying Informal Settlements Using Contourlet Assisted Deep Learning. *Sensors*, 20(9): 2733.

Arndt, J.; and Lunga, D. 2021. Large-Scale Classification of Urban Structural Units From Remote Sensing Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14: 2634–2648.

Dufitimana, E.; and Niyonzima, T. 2023. Leveraging the Potential of Convolutional Neural Network and Satellite Images to Map Informal Settlements in Urban Settings of the City of Kigali, Rwanda. *Rwanda Journal of Engineering, Science, Technology and Environment*.

Falco, E.; Zambrano-Verratti, J.; and Kleinhans, R. 2019. Web-based participatory mapping in informal settlements: The slums of Caracas, Venezuela. *Habitat International*, 94: 102038.

Fallatah, A.; Jones, S.; Wallace, L.; and Mitchell, D. 2022. Combining Object-Based Machine Learning with Long-Term Time-Series Analysis for Informal Settlement Identification. *Remote. Sens.*, 14: 1226.

Fan, R.; Li, F.; Han, W.; Yan, J.; Li, J.; and Wang, L. 2022. Fine-Scale Urban Informal Settlements Mapping by Fusing Remote Sensing Images and Building Data via a Transformer-Based Multimodal Fusion Network. *IEEE Transactions on Geoscience and Remote Sensing*, 60: 1–16.

Gram-Hansen, B.; Helber, P.; Varatharajan, I.; Azam, F.; Coca-Castro, A.; Kopackova, V.; and Bilinski, P. 2019. Mapping Informal Settlements in Developing Countries using Machine Learning and Low Resolution Multi-spectral Data.

Ibrahim, M. R.; Haworth, J.; and Cheng, T. 2021. URBAN-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. *Environment and Planning B: Urban Analytics and City Science*, 48(1): 76–93.

Kuffer, M.; Thomson, D. R.; Boo, G.; Mahabir, R.; Grippa, T.; Vanhuysse, S.; Engstrom, R.; Ndugwa, R.; Makau, J.; Darin, E.; de Albuquerque, J. P.; and Kabaria, C. 2020. The Role of Earth Observation in an Integrated Deprived Area Mapping "System" for Low-to-Middle Income Countries. *Remote Sensing*, 12(6).

Lobo, T. 2023. The Ethics of Mapping Slums—And How AI Complicates the Picture. *Philosophy of the City Journal*.

Lorraine Trento Oliveira, N. S., Monika Kuffer; and Pedrassoli, J. C. 2023. Capturing deprived areas using unsupervised machine learning and open data: a case study in São Paulo, Brazil. *European Journal of Remote Sensing*, 56(1): 2214690.

Mahabir, R.; Agouris, P.; Stefanidis, A.; Croitoru, A.; and Crooks, A. T. 2020. Detecting and mapping slums using open data: A case study in Kenya. *International Journal of Digital Earth*, 13(6): 683–707.

Mast, J.; Wei, C.; and Wurm, M. 2020. Mapping urban villages using fully convolutional neural networks. *Remote Sensing Letters*, 11(7): 630–639.

Matarira, D.; Mutanga, O.; and Naidu, M. 2022. Google Earth Engine for Informal Settlement Mapping: A Random Forest Classification Using Spectral and Textural Information. *Remote Sensing*, 14(20): 5130. Number: 20 Publisher: Multidisciplinary Digital Publishing Institute.

Miranda, A. S.; Du, G.; Gorman, C.; Duarte, F.; Fajardo, W.; and Ratti, C. 2021. Favelas 4D: Scalable methods for morphology analysis of informal settlements using terrestrial laser scanning data. arXiv:2105.03235.

Mudau, N.; and Mhangara, P. 2021. Investigation of Informal Settlement Indicators in a Densely Populated Area Using Very High Spatial Resolution Satellite Imagery. *Sustainability*.

Najmi, A.; Gevaert, C. M.; Kohli, D.; Kuffer, M.; and Pratomo, J. 2022. Integrating remote sensing and street view imagery for mapping slums. *ISPRS International Journal of Geo-Information*, 11(12): 631.

Owusu, M.; Kuffer, M.; Belgiu, M.; Grippa, T.; Lennert, M.; Georganos, S.; and Vanhuysse, S. 2021a. Geo-ethics in slum mapping. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 5700–5703. IEEE.

Owusu, M.; Kuffer, M.; Belgiu, M.; Grippa, T.; Lennert, M.; Georganos, S.; and Vanhuysse, S. 2021b. Towards user-driven earth observation-based slum mapping. *Computers, environment and urban systems*, 89: 101681.

Owusu, M.; Nair, A.; Jafari, A.; Thomson, D.; Kuffer, M.; and Engstrom, R. 2024. Towards a scalable and transferable approach to map deprived areas using Sentinel-2 images and machine learning. *Computers, Environment and Urban Systems*, 109: 102075.

Prabhu, R.; and Parvathavarthini, B. 2022. Morphological slum index for slum extraction from high-resolution remote sensing imagery over urban areas. *Geocarto International*, 37(26): 13904–13922.

Prabhu, R.; Parvathavarthini, B.; and Alagu Raja, R. A. 2021. Slum Extraction from High Resolution Satellite Data using Mathematical Morphology based approach. *International Journal of Remote Sensing*, 42(1): 172–190. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01431161.2020.1834167.

Quinn, J. 2021. Mapping Africa's Buildings with Satellite Imagery.

Rehman, M. F. U.; Aftab, I.; Sultani, W.; and Ali, M. 2022. Mapping Temporary Slums From Satellite Imagery Using a Semi-Supervised Approach. *IEEE Geoscience and Remote Sensing Letters*, 19: 1–5.

Samper, J.; Shelby, J. A.; and Behary, D. 2020. The Paradox of Informal Settlements Revealed in an ATLAS of Informality: Findings from Mapping Growth in the Most Common Yet Unmapped Forms of Urbanization. *Sustainability*, 12(22).

Sirko, W.; Brempong, E. A.; Marcos, J. T. C.; Annkah, A.; Korme, A.; Hassen, M. A.; Sapkota, K.; Shekel, T.; Diack, A.; Nevo, S.; Hickey, J.; and Quinn, J. 2023. High-Resolution Building and Road Detection from Sentinel-2.

Sirko, W.; Kashubin, S.; Ritter, M.; Annkah, A.; Bouchareb, Y. S. E.; Dauphin, Y.; Keysers, D.; Neumann, M.; Cisse, M.; and Quinn, J. 2021. Continental-Scale Building Detection from High Resolution Satellite Imagery. *arXiv*. ArXiv:2107.12283 [cs].

Stark, T.; Wurm, M.; Zhu, X. X.; and Taubenböck, H. 2020. Satellite-Based Mapping of Urban Poverty With Transfer-Learned Slum Morphologies. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13: 5251–5263.

Tingzon, I.; Dejito, N.; Flores, R. A.; De Guzman, R.; Carvajal, L.; Erazo, K. Z.; Cala, I. E. C.; Villaveces, J.; Rubio, D.; and Ghani, R. 2020. Mapping new informal settlements using machine learning and time series satellite images: An application in the Venezuelan migration crisis. In *2020 IEEE/ITU International Conference on Artificial Intelligence for Good (AI4G)*, 198–203. IEEE.

United Nations. 2019. Goal 11: Make cities and human settlements inclusive, safe, resilient and sustainable. https://unstats.un.org/sdgs/report/2019/goal-11/.

Verma, D.; Jana, A.; and Ramamritham, K. 2019. Transfer learning approach to map urban slums using high and medium resolution satellite imagery. *Habitat International*, 88: 101981.

Williams, T. K.-A.; Wei, T.; and Zhu, X. 2020. Mapping Urban Slum Settlements Using Very High-Resolution Imagery and Land Boundary Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13: 166–177.

Wurm, M.; Stark, T.; Zhu, X. X.; Weigand, M.; and Taubenböck, H. 2019. Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks. *ISPRS Journal of Photogrammetry and Remote Sensing*, 150: 59–69.

Appendix

Paper Summaries

In this section, we briefly summarize each of the 30 papers that we identified for this survey. We list the paper summaries in no particular order.

(Rehman et al. 2022) Could give more context on the specific datasets in the final survey This paper proposes a method to aid the discovery of temporary slums through a semi-supervised deep learning segmentation-based approach. Specifically, Rehman et al.'s approach promises to help with data collection and labeling of temporary slums. The authors define temporary slums as a slum that is temporary in time and in the context of its building structures. Their approach consists of two parts, a segmentation module (based on the U-Net architecture) and a learning module. Initially, the segmentation and learning module are trained by feeding it 32 manually labeled images. After that, they use a scoring module to sample unlabeled images and to generate pseudo-labels for them. Next, they add these newly labeled images to the training set and update the segmentation and representation learning modules iteratively by repeating this process. To evaluate the effectiveness of their approach, the authors construct a large geographically marked dataset of remotely sensed temporary slums consisting of more than 200 potential temporary slum locations in Pakistan. Their approach outperforms existing semi-supervised data collection and labeling methods on a variety of benchmarks including mIoU, Precision, Recall, and F1. The paper does not explicitly measure any social impact.

(Stark et al. 2020) Could give more context on the specific datasets in the final survey This paper proposes a convolutional Xception network (XFCN) that can identify various forms of slums in PlanetScope, a high-resolution satellite image dataset. The authors motivate this problem by pointing to the increase in informal settlements, particularly in the Global South. While slum mapping can provide valuable information about the settlement's location and size, they argue that the task of mapping slums is difficult because of the imbalance of slum occurrences opposed to formal settlements, and the fact that slums express a variety of different topological and morphological features. The authors further identify heterogeneous roof-structures varying in shape and color, and data availability as well as quality as challenges. To make sure the XFCN generalizes, they train the model on slums from different geographies with a variety of morphological features (located in the 10 cities of Cape Town, Caracas, Delhi, Lagos, Medellin, Mumbai, Nairobi, Rio de Janeiro, São Paulo, and Shenzhen). Further, they find that transfer learning and auxiliary data (such as road networks from https://www.openstreetmap.orgOpenStreetMap) helps with training. The paper assesses the results on a set of classification evaluations, including IoU and F-1. As a test set, they manually labeled slums with the help of experts. The authors do not state any measure of social impact.

(Miranda et al. 2021) Could give more context on the specific datasets in the final survey This paper proposes a method to study the morphological features of informal settlements baesd on terrestial LiDAR (Light Detection and Ranging) data that was collected in Rocinha, the largest favela (informal settlement) of Rio de Janeiro, Brazil. The authors of this study argue that informal settlements, because of challenges with data quality of remotely sensed imagery and aerial images, have been understudied in the context of urban planning research. Yet, they argue that the morphological analysis of favelas is foundational to the study of important societal and environmental issues, such as airflow, landslide risk and structural safety, property rights, and accessibility. The paper shows that LiDAR data can be used to create maps at high spatial resolution that can inform the study of such issues. In particular, the authors propose five spatial metrics that can aid in urban research: *street width*, *street elevation*, *facade heterogeneity* (a measure of inconsistency in facade height), *facade density* (a measure of crowding among buildings), and *street canyon*, a metric that captures the width and depth of the facade relative to the street. While the paper only collects LiDAR data for two small sections of Rocinha, the authors argue that their method can be easily scaled to analyze entire informal settlements. There's no explicit impact assessement.

(Wurm et al. 2019) Could give more context on the specific datasets in the final survey This paper studies the transfer learning capabilities of fully convolutional networks (FCNs) to slum mapping in various satellite images. Specifically, it proposes a transfer learning regime in which a FCN is pre-trained on high-resolution optical satellite data (QuickBird) and is then transferred to relatively lower-resolution optical satellite data (Sentinel-2) and high-resolution SAR data (TerraSAR-X). Wurm et al. found that transferring the model to Sentinel-2 improves accuracy of the model on semantic segmentation tasks. While Quickbird images obtains 86–88% (positive prediction value (PPV) and sensitivity), the transferred model on Sentinel-2 improved from 38 to 55% and from 79 to 85% for PPV and sensitivity, respectively. Transfering to TerraSAR-X did not improve the performance on building segmentation. While the method presented in the paper is general, it was tested on satelite image data of Mumbai, India. The author points out that future experiments need to focus on large-area approaches and the transfer between different geographical regions. Could give more context on the specific datasets in the final surveyThis was done in Stark et al. 2020.

(Williams, Wei, and Zhu 2020) Could give more context on the specific datasets in the final survey Williams, Wei, and Zhu propose a machine learning and hierarchical object-based method to identify slum settlements using very high-resolution (VHR) imagery and land boundary data. They motivate their method by the goal of slum upgrading, a process that aims to turn around downward trends in a slum. Their hierarchical method works in a vie step process: First, multi-scale segmentation is run on the VHR images to obtain homogeneous objects. Second, the homogeneous objects are classified into five major land cover classes (Road, Waterway, Vegetation, Shadow, Built-Up). Third, a land boundary layer is used to segment the image into parcel objects, which are together with image features used to create homogeneous neighborhoods (NHs). Fourth, the image features of each NH is extracted. Finally, classification and regression trees (CART) are used to classify the NHs into slum and non-slum areas using the extracted features. To test their method, the authors use manually labeled satellite images from the Kingston Metropolitan Area, Jamaica, as their test set, and achieve 93.5% accuracy on it. Image features from the third step in the hierarchical algorithm include the building layout, building density, building roof characteristics, and distance from buildings to gullies. Further, they test their model on validating sites that are similar to the test site and achieve similar accuracies above 90%, suggesting that their model generalized to other slums in Jamaica and the possibly the Carribean region.

(Verma, Jana, and Ramamritham 2019) This study uses pre-trained al neural networks to detect slums in Very High Resolution (VHR) and Medium Resolution satellite images from Pleiades-1A and Sentinel-2B respectively. Verma et al. evaluated the model's perforamnce on a manually labeled test set, consisting of slum boundaries gathered from urban local authorities of Mumbai. They achieved an overall accuracy of 94.2 and 90.2 and Kappa of 0.70 and 0.55 for VHR and MR imagery respectively.

(Sirko et al. 2021) This paper used a dataset of over 99k satellite images that covered a range of types of urban environments including rural, suburban and dense. Using a combination of human labelling methods (on a subset of 1M satellite images) and a U-Net that contained an encoder-decoder technology, the encoder being based off of ResNet-50-v2. The paper used a self-training method, which was based on a teacher and student based method, and a supervised learning method (using the human labels). The evaluation method used mean average precision over the labelled data. They found that larger buildings in dense urban environments tended to be split into multiple buildings, lowering the accuracy in "displaced" communities (as per the paper's categorization). This supervised learning model was able to model 516M buildings on the continent of Africa using the dataset created by the self-training method. The Open Buildings Dataset is used in multiple projects across the world. For example, in Lamwo, a northern Ugandan province, the Open Buildings Dataset was used to identify priority areas for electrification using solar panels and grid infrastructure. Further, by using an https://sites.research.google/open-buildings/Open Buildings Dataset and https://maps.google.com/pluscodes/PlusCode, the team was able to assign a unique alpha-numeric address to each building which allowed households to engage with the formal economy (i.e. receive deliveries) and access emergency or social services. The UN Refugee Agency has been deploying the Open Buildings tools to more efficiently sample locations to survey, particularly in areas that have been more displaced. Additionally, the UN Habitat has been using the databse to study urbanization in Africa, particularly observing urban growth in areas that are hard to survey on the ground.

(Matarira, Mutanga, and Naidu 2022) This paper identifies the locational and spatial extent of the informal settlements in Durban, South Africa using spectral and textural data from three Sentinel 2A images. The informal settlements in these regions are typically on steep hills with dense road networks. Using the textural features, such as homogeneity, of the landscape, and the land use patterns, such as density), a supervised random forest classification algorithm was used on 782 training samples (of small polygons), to identify the land use. The truth values were extracted from Google Earth Engine platform. The methodology was useful to identify the most important predictors of identifying urban settlements. The accuracy of the model reached 94% in identifying informal settlements. The motivation for this paper was an intellectual exercise to observe characteristics of informal settlements, rather than to offer a useful tool to Durban.

(Prabhu, Parvathavarthini, and Alagu Raja 2021) This paper developed an algorithm to automatically identify urban slums in Madurai, India. The motivation behind the paper was to provide a service to government agencies to use to more effectively allocate resources for poverty alleviation and other government services. In these low-data environments, the authors opted to choose a methodology that relied less on labelled data (such as a CNN) and more on morphological techniques. The data was sourced from WorldView-2, which contained high-resolution satellite imagery. The methodology constructed different profiles of the shapes within the image and used a support vector machine (SVM) algorithm to classify the pixels within the image as informal settlements or not. The morphological approach had an accuracy of at least 89%. This work was useful in exploring a methodology that that could work well in low-data environments. The exercise was published to the Journal of Remote Sensing, but was not in collaboration with the city of Madurai, India.

(Ibrahim, Haworth, and Cheng 2021) This paper's objective was to identify informality and slums, as well as transportation modes, from aerial and street-level images, developing both the SlumsNet model, an object-based detection model, and a spatiotemporal data extraction method. The SlumsNet is a deep CNN model that depends on high resolution data for higher accuracy. SlumsNet relys on 3000 images of varying quality downloaded from the internet from various queries relating to slums. The object based model was used to identify people and transport modes in the urban scene, using an SSD, and creating a real-time identification software. The spatiotemporal data extraction observes the time data of the images and creates an image of these informal settlements on the time scale. The SlumsNet had a 85% accuracy, and using object detection, had an overall lower accuracy. Because of the reliance on data from the internet, there could be several data biases as the types of slums that are on the internet may be more selected to be identifiable or have some stereotypical characteristics. This would lead to other slums or informal settlements that don't exhibit these characteristics to have a worse accuracy. Additionally, this methodology does not rely on satellite imagery, so the methodology would not be applicable to informal settlements that have not been photographed and posted to the internet.

(Sirko et al. 2023) The student-teacher model used in Sirko et al. (2021) was extended to also detect roads in a variety of urban environments. This paper used Sentinel-2 satellite images to collect road and building information in low-data environments (such as informal settlements). The teacher truth labels are the Open Buildings dataset. With a training on 10 million images, the teacher model reached a model accuracy of 85%. This methodology relied on high resolution satellite imagery to train the teacher model in order to generate a large dataset to train the student model. Additionally, the teacher model relies on the Open Buildings dataset which is less accurate in dense urban environments with lot's of vegetation (such as informal settlement environments).

(Ansari, Malhotra, and Buddhiraju 2020) Can you include the figure a bit more in your analysis. I wrote the following sentence just so we have something, but I think you need to make the connection a bit more clear. Researchers have employed multiscale deep learning approaches to identify informal settlements in Mumbai and Pune, India. They develop an integrated tool leveraging a combination of U-net architecture and contourlet transform for pre-processing remote sensing data. After comparing their algorithm's performance to traditional U-net and wavelet-assisted models, they find that their multiscale contourlet approach outperforms these models on a number of evaluation metrics including precision, recall, F-score, and overall accuracy. They attribute this improved performance to better class discrimination in both geographies.

(Arndt and Lunga 2021) Can you include the figure a bit more in your analysis. I wrote the following sentence just so we have something, but I think you need to make the connection a bit more clear. Existing informal settlement classification systems suffer from a lack of generalizability, typically only able to be applied to individual cities. Arndt and Lunga (2021) propose an urban structural units characterization approach for 13 cities in Africa, Latin America, Asia, and North America. By capturing a diverse group of cities, policymakers and technologists across the world can more seamlessly build off of their work. They develop two CNNs, USU-Net and DenseNet-42-SPP that are augmented with spatial pyramid pooling (SPP) layers and compare their performance to 8 existing CNN architectures. SPP layers enables the CNN to capture additional context in remote sensed images at different levels of detail. USU-Net is a shallow architecture containing less SPP layers, while DenseNet has a greater depth and more trainable parameters. They test all 10 CNNs, including USU-Net and DenseNet, in the smaller Venezuelan cities and in megacities such as Bangkok and Rio de Janeiro. They find that CNNs such as ResNet, USU-net, DenseNet, and Inception tend to outperform more classical methods for urban structural unit classification tasks.

(Kuffer et al. 2020) Can you include the figure a bit more in your analysis. I wrote the following sentence just so we have something, but I think you need to make the connection a bit more clear. This paper synthesizes findings from research conducted by deprived area mapping experts. They evaluate existing approaches for deprived area mapping including aggregated slum household, field-based mapping, human imagery interpretation, and machine imagery classification and design an Integrated Deprived Area Mapping System (IDeAMapS) that incorporates the strengths of each. Their primary objective is to integrate both top-down and bottom-up approaches such that technologists, policymakers, and community stakeholders can provide meaningful input in this process. IDeAMapS pulls together Earth Observation (E0) data and community-based contributions to create a transparent, open-access system. They acknowledge some of the limitations associated with EO; for example, EO only captures physical deprivation but not social covariates necessary to comprehensively map deprivation. However, the inclusion of community stakeholders serves to balance the shortcomings presented by this technology.

(Prabhu and Parvathavarthini 2022) Can you include the figure a bit more in your analysis. I wrote the following sentence just so we have something, but I think you need to make the connection a bit more clear. In this paper, the authors build the Morphological Slum Index (MSI) to classify slum areas in Very High Resolution (VHR) Worldview2 satellite imagery by using a number of morphological operators. MSI categorizes objects within these remote-sensed images as slum or non-slum elements. They discover some issues from the results yielded by MSI, specifically non-slum objects such as roads, vegetation, and buildings that are erroneously labeled as slum objects. Prabhu and Parvathavarthini develop a post-processing method, Morphological Spatial Pattern Analysis (MSPA), to correct these errors. Used in tandem, MSI and MSPA are able to accurately classify informal settlements for satellite images of Madurai, India and Kibera, Kenya. Their high accuracy in two very distinct locations indicates the generalizability of their approach, which could be deployed in other geographies to identify their slums.

(Mast, Wei, and Wurm 2020) Can you include the figure a bit more in your analysis. I wrote the following sentence just so we have something, but I think you need to make the connection a bit more clear. This paper proposes a novel method for mapping urban villages in Shenzen, China. Urban villages arise from China's hukou system, which strictly labels land and people as either rural or urban. They are initially classified as rural but develop urban characteristic as they become enveloped by urban sprawl when cities inevitably grow. The authors synthesize VHR satellite imagery from Google Earth and create a map of land-use classes including Water, Vegetation, and Artificial Land using random forest. The resulting map included over 300 urban villages. They pre-process the image using the fully convolutional neural network architecture and perform data augmentation to address class imbalance in their dataset. Then, they adapt an existing network, VGG19, into a fully convolutional network called FCN-VGG19 and leverage it for land-use and UV identification. They find that their FCN is highly accurate and effective for mapping UVs in Shenzen and other Chinese cities. Future work in this area should incorporate urban planning, urban climatology, and socioeconomic perspectives, ideally incorporating input from UV residents and other stakeholders.

(Lobo 2023) This article conducts an interview with a philosopher who completed field work in the realm of informal settlement mapping. It discusses key ethical issues regarding the act of using machine learning to assist with and take over completely the action of mapping such settlements. The interviewee emphasizes foremost the importance of understanding the tensions between existing stakeholders in the prospective mapped community, such as between the gangs, politice, and greater community. For example, maps coming from external entities such as Western researchers will seldom be trusted by those communities in a vacuum and thus can only set into motion and unleash the coercive potentials rather than the aforementioned liberatory ones. Another idea discussed by the author is the idea of machine hermeneutics and hermeneutic injustice. Very much proliferated by the AI phenomenon, these ideas illustrate the embedded technological power of AI in elevating some voices and ways of living while downplaying others. Whereas normal mapping may involve community stakeholders to some extent, AI comes at them from a completely new lens of knowledge (AI/ML) which may limit the extent to which they are able to engage authentically with stakeholders in those informal communities. This is particularly because of the widening gap of education on these more technical matters.

(Falco, Zambrano-Verratti, and Kleinhans 2019) Falco et al. (2019) discusses the notion of participatory mapping, wherein stakeholders are not forced to use or contribute to an AI model which does the mapping, but rather the map is crowdsourced through Google's MyMaps service—which allows group access to a big map for free. This experiment was conducted in Caracas, Venezuela, which, as the nation's capital, is known for its urban environment. The article describes, in depth, the experience of engaging stakeholders to contribute maps of their own instead of imposing an understand of maps and their functions through the seamless integration of Google and Apple maps.

(Gram-Hansen et al. 2019) Gram-Hansen et al. partnered with the UN to create two separate machine learning models—one cost-prohibitive and the other cost-efficient—in order to allow for low resolution images to effectively map informal settlements in Kenya, South Africa, Nigeria, Sudan, Colombia and Mumbai. In places where the informal settlements are visually distinct from the surrounding area, the cost-efficient method works by taking low-resolution color data from a 10-band spectra dataset and applying a Canonical Correlation Forest (CCF), or a type of random forest that works well with small datasets for reducing noise. This ML can separate groups of pixels as fitting or not fitting into those of a region's known informal settlements. The more challenging method is best used in places where the color spectrum of the slum doesn't differ wildly from the surrounding area—such as in areas of Sudan. For this, the latter method uses deep learning to conduct semantic segregation and split up areas by their distinct, but non-color related aspects. Ultimately, the researchers found that the low-resolution, CCF method could get close to the latter method in many cases while saving the mapper tremendous computational resources.

(Lorraine Trento Oliveira and Pedrassoli 2023) Oliveira et al. This study uses unsupervised machine learning in order to map informal settlements in São Paulo, Brazil. It starts by outlining a workflow for informal settlement mapping, involving data collection (through open, readily obtainable visual data), data processing (choosing a spatial unit of analysis, and then utilizing the strengths of that unit to extract certain features), integrating the data as input for an unsupervised ML model (in this case, K-Means), and then evaluating the model using its output and an external mechanism (in their case, by combining a personal sense check with images from a ground view, some statistical analysis, and an interview with a local specialist). Ultimately, they found that, through this workflow, they were able to accurately capture morphological differences between depraved and non-depraved areas in the city, classifying the former into four different clusters, each representing various elements and stages of an informal settlement.

(Alrasheedi, Dewan, and el Mowafy 2023) This paper maps a small, urban informal settlement in Riyadh City, Saudi Arabia using a combination of expert knowledge, satellite imagery, and a custom ML random forest program. The imagery included multispectral visual data, some preliminary informal settlement boundaries, and an overlay of existing road networks. Ultimately, the software was able to distinguish between formal and informal settlements, as well as roads, shadows, vacant lots, and vegetation. The unique combined approach took expert knowledge in the form of a disseminated survey to find parameters that could be used to identify informal settlements. Through the survey, sixteen indicators were chosen and tested in the random forest, which was ultimately refined further until achieving optimal results—as assessed by a confusion matrix. Although the paper isn't clear on what the expert contributions were, or the extent to which those experts were part of the informal settlement community, the paper does acknowledge that this integration of localized knowledge with AI had not performed before.

(Mudau and Mhangara 2021) This study, conducted in Mamelodi, South Africa tests the accuracy of twelve informal settlement indicators differentiating between formal and informal urban areas. The primary data source is very high spacial resolution satellite images from WorldView-2 8-band multispectral and panchromatic images acquired on 28 July 2015, provided by Maxar Technologies. These images cover the Mamelodi East area and have spatial resolutions of 2.4 m for multispectral bands and 46 cm for panchromatic bands. The paper tests the effectiveness of various indicators to identify informal settlements such as spectral indices, first and second-order statistical measurements, and also examines state-of-the-art metrics such as the potential of built-up area and iron cover. The primary finding is that traditional GLCM textural measures are less effective in distinguishing between settlement types compared to spectral indices and first-order statistical evaluations. In particular, the built-up area index, coastal blue index, and mean measurements of first-order statistics are found to be the most significant features.

(Fallatah et al. 2022) This article presents the results of research conducted in Jeddah, Saudi Arabia, to identify formal settlements. The article key differentiating aspect is that it merges object-based machine learning (ML) with time-series analysis (TSA), utilizing a blend of very-high-resolution (VHR) GeoEye-1 satellite imagery alongside extensive Landsat time-series data for both detection and examination of informal settlements. This new method uses a variety of indicators across environmental, settlement, object, and temporal dimensions to cluster the unique attributes of informal settlements. Implementing an object-based image analysis (OBIA) along with a random forest classifier, the research attains a mapping accuracy of 95%. While temporal markers from TSA played a less important role in the immediate classification accuracy, they provided important historical context to the expansion and development patterns of the settlements, providing insights into urban transformation.

(Fan et al. 2022) In this study addressing urban informal settlements (UISs) in Shenzhen City, the researchers developed UisNet, a semantic segmentation method leveraging transformer-based blocks for multimodal data processing, encompassing high-spatial-resolution remote sensing images and object-level building polygon data. This innovative approach aimed at enhancing UIS mapping's fine-scale accuracy. The experimental validation in Shenzhen City demonstrated UisNet's superior performance, achieving an overall accuracy of 94.80% and a mean intersection over union (mIoU) of 85.51% on a manually labeled UIS semantic segmentation dataset (UIS-Shenzhen dataset). These results significantly outperformed existing semantic segmentation models. UisNet incorporates a spatial-channel feature fusing module that synergizes spatial and channel features from diverse data types, improving segmentation results over traditional methods reliant on single-modal data sources. Comparative experiments on a public dataset, the Gaofen Image Dataset (GID), further underscored UisNet's efficacy, where it showed improvements in mIoU by 1.64% to 7.58% over state-of-the-art counterparts.

(Owusu et al. 2024) Owusu et al. propose a scalable and transferable approach to mapping slums using freely available Sentinel-2B data, thereby tackling two common challenges in the literature for detecting slums: First, they argue that while Very High Resolution (VHR) satellite data has shown promising potential for detecting slums, they often cover only small areas and are cost prohibitive. Second, they point out that model transferability to new cities often remains a challenge. In particular, their model is trained and tested on three cities: Lagos (Nigeria), Accra (Ghana), and Nairobi (Kenya). A model trained on Accra data and tested on Nairobi yielded a deprived F1 score of 0.81, showcasing some level of transferability between these cities. Though, when evaluating the generalized model, which combined training data from all three cities, the performance varied: the model achieved an F1 score of 0.78 for Accra, but only 0.68 for Lagos, indicating significant challenges in creating a universally applicable model. The study suggests that the impact of geographical morphology and local urban characteristics are likely to have a profound impact on model performance, highlighting the importance of city-specific adaptations.

(Dufitimana and Niyonzima 2023) This study explores the application of a Convolutional Neural Network (CNN) combined with Very-High Resolution (VHR) satellite imagery to map informal settlements in Kigali, Rwanda. Utilizing a modified U-Net model with MobileNetV2 as the base, the study incorporates dilated convolutional operations to enhance feature detection at the outset of the network. The research reveals that the modified model successfully identifies informal settlements, achieving a recall of 0.862, precision of 0.810, and an F1-Score of 0.809. These findings underscore the potential of CNN and VHR satellite images in providing critical data for addressing informal settlements.

(Najmi et al. 2022) Naomi et al. are motivated to address the challenge of mapping slums to support the UN's Sustainable Development Goal (SDG) indicators, in consideration of the growing urbanization and the deficient infrastructures that lead to slums. They claim that the advent of Very High Resolution (VHR) Remote Sensing Imagery (RSI) and Deep Learning (DL) methods presents a new alternative to traditional, more resource-intensive mapping approaches, since it produces regular updates and bypasses inaccessible areas. However, the nuanced nature of slums, both across and within cities, poses a challenge for a single-method approach. Their research proposes a novel integration of RSI and Street View Images (SVI) methods for more accurate slum identification and mapping. They offer a proof-of-concept in the slums of Jakarta, Indonesia; where almost 60% of the population reside in slums and local informal settlement structures known as kampungs. The study explores the tradeoffs between four kinds of DL networks: one utilizing only RSI; one utilizing only SVI; two that integrate both data types. Out of the four networks, the Modified FCN-DK6 network, integrates SVI at various convolutional layers, which showed great potential. They discuss that this demonstrates how integrating different data types can improve accuracy when applied to this problem. Indeed, the authors show that a more comprehensive understanding of slums should combine both the bird-eye-view with ground-level details. The paper acknowledges the limitations of using SVI alone (restrictive information) and argue that combining with RSI can help bridge these limitations of a pure SVI approach. Ultimately, the integrated method may significantly improve slum mapping efforts, thus promoting their larger efforts to meet the SDG goals motivating them.

(Owusu et al. 2021b) Owusu et al. are motivated to center the end-user's requirements and align these societal needs and concerns with slum-mapping efforts. They propose a user-driven approach to slum mapping—using Accra, Ghana as a case study—which emphasizes the explicit consideration of societal needs and concerns. The authors point out that most slum efforts are currently utilizing a data-driven approach, without explicit awareness or consideration of the end-user requirements. By integrating in-situ observations and interviews with slum experts, the study generated a "user-driven slum map" using a Random Forest classifier, SPOT 6 imagery, and ancillary geospatial data. This user-driven slum map satisfies the users' expectations as well as achieves a classification accuracy of 84%. The study demonstrates the value of considering geo-ethics, local knowledge, end-user requirements, in order to better understand slums. This paper speaks to wider sociotechnical system considerations that are incredibly important to all AI for social good efforts; particularly for slum mapping, the underserved users are often underrepresented in these projects—this paper thus serves as a proof-of-concept for a different approach. By incorporating user feedback and ethical considerations, this approach both enhances the accuracy of slum mapping and ensures the responsible protection and service of vulnerable populations such as slum dwellers.

(Mahabir et al. 2020) Mahabir et al. are motivated to understand how combining traditional open data sources with emerging open data sources can improve slum detection and mapping efforts. Using Kenya as a case study, they apply their proposed method to three Kenyan cities (Nairobi, Mombasa, and Kisumu) each of which have extremely high slum populations. The end goal of the study is to develop an indicators database based on open sources of physical and socioeconomic data. They then applied data mining techniques to identify the most effective combinations of these indicators. There were several steps in the method, such as defining candidate indicator requirements, extracting candidate indicators from various data sources, processing the data, and validating the created model. They then evaluated the model by comparing it to traditional models like logistic regression, discriminant analysis, and the See5 decision tree. Their results demonstrated that the integration of emerging data sources could improve the mapping accuracy of slums. Notably, the model utilizing the See5 decision tree achieved the highest classification accuracy on all three cities. Their study highlight a new potential avenue researchers can take: namely, combining open data sources with data mining techniques to yield more comprehensive slum mappings. This approach bridges the infamous challenge of data poverty in less-developed countries, as exemplified by a developing country like Kenya.

(Tingzon et al. 2020) Tingzon et al. are motivated to investigate a novel cost-effective approach in identifying new and emerging informal settlements in Colombia resulting from the Venezuelan migration crisis. 2 million Venezuelans have migrated to Colombia since 2014, resulting in one of the largest forced displacements to informal settlements in South America. The authors hope to tackle some of the difficulty in locating these rapidly growing informal communities. The study proposes a novel method which combines machine learning methods with public Sentinel-2A time series satellite imagery. The approach was designed to time-efficiently and cost-effectively identify potential Venezuelan migrant settlements. The approach involves producing an informal settlement probability map and on-the-ground verification. This ultimately allows the targeted distribution and allocation of humanitarian aid. The method involves integrating several sampling strategies, feature extraction from satellite imagery, and model training and evaluation using machine learning models like logistic regression, support vector machines, and random forest classifiers. After classification, a two-step verification process is used, involving remote validation through GIS applications and on-the-ground validation via a mobile crowd-sourcing app. Particular attention is given to the post-classification verification process to ensure validity and reliability of the probability map. The approach demonstrates the importance of tailoring the AI for social good efforts to the nuances of a local and economic need (in this case, the Venezuelan migration crisis) in order to achieve tangible end-goals (in this case, the distribution of humanitarian aid).

(Owusu et al. 2021a) Owusu et al. are motivated to uncover and address some of the ethical considerations pertaining to the use of Earth Observation (EO) data for mapping slums, with Accra, Ghana as a case study. The paper highlights the challenges and unintended consequences of making slum information publicly available without due consideration of geo-ethical concerns. By conducting interviews with experts and institutions involved in urban planning and slum management, the study takes a deeper dive into such ethical considerations. This qualitative approach enables in-depth insight into the ethical concerns related to EO slum mapping. According to the authors, the field should embrace a more ethical approach to slum mapping, centering fairness, accountability, and transparency. The authors identify several key challenges include balancing the need for detailed slum data with protecting vulnerable communities from potential bad actors. Stakeholder interview show that there is an imbalance in engagement, with users having little knowledge of machine learning-based slum mapping. This implies a need for improved communication and education to enhance the interpretability of EO across different socio-economic groups. The research identified several ethical concerns to watch out for, including the risk of stigma and the misuse of slum data for slum elimination rather than improvement. The authors ultimately call for a careful approach to data sharing that considers the impact on marginalized communities, as exemplified by the user-driven slum mapping paper also authored by Owusu (Owusu et al. 2021b).