Measuring slums from space

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- Even though informal settlements house millions, they are poorly mapped, making service delivery and policy planning difficult.
- Satellite imagery combined with AI models can reliably identify informal settlements at low cost.
- Models trained in one city in India and in Burkina Faso also produce accurate maps in other cities, illustrating the potential to save on expensive ground surveys and deliver up-to-date policy responses.
- Local mapping efforts remain important for model training and validation.

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Unlocking data on the location of informal settlements

Rapid urbanisation in low- and middle-income countries has driven the growth of informal settlements, which now house more than a billion people worldwide. These communities are often excluded from public services and are highly exposed to climate risks. Yet governments lack reliable, up-to-date information on where informal settlements are located and how they expand. Traditional mapping and household surveys are costly and slow to update, leaving policymakers without the evidence needed for timely interventions.

New advances in satellite imagery and AI can help fill this gap. By training algorithms to detect settlement patterns from high-resolution images, researchers can produce consistent, city-wide maps at a fraction of the cost of manual surveys. This opens the door to rapid, low-cost tools to support policy decisions on housing, land-use planning, and service provision.

Overview of the research

The research developed an AI pipeline to identify informal settlement locations using high-resolution daytime satellite imagery. The pipeline:

1. starts with raw satellite imagery from a location where informal settlement maps are available, and a location where settlements are to be identified
2. processes the images to a) account for differences between the sensors taking them (for example, by harmonising brightness) and b) avoid the AI models' basing identification on idiosyncratic features of the cities with maps available
3. 'trains' a set of workhorse AI models to fit the relationship between image features and informal settlement location in cities where maps are available, then
4. infers the location of informal settlements in the city without maps using trained models.

The rest of the research involved assessing the performance of this pipeline by inferring the locations of informal settlements in cities and in parts of cities where settlement maps are in fact available.

The remainder of this policy brief summarises the results from these assessments. They illustrate the potential of AI pipelines to produce timely assessments of informal settlement locations at a low cost, facilitating timely policy responses.

Assessing AI pipelines' ability to map informal settlements

Table 1 provides an overview of the assessments of the AI pipeline. In the first row, we split the Greater Mumbai metropolitan area into its two component regions: the Mumbai Suburban district and the Mumbai district. We assess how the AI pipeline performs at identifying informal settlements in the Mumbai Suburban district by examining the relationship between settlement maps and satellite image features in the Mumbai district. The second row uses the same AI pipeline to identify informal settlements in the Pune metropolitan area. The third row moves to Burkina Faso, training the AI pipeline in Bobo-Dioulasso and identifying informal settlements in the capital, Ouagadougou.

When assessing the AI pipeline, we look at two main numbers—precision and recall—which together show how accurate and reliable the informal settlement mapping exercise is. For example, the first row reports a precision of 0.76, meaning about 76% of the area the model marked as informal settlements are, in fact, informal according to the official map. The recall of 0.77 means the model successfully found 77% of all informal settlements.

Table 1: Model performance across the city

Training city	Prediction city	Evaluation metrics
Mumbai – Suburban area (India)	Mumbai – Downtown area (India)	Precision 0.76, Recall 0.77
Mumbai – Suburban area (India)	PCMC (India)	Precision 0.76, Recall 0.57
Bobo-Dioulasso (Burkina Faso)	Ouagadougou (Burkina Faso)	Precision 0.86, Recall 0.86

Note: This table shows the performance of the exercises presented in this brief. Training city is the city on which the AI pipeline was trained. Evaluation city is the city for which the AI pipeline produced an informal settlement map. Evaluation metrics are precision (True Positive / True Positive + False Positives) and recall (True Positive / True Positive + False Negatives).

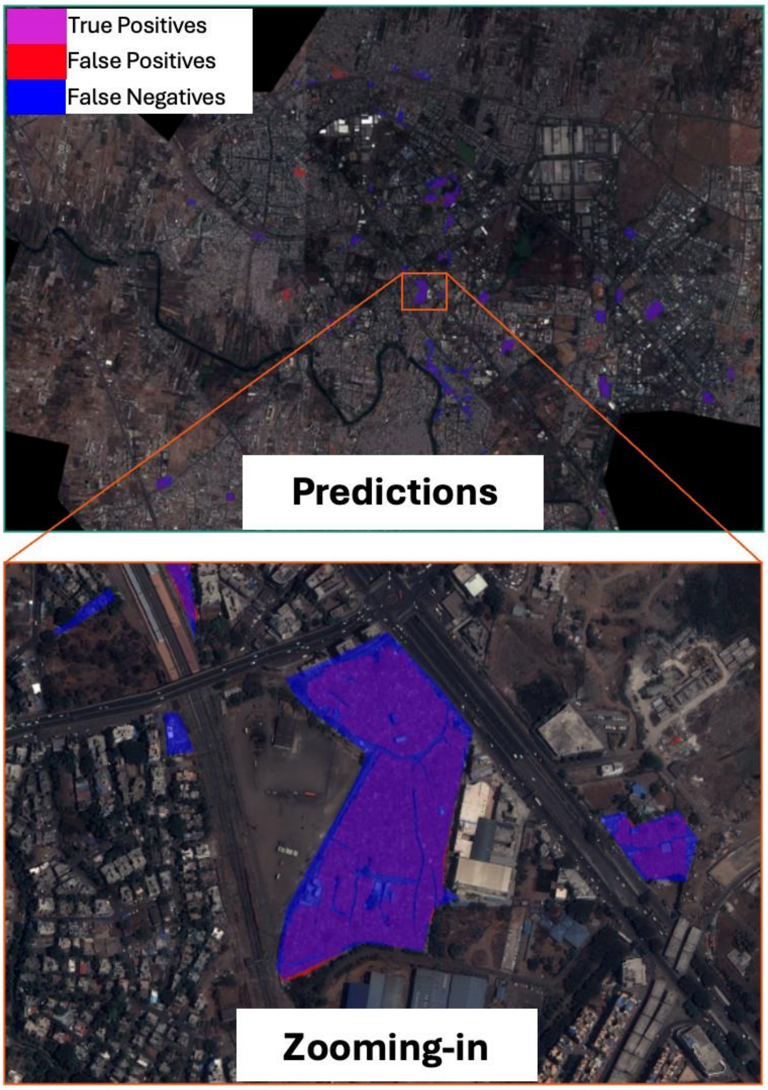
Table 1 shows that AI pipelines can produce accurate informal settlement maps. In Burkina Faso, the AI pipeline maps informal settlements extremely accurately, at very low cost. Performance in Mumbai is also good, with the identified areas accounting for 75% of the city's informal settlements. The map for the Pune metropolitan area is not quite as good, containing only 57% of informal settlements there. Error rates are relatively low across all contexts.

Figure 1 gives a visual assessment of the quality of the AI-inferred informal settlement map in the Pune metropolitan area. The colour of a region in the image shows whether the inferred settlement locations are correct, incorrect, or missed.

Key takeaways from Figure 1 are the following.

1) The poor rate of informal settlement identification by the AI pipeline in the Pune metropolitan area is largely due to the omission of just three settlements.
2) The bottom, zoomed-in panel of the figure shows that AI pipelines can infer highly localised features of informal settlement locations.

Figure 1: Informal settlement locations in the Pune metro area, inferred using an AI pipeline trained in Mumbai



Notes: True positives are correctly identified informal settlement areas, false positives are incorrectly identified, and false negatives are informal settlements not identified by the AI pipeline.

Implications for policymakers

1. AI pipelines developed for informal settlement identification can achieve high accuracy and thus represent a low-cost complement to on-the-ground settlement mapping.
2. On-the-ground informal settlement mapping still plays a key role in providing the information that trains AI pipelines. But AI pipelines can greatly increase the impact of any manual mapping by extending the findings to other areas. Our pipeline is built to be easily transported to work on other sets of cities. In ongoing work, we continue to improve pipeline performance, and welcome collaboration with parties interested in building on these results.