Mapping changes in urban informal settlements in sub-Saharan Africa from 2016 to 2022

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More than one billion people worldwide live in informal settlements[1], often called ‘slums’. In sub-Saharan Africa, the world’s fastest urbanizing region[2], every second urban resident is considered a ‘slum-dweller’[1]. Identifying and mapping the locations of informal settlements at scale and tracking their development over time is thus crucial for adequate policies to alleviate urban poverty and inequality. However, given the rapid and often unplanned urbanization dynamics in African cities, existing monitoring systems are insufficient for tracking the development of informal settlements. Here we show how open-access satellite imagery and machine learning can be used to identify and map urban informal settlements in sub-Saharan Africa across space and time. We developed a machine learning model that combines satellite images with ground truth data on informal settlements from various African cities. Our machine learning pipeline produced 10m resolution probability maps of informal settlements, based on which we calculated estimates of the prevalence and change of informal settlements in 529 cities from 44 countries from 2016 to 2022. We found a high prevalence of informal settlements in many African cities, with particularly high growth rates in Middle and West Africa. In 2022, in 274 of 529 cities the share of the urban population living in informal settlements exceeded 50%, and in 84% of cities, this share increased between 2016 and 2022. Our approach facilitates tracking the spatiotemporal development of informal settlements within cities in a timely and cost-effective manner. Furthermore, it provides first-time estimates of the share and number of people living in informal settlements across sub-Saharan African cities.

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Introduction

More than one billion people – a quarter of the world's urban population – are currently living in informal settlements, often referred to as 'slums'. In sub-Saharan Africa, every second urban resident is considered a so-called 'slum-dweller'[1]. UN-Habitat defines a 'slum-dweller' as a person affected by at least one of the following five 'household deprivations': Lack of 1) access to an improved water source, 2) access to an improved sanitation facility, 3) sufficient living area, 4) housing durability of dwelling, and 5) security of tenure[3]. Informal settlement dwellers are thus particularly vulnerable to infectious diseases[4] and natural disasters[5], suffer from a lack of privacy[6] and face the constant threat of eviction[7].

With an annual growth rate in the urban population of consistently around 4% in the past two decades, sub-Saharan Africa is the world's fastest urbanizing region. Its urban population is expected to grow from half a billion to 1.3 billion by 2050, corresponding to an increase in the urbanization rate from 41% to 58%[2]. The region already hosts two megacities (Lagos and Kinshasa), i.e., cities with a population exceeding 10 million, with another four (Luanda, Dar es Salaam, Nairobi, and Khartoum) projected to pass this threshold by 2050[8]. Given the rapidness of the urbanization process, the lack of planned urban development, and insufficient provision of basic infrastructure, such as clean water sources and modern sanitation, a large share of these new urban dwellers will likely live in informal settlements[9].

Tracking the emergence and development of informal settlements is thus crucial for monitoring progress towards Sustainable Development Goal (SDG) 11.1 – "ensuring access for all to adequate, safe and affordable housing and basic services and upgrade slums"[10] – as well as an important information tool for African policymakers to alleviate potentially adverse living conditions of the region's rapidly growing urban population. Timely identification of 'informal growth hotspots' can help allocate resources where they are most needed – at the national, regional, and local level.

However, established methods of data collection on informal settlements have several drawbacks which bedevil prompt, targeted, and adequate policy responses to informal settlement formation. Most estimates on informal settlements at the national, continental, or global level are based on national censuses and household surveys (e.g., Demographic and Health Surveys (DHS)[11], Multiple Indicator Cluster Surveys (MICS)[12], which are typically carried out every ten and every three to five years, respectively[13] – too infrequently for timely tracking of rapid informal settlement formations. Political instability and violent conflict regularly delay or prevent data collection leading to even longer intervals[14]. Additional problems are that informal settlement dwellers tend to be under-sampled in household surveys[15] and that most censuses and household surveys do not contain information on the security of tenure (one of the five criteria related to slum households)[3]. As a consequence, a non-negligible portion of affected individuals is not considered in current statistics on informal settlements.

Lastly, a major drawback of survey- or census-based methods is spatial imprecision. While the UN-Habitat definition is based on *households*, informal settlements arguably pertain to a *geographic area*. This issue has been tackled, for example, by defining an urban DHS[11] Primary Sampling Unit (PSU) as an informal settlement if the proportion of informal settlement dwellers exceeds a certain threshold, e.g., 50%[16]. However, this approach misses small pockets of informal settlement households in mostly formal areas (potential underestimation). At the same time, a PSU with 51% informal settlement dwellers is considered informal in its entirety, even though a substantial share of 49% of residents do not suffer from the above-mentioned household deprivations (potential overestimation). In addition, even though most censuses and household surveys provide geocoded information, it is not sufficiently precise to map the spatial extent of informal settlements. The DHS[11], for example, generally provide information on the coordinates of PSUs, yet with two major shortcomings. First, to ensure the confidentiality of respondents, the coordinates are randomly displaced, at a random angle and at a random distance (within a 2km radius for urban PSUs). Second, these displaced coordinates refer to the

PSU centroid only, and there is no information on the surface area or boundary shape of these PSUs[17]. Hence, one can only very roughly infer the potential locations of informal settlements – accurate maps delineating informal from formal settlements in cities cannot be produced. Alternatively, geocoded surveys and censuses have been used to map housing conditions (based on UN-Habitat's definition of 'slum households') in sub-Saharan Africa in 5km grids[18]. While insightful to estimate spatial heterogeneities across and within countries in the prevalence of insufficient housing conditions, the coarse spatial resolution does not allow precise mapping and tracking of informal settlements in cities.

In light of the shortcomings of survey- or census-based methods, an emerging literature increasingly uses remote sensing data, in particular satellite imagery, to map informal settlements. One strand of this literature is based on (human) visual interpretation of very high resolution images[19,20]. A growing body of studies employs machine learning methods enabling automated (machine-based) identification of informal settlements, such as object-based image analysis[21,22] and more recently deep learning[23–25]. However, these studies are typically restricted to one or very few small geographic areas (e.g., mapping several informal settlements in one specific city or in a few different cities) due to the enormous data storage and computing capacity required for processing very high resolution (<1m/pixel) satellite imagery. Few studies so far have mapped informal settlements on a larger geographical scale using high (1m-5m/pixel) or medium resolution (5m-30m/pixel) satellite imagery, and even these are restricted to only a few cities and do not track changes over time[26,27]. While few studies have applied deep learning to map economic conditions at a larger scale, e.g., across Nigeria at 7.65 km grids[28] and across sub-Saharan Africa at 1.6km grids[29], these studies did not focus on urban informal settlements but mapped poverty and wealth. Further, their approach doesn't allow tracking spatiotemporal dynamics within cities.

Here we apply deep learning to open-access Sentinel-2 optical satellite imagery[30] to identify and map informal settlements in 529 cities from 44 countries across sub-Saharan Africa from 2016 to 2022. We use these predictions to estimate the share of the urban area covered by, and the share and total count of the urban population living in informal settlements, as well as changes in these three indicators during the study period – both at the city and at the country level. By utilizing open-access medium resolution instead of commercial very high resolution imagery, any purchasing costs were avoided making our study fully reproducible. In addition, computational and data storage requirements were significantly reduced – enabling us to strongly expand the spatial and temporal coverage in comparison to existing studies. Our prediction models combine Sentinel-2 satellite images[30] with shapefiles of the exact locations and boundaries of known informal settlements in 16 African cities from six countries (Extended Data Fig. 1) to predict the locations and extent of informal settlements in cities and years without existing ground truth data. For a given city in a specific year, the algorithm produced a raster map with pixel values ranging from 0 to 1. While the pixel values are not rigorous, calibrated probabilities, but rather approximations through our learned classifier, they can be interpreted as a score of informal settlement probability. These 'probability maps' can be used to infer the locations and extent of informal settlements within cities and track their spatial development over time. Calibrated threshold values were then applied to produce binary maps of informal settlement locations. In conjunction with Africapolis shapefiles on city boundaries[31] and WorldPop data on within-city population distribution[32], these were used to calculate city- and country-level estimates of informal settlement prevalence, including population shares and totals.

Results

Case study: Mapping informal settlements in Johannesburg/Pretoria, South Africa

We first present a case study of the greater area of Johannesburg/Pretoria, South Africa (for which we did not have any ground truth data) that demonstrates how our prediction maps can be used to identify locations of informal settlements within cities and new hotspots areas.

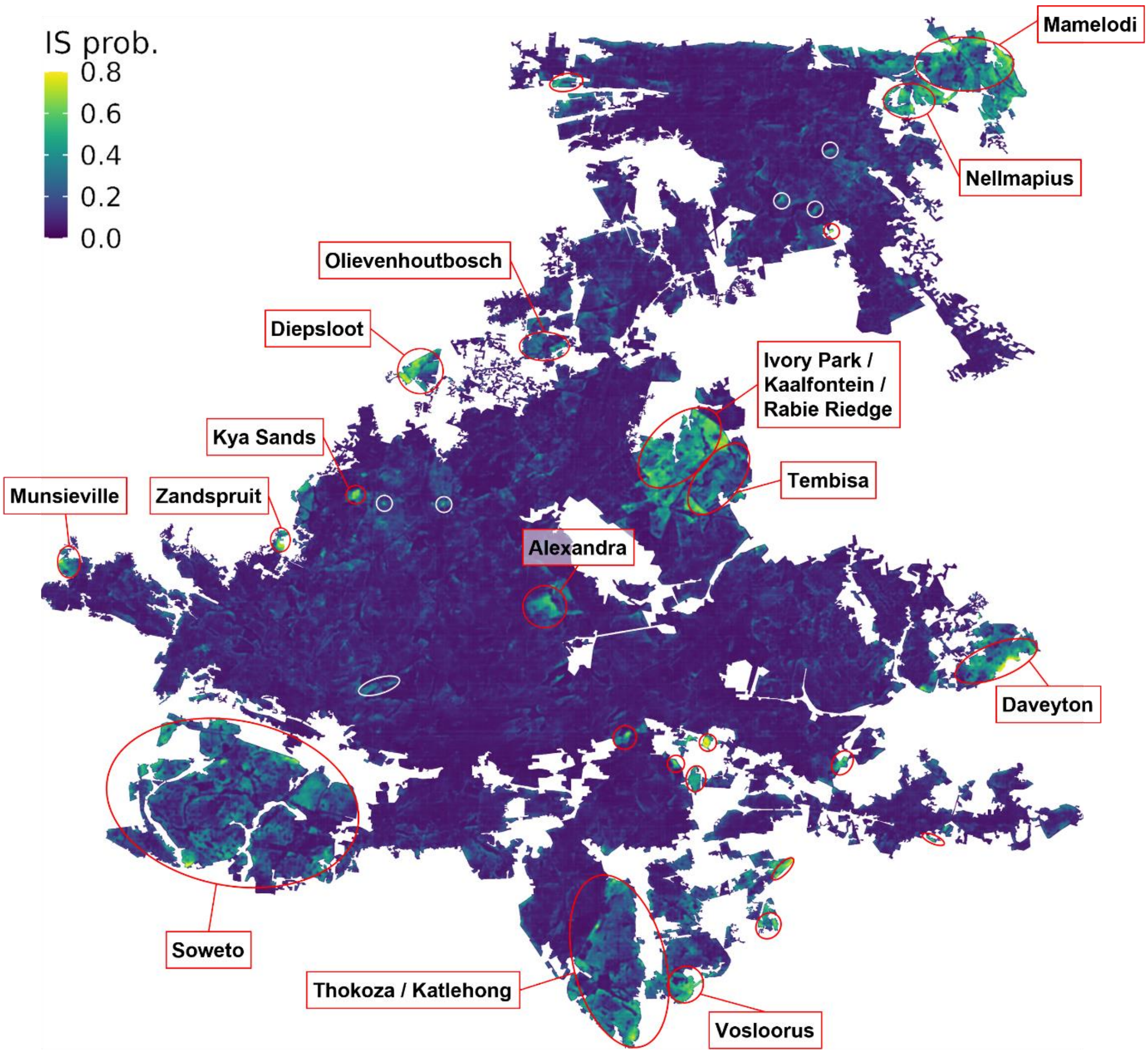

Figure 1 | Predicted informal settlement locations in Johannesburg/Pretoria, South Africa (2022). Brighter yellow indicates a higher probability of informal settlement coverage. IS prob. stands for informal settlement probability. Red ellipses with name tags correspond to known and verified informal settlements. Unnamed red ellipses correspond to unknown but verified informal settlements. Unnamed white ellipses mean verified as not informal settlements.

Figure 1 shows a 10m resolution map of the probability that each 10m pixel in this urban agglomeration contains informal settlements – with brighter yellow indicating higher probabilities. The map was annotated with the names and approximate locations and sizes of 17 of the largest and commonly known informal settlements – called "townships" in South Africa – (red ellipses with name tags), visually verified on concurrent high resolution earth observation data[33]. All 17 townships can be visually identified in our prediction map. Notably, the predicted probability varies also across townships, potentially indicating varying degrees of deprivation, from very poor settlements characterized by high population and building density and mostly small corrugated-iron shacks (e.g., Diepsloot)[34] versus more diverse settlements with mixed-income groups and a history of slum upgrading (e.g., Soweto)[35]. In addition, several other smaller informal settlements with unknown names (unnamed red ellipses) are apparent in the map – visual interpretation of concurrent Google Maps/Satellite images[33] verified that these locations coincide with informal settlements. While there are also cases of locally brighter areas on the map that turned out to be misclassifications after verification (unnamed white ellipses), these were few and they only cover very small areas with ambiguous visual and spectral appearance. Consequently, such misclassifications should not have a tangible effect on city- or country-level estimates of informal settlement prevalence.

Mapping the spatiotemporal development of informal settlements within cities

Next, we show the spatial development of informal settlements over time. We present exemplarily the results for four major cities in four regions in sub-Saharan Africa (Extended Data Fig. 2): Accra, Ghana (West); Luanda, Angola (Middle); Dar es Salaam, Tanzania (East); and Windhoek, Namibia (Southern). Results are available for all 529 studied cities (https://gitlab.renkulab.io/deeplnafrica/deepLNAfrica/-/tree/main/change_figures).

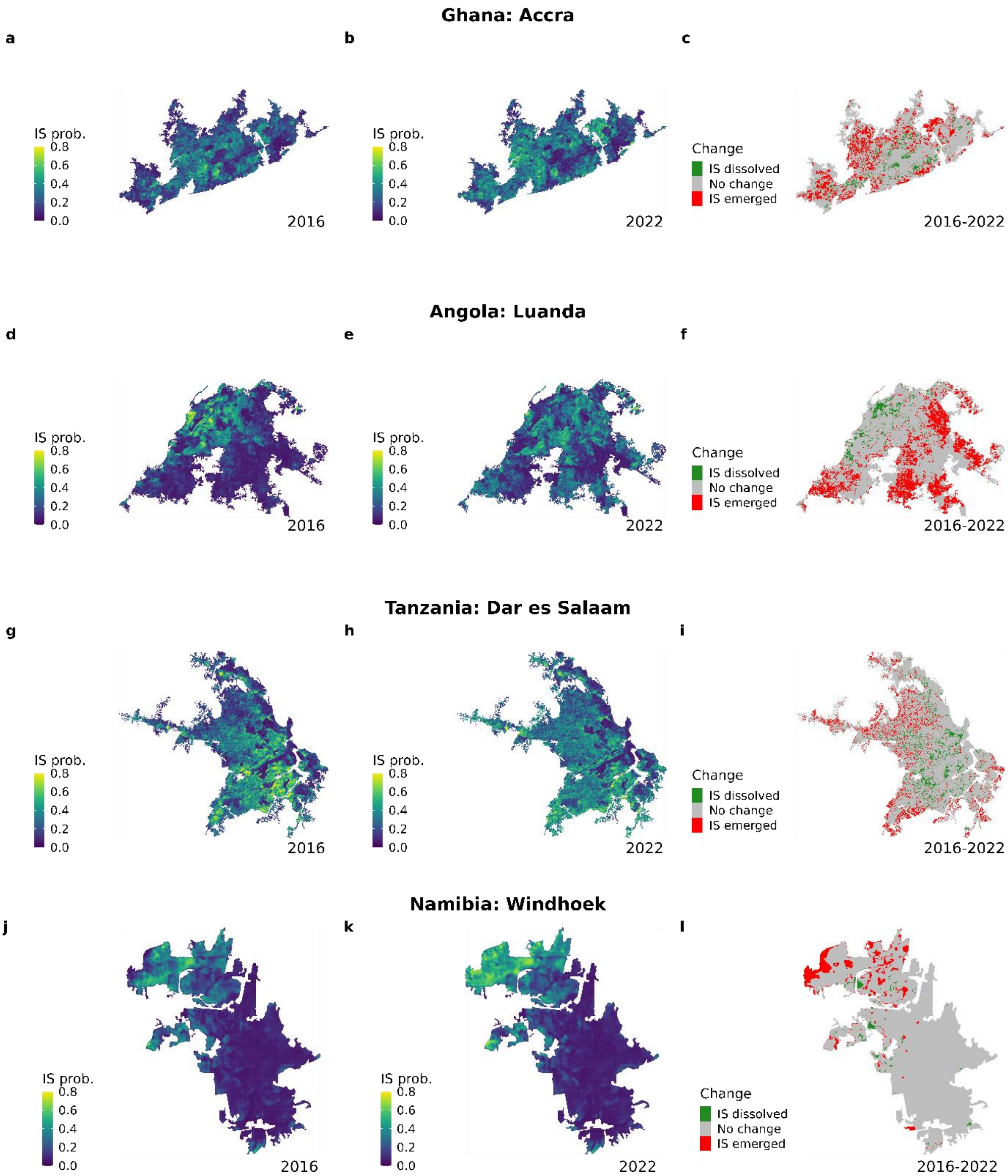

Figure 2 | Predicted spatiotemporal development of informal settlements in four major sub-Saharan African cities (2016–2022). Predicted probability of informal settlement coverage in 2016 (**a, d, g, j**), 2022 (**b, e, h, k**), and change in predicted informal settlement status between 2016 and 2022 (**c, f, i, l**). IS stands for informal settlement. The color scale is truncated at 0.8 in in first two columns.

Figure 2 shows the predicted informal settlement probabilities in 2016 and 2022 and where, over the observation period, new informal settlements emerged, existing ones dissolved, or nothing changed (based on binary segmentation maps, see Methods). The four cities displayed vastly different spatiotemporal dynamics between 2016 and 2022. In Ghana, informal settlements were most common in the Central/Southern area (in coastal proximity) of the city in 2016, while the East, and the far Southeast and North were least affected. However, informal settlements seem to have expanded strongly into the Southwest and North of the city until 2022, while the center experienced occasional improvements in housing conditions. In Luanda, informal settlements were located mostly in the North, but expanded into vast parts of the Southwest, South, and East of the city (with improving conditions in the Northwest). Dar es Salaam, a city with large shares of its area covered by informal settlements (with the highest severity in 2016 in the Center/South), experienced moderate growth of informal settlements in its entire periphery and moderate improvement in the Center/South area. Informal settlements in Windhoek were concentrated almost exclusively in the North and Northeast – and this spatial pattern intensified between 2016 and 2022.

City-level estimates of informal settlement prevalence and growth across sub-Saharan Africa

Calibrated binarization and aggregation of the raw within-city prediction maps (see Methods) enabled us to estimate the prevalence and growth of informal settlements at the city level. Figure 3 maps the share of the urban population living in and the share of the urban area covered by informal settlements for 529 major cities (>100,000 inhabitants in 2015) in 2016 and 2022, and its change between 2016 and 2022. The maps show a high prevalence as well as an expansion of informal settlements (both in area and population share) in many African cities. The full results for all 529 covered cities, including additional estimates on the total urban population living in informal settlements, are provided in the Supplementary Information (Supplementary Table 4).

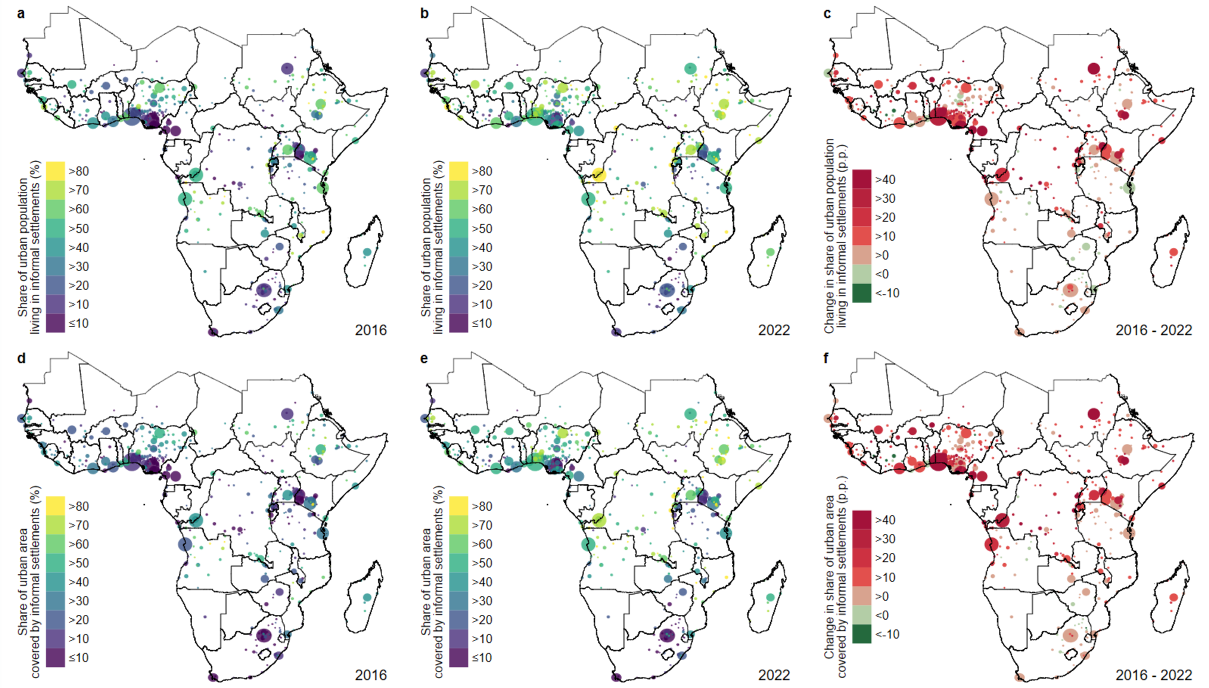

Figure 3 | City-level estimates of informal settlement prevalence and growth across sub-Saharan Africa (2016–2022). a-c, Share of the urban population living in informal settlements in 2016 (**a**), 2022 (**b**), and change between 2016 and 2022 (**c**). **d-f,** Share of the urban area covered by informal settlements in 2016 (**d**), 2022 (**e**), and change between 2016 and 2022 (**f**). Circle area is proportional to cities' total population size (in 2015, according to Africapolis estimates[31]).

The number of cities with a share of the urban population living in informal settlements exceeding 50% increased from 155 in 2016 to 274 out of 529 in 2022. In the same period, the share of the urban population living in informal settlements increased in 84% of all cities – the majority (320 cities) experienced an increase of between 0 and 25 percentage points (pp). Only in 82 of 529 cities a decrease in the share of the urban population living in informal settlements was observed (Extended Data Figs 3 and 4).

Our estimates also reveal interesting spatiotemporal dynamics. In 2016, on average, the share of the urban population living in informal settlements was highest in East African cities with 40%, followed by Middle (37%), West (30%), and lastly Southern African cities (17%). However, due to differential growth dynamics, this order changed until 2022 with Middle African cities now having the largest share of the urban population living in informal settlements (58%), followed by East (52%), West (48%), and lastly Southern African cities (19%).

In 2022, there were 41 cities with more than 80% of their population living in informal settlements – among them 11 in DR Congo, 10 in Ethiopia, 5 in Kenya, and 4 in Angola. The ten cities with the highest estimated total number of inhabitants living in informal settlements were Luanda, Angola (5.9M); Lagos, Nigeria (5.7M); Kinshasa, DR Congo (3.6M); Dar es Salaam, Tanzania (3.2M); Kampala, Uganda (2.9M); Nairobi, Kenya (2.9M); Abidjan, Côte d'Ivoire (2.7M); Addis Ababa, Ethiopia (2.5M); Bamako, Mali (2.4M); and Kano, Nigeria (2.4M).

In 50 cities, the share of the population living in informal settlements had increased by more than 40 pp between 2016 and 2022 – among them 23 in Nigeria, 11 in DR Congo, and three in Kenya and Uganda each. The ten cities with the highest estimated absolute increase in their population living in informal settlements were Lagos, Nigeria; Luanda, Angola; Ibadan, Nigeria; Kinshasa, DR Congo; Yaoundé, Cameroon; Douala, Cameroon; Khartoum, Sudan; Bamako, Mali; Hawassa, Ethiopia; and Abidjan, Côte d'Ivoire – each with more than 800,000 additional informal settlement dwellers in 2022 compared to 2016.

Middle African cities also displayed the highest estimated shares of their area covered by informal settlements (56%), followed by similar shares in East (45%) and West (44%), and markedly lower shares in Southern African (13%) cities in 2022. Overall, informal settlement prevalence was noticeably lower when measuring it as the area covered by them as compared to the population living in them. However, this difference decreased over the study period, i.e., the growth of informal settlements was, on average, driven more by their spatial expansion than by population growth within already existing informal areas. Yet the gap between the area-based and the population-based measure remains pronounced, indicating a comparably high population density in informal settlements – which is to be expected in light of the UN-Habitat slum deprivation criteria "lack of sufficient living area"[3].

Country-level estimates of informal settlement prevalence and change in sub-Saharan Africa

Figure 4 maps the share of the urban population living in, and the share of the urban area covered by informal settlements for 44 countries in sub-Saharan Africa in 2016 and 2022, and its change between 2016 and 2022, according to our model. The full results for all 44 covered countries, including additional estimates on the total urban population living in informal settlements, are provided in the Supplementary Information (Supplementary Table 5).

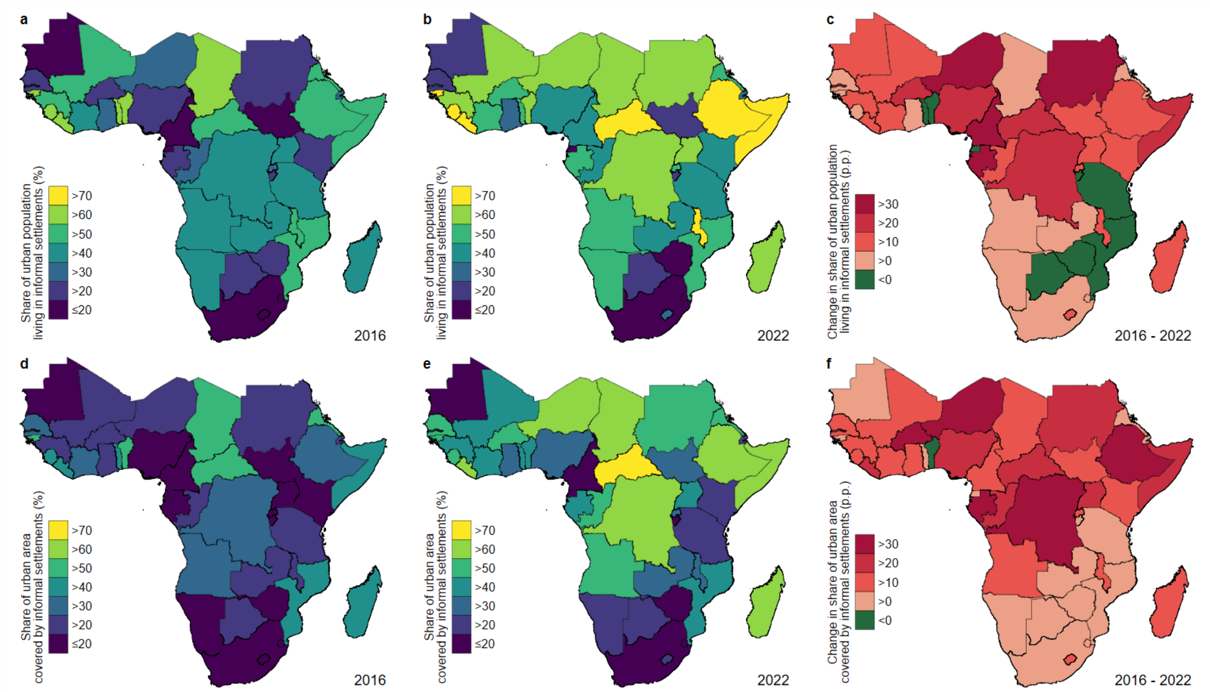

Figure 4 | Country-level estimates of informal settlement prevalence and growth across sub-Saharan Africa (2016–2022). a-c, Share of the urban population living in informal settlements in 2016 (**a**), 2022 (**b**), and change between 2016 and 2022 (**c**). **d-f,** Share of the urban area covered by informal settlements in 2016 (**d**), 2022 (**e**), and change between 2016 and 2022 (**f**).

While in 2016 the share of the urban population living in informal settlements exceeded 50% in 14 out of 44 countries, this increased to 25 countries in 2022. Between 2016 and 2022, in all except eight countries, the share of the urban population living in informal settlements increased, and the unweighted mean share across all 44 countries increased from 40% in 2016 to 51% in 2022.

The spatial patterns at the country level differ to some extent to those observed at the city level. In 2016, West African countries had on average the highest estimated share of their urban population living in informal settlements with 44%, followed by East (41%), Middle (37%), and with much distance Southern African countries (24%). By 2022, these numbers rose to 55% in both West and Middle African countries, closely followed by East (51%), and again at last Southern African countries (29%). Stark regional discrepancies also pertain to the growth of the informal settlement population. Between 2016 and 2022 the share of the informal settlement population grew by far the strongest in Middle African countries with on average 18 pp, and by 11 pp, 10 pp, and 5 pp in West, East, and Southern African countries, respectively.

In 2022 the ten countries with the highest share of urban dwellers in informal settlements were Central African Republic (85%), Liberia (76%), Somalia (75%), Ethiopia (72%), Sierra Leone (72%), Malawi (71%), Guinea-Bissau (71%), Chad (69%), Uganda (69%), and Niger (67%) – four in each East and West and two in Middle Africa. The ten countries with the highest increase between 2016 and 2022 were Cameroon (41 pp), Niger (36 pp), Sudan (34 pp), Gabon (30 pp), Central African Republic (26 pp), Burkina Faso (25 pp), DR Congo (25 pp), Nigeria (25 pp), Somalia (23 pp), and Uganda (18 pp).

As in the city-level analysis, the spatiotemporal patterns of informal settlement prevalence and growth remain similar when focusing on an area-based rather than on a population-based measure.

Discussion

Our findings suggest a high prevalence as well as a fast expansion of urban informal settlements across sub-Saharan Africa. According to our estimates, 84% of all analyzed cities experienced an increase in the share of the population living in informal settlements between 2016 and 2022. By 2022, in more than half of all cities, at least half of the population lived in informal settlements. We also found strong heterogeneities in both prevalence and growth between and within countries. Overall, both the share of the urban informal settlement population in 2022 as well as its growth between 2016 and 2022 tend to be particularly high in Middle and West Africa, closely followed by East Africa, whereas both the level and growth rates are much lower in Southern Africa. The observed increase in the share of the population living in informal settlements across most major cities in sub-Saharan Africa stands in contrast to the trends published by UN-Habitat. According to their Urban Indicators Database, the share of the urban population living in informal settlements in sub-Saharan Africa has continuously (though slowly) decreased in the past two decades – from 64.1% in 2000 to 57.3% in 2010 and 50.2% in 2020[1].

This discrepancy might partly be explained by some key differences between our estimation approach and the conventional survey- and census-based approach employed by UN-Habitat and other institutions to track SDG 11.1. First, given the three- to five-year survey intervals[13], the biannual publications of UN-Habitat have to conduct some extrapolations, while satellite data allows estimates for all places of interest on a true annual basis. For example, only four DHS (2003, 2010, 2014, 2018) were conducted in Burkina Faso between 2000 and 2020[36].

Second, survey-based approaches capture informal settlements based on household-level data, while our approach more accurately classifies contiguous geographic areas as informal settlements. Our estimates should thus be less sensitive to improvements in specific deprivation indicators of a few households when the neighborhood overall remains deprived. An analysis of DHS data from Ouagadougou, Burkina Faso, suggests a strong decrease in the share of inhabitants living in informal settlements between 2014 (40%) and 2018 (29%), mostly driven by a decrease in overcrowded households[37,38]. By contrast, we estimated a strong increase between 2016 and 2022, from 29% to 54%. Our approach also focuses, by definition, on geographical and morphological characteristics of areas detected by satellite sensors. Dense, unstructured construction patterns and substandard roof materials are more easily captured than lack of access to water and sanitation, yet these indicators are generally strongly correlated.

The third and most important difference lies in the sampling procedure of cities within countries and of the population within cities. While the delineation between urban and rural PSUs in surveys may differ between countries (and over time), we use one standardized database of cities across all countries[31]. Further, instead of a random sub-sample of cities, we use all (major) cities of a country. Our city database also has the advantage that it generally encompasses not just the official city proper but the entire contiguously built-up area of an urban agglomeration, including the periphery[39]. The latter might be missed in many household surveys, especially if growth in the urban periphery is unplanned and if sampling frames are not continuously updated. Extended Data Figure 5 illustrates this issue exemplarily for Ouagadougou, Burkina Faso. It shows that almost all DHS 2018[38] PSUs were located in the city's central area, while large parts of the urban periphery were not covered. According to our predictions, however, these were exactly the areas where Ouagadougou experienced most of its informal settlement growth. Importantly, our probability maps (Fig. 2 and https://gitlab.renkulab.io/deeplnafrica/deepLNAfrica/-/tree/main/change_figures) reveal that informal settlement expansion in many cities took place predominantly in such peripheral areas of urban agglomerations.

UN-Habitat continues to emphasize the responsibility of National Statistical Offices (NSOs) for the collection and analysis of household survey and census data on informal settlements[40].

Given the above-described limitations of survey and census data, monitoring SDG 11.1 solely based on these data sources certainly remains challenging. At the same time, UN-Habitat also acknowledges the capacity of satellite imagery and machine learning methods to "provide precise information on the area physical [and] social characteristics […] generating results comparable across cities and countries" in its Urban SDG Monitoring Series[13].

In light of the high prevalence of urban informal settlements across sub-Saharan Africa and in particular given the adverse trends observed between 2016 and 2022, achieving SDG 11.1 is a long way away, according to our estimates. Extrapolating our estimated trends suggests that not a single country in sub-Saharan Africa will reduce the share of its urban population living in informal settlements to less than 10% by 2030. Furthermore, the growth rate of the urban population is projected to stay over 3% per year in sub-Saharan Africa over the next two decades[2]. This puts additional pressure on African cities and potential progress in relative terms might in many cities be counteracted by a regress in absolute terms, i.e., increasing total numbers of informal settlement dwellers despite a decrease in the share of the urban population living in informal settlements. Targeted efforts of slum upgrading and provision of new and adequate housing in Africa's megacities as well as in other large and fast-growing cities could improve the living conditions of many current and future urban dwellers.

In addition to continuously monitoring city- and country-level trends on an annual basis, our proposed machine learning pipeline is well-suited to identify likely locations of informal settlements within cities and track their spatial-temporal development (expansion or reduction). Our approach can support international organizations in allocating resources between countries and national policymakers in sub-Saharan Africa to balance efforts between cities as well as to identify those locations and populations most in need even within cities.

Future work and caveats

Our present study offers a methodological and analytical framework to map urban informal settlements across sub-Saharan Africa and monitor their spatiotemporal development. Along these lines, we plan to provide annual extensions of our estimates. In this study, we focused on major cities of at least 100,000 inhabitants, but future work could extend our estimates to include also smaller cities. Moreover, on the condition of the availability of suitable ground truth data, our approach could potentially be applied in other world regions, in particular those affected by high levels of urbanization and informal settlement prevalence, such as South Asia[1]. As a next step, we plan to combine the data products of the present study – maps of predicted informal settlement locations in sub-Saharan African cities – with georeferenced survey data to investigate disparities in socioeconomic development between residents of informal settlements and formal neighborhoods.

The accuracy of our results depends primarily on the quality and quantity of ground truth data on informal settlements and of satellite images. First, including ground truth data from additional cities, in particular from countries without any ground truth data yet, could further improve the accuracy of our predictions by increasing the geographical and morphological diversity of the training data. Whenever such novel ground truth data becomes publicly available, it could easily be added to our machine learning pipeline and used to refine and update our predictions. Second, the accuracy of a prediction for a given city depends on the number of available satellite images with sufficiently low cloud coverage for this city. Naturally, this is highly correlated with climatic conditions, so that some cities are more affected by this caveat. However, limited availability of low-cloud-coverage images concerns only few cities (Supplementary Figs 1 and 2), and any biases should be negligible at the country-level. In addition, continuous improvements in cloud coverage correction algorithms will further mitigate this issue. Lastly, our predictions could be further improved by using satellite imagery products of higher spatial resolution once these still prohibitively costly products become publicly accessible.

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Methods

Overview

Our study provides estimates of the prevalence of informal settlements in sub-Saharan Africa at the city- and country-level, based on a machine learning pipeline utilizing state-of-the-art deep learning methods for computer vision applications. We estimated the share of the urban area covered by, the share of the urban population, and the total urban population living in informal settlements in 2016 and 2022, as well as the changes in these measures over the study period. The study covers 529 cities from 44 countries – 195 (16) cities (countries) in East, 85 (8) in Middle, 56 (5) in Southern, and 193 (15) in West Africa (Extended Data Fig. 2). Our primary goal was to map the prevalence and spatiotemporal development of informal settlements across urban sub-Saharan Africa. Our machine learning pipeline combines ground truth data on known informal settlements from 16 cities in six countries and open-access Sentinel-2 satellite imagery[30] and uses ensemble models for out-of-sample predictions (i.e., cities or years not seen at training time) producing raster files that map the pixel-level probability of informal settlement coverage at 10m resolution. These raster files are readily usable to identify informal settlements within cities and track their spatiotemporal development. After binarization of these raster files with calibrated threshold values, geospatial analysis techniques were applied to calculate the aforementioned aggregate city- and country-level estimates. A detailed description of all data sources, the machine learning model, the analysis, and the associated limitations are provided below and in the Supplementary Information.

Data

Ground truth data of known informal settlements

Extended Data Figure 1 and Supplementary Table 1 provide an overview of our ground truth data of informal settlements. We were able to identify and access geospatial data on informal settlements from 16 cities in six countries: Kenya (Kisumu and Nairobi), Sierra Leone (Freetown), South Africa (Cape Town, Durban, Embalenhle, Lebohang), Sudan (Nyala), Tanzania (Arusha, Dodoma, Kigoma, Mbeya, Mtwara, Mwanza, Tanga), and Uganda (Kampala).

As the various datasets come from different providers, they differ in terms of their geographic coverage (covering selected areas of a city versus the entire city), their reference year (data collection/map creation), and data format (shapefile/GeoPDF). They also differ to some extent in what exactly is mapped. Some providers map informal settlements in a rather fragmented way, including many very small clusters/pockets of sometimes just a few informal dwellings, while other approaches are broader, focusing on the exterior boundaries of a bigger informally dominated neighborhood (also including some open spaces, roads, public buildings, etc.). In addition, some providers not only map informal settlements but provide explicit spatial information on formal residential areas and other land use categories.

The ground truth datasets used to train our models were created by third parties, following three different approaches. 1) Field-based mapping: A team of fieldworkers equipped with GPS-tracking devices walks through areas pre-selected by domain and local experts to outline the boundaries of informal settlements. 2) Visual interpretation: Domain experts visually interpret very high resolution satellite images and identify informal settlements based on physical features under consideration of the local context. 3) Digitization of hard copy maps (issued by government authorities) where informal settlements are already outlined. All three methods generally provide maps of very high accuracy due to a high level of expert knowledge involved and a narrow geographic focus.

We used the ground truth data from all cities in South Africa and Tanzania without further manipulation. In the case of Sierra Leone, we applied minor adjustments, like dissolving overlapping polygons of adjacent settlements and filling small holes within polygons. In the case of Kenya, Sudan, and Uganda, however, we had to manually create polygons by hand-drawing boundaries of informal settlements in QGIS[41], based on maps provided in GeoPDF or PDF format. In all cases, the final product for each city was a raster map in GeoTIFF format with a spatial resolution of 10m per pixel, with each pixel classified as 1 (= informal settlement) or 0 (= no informal settlement).

Satellite imagery – Sentinel-2

We used openly accessible satellite imagery from the *Sentinel-2* mission of the European Union's Earth Observation Programme *Copernicus*[30] to train a deep neural network based on deep learning methods. The Sentinel-2 mission was launched in June 2015 and since then provides daytime satellite images of the entire globe, recorded every few days and with a maximum spatial resolution of 10m per pixel. Sentinel-2 images are pre-processed, including corrections for atmospheric distortions, and contain pixel-level information, for example on cloud coverage, which is important for neural network training. From the 13 available spectral channels, we only kept the Red, Green, Blue, and Near Infrared (NIR) bands, as these are the only ones that come at the maximum spatial resolution of 10m per pixel and contain the necessary visual attributes to distinguish patterns of informal settlements.

For each city and year of interest, we used all available images with a cloud coverage of less than 15%. Images with higher cloud coverage are undesirable, as pixels covered by clouds cannot be assessed accurately and are thus simply set to 0 (see below). Information on the number of utilized images per city (Supplementary Fig. 1) and per country (averaged, Supplementary Fig. 2) are provided in the Supplementary Information and further discussed in the Limitations. Before using the satellite images in neural network training, we clipped Sentinel-2 images[30] to a bounding box around the ground truth data representing informal settlements, such that the satellite images and the ground truth maps align. When evaluating the neural network on other African cities without ground truth data, we clipped the satellite images to the city boundaries defined by Africapolis[31,39] (see below).

City polygons – Africapolis

Mapping informal settlements in African cities requires a database with information on the location, size, and boundaries of the continent's cities. This is not trivial given that the very definition of what a city is and how exactly its boundaries should be delineated varies from country to country and over time. It can be based on administrative, numerical, or functional criteria or a combination of these. We thus drew on the Africapolis database which provides a shapefile containing polygons of urban agglomerations from 54 African countries[31]. Africapolis utilizes data from censuses, electoral registers, and official administrative boundaries, and combines them with satellite and aerial images to map urbanization on the African continent. Using these data sources, Africapolis forms agglomerations based on a physical criterion (continuously built-up area: less than 200 meters distance between buildings and constructions) and a demographic criterion (more than 10,000 inhabitants in 2015)[39]. In high-density areas, this regularly leads to city polygons combining two official cities into one and including several suburbs, such as for Maputo-Matola in Mozambique and Johannesburg-Pretoria in South Africa (Extended Data Fig. 6). The Africapolis database contains a total of 7,720 urban agglomerations: 75 with more than 1 million inhabitants, 644 with between 100,000 and 1 million inhabitants, and 7,001 with between 10,000 and 100,000 inhabitants (in 2015, estimates by Africapolis). We restricted our analysis to all major cities (>100,000 inhabitants) in sub-Saharan Africa (excluding the North African countries Algeria, Egypt, Libya, Morocco, and Tunisia; and the small island states Comoros, Cape Verde, Mauritius, Réuntion, and São Tomé and Príncipe), leading to a total of 529 cities. The restriction to cities with more than 100,000 inhabitants served to increase computational efficiency and save data storage demands and the focus on sub-Saharan Africa, excluding small island states, served to increase comparability across cities and countries.

Population distribution data – WorldPop

In order to estimate not just the share of the urban area covered by informal settlements, but also the share of the urban population living in these areas, information about the spatial distribution of the population within cities and over time is necessary. We retrieved this information from the WorldPop database of population counts, specifically from their product "Unconstrained individual countries 2000-2020 UN adjusted (100m)"[32]. The population counts datasets come as raster files with a spatial resolution of approximately 100m per pixel and provide for each country globally and from 2000 to 2020 an estimate of the number of inhabitants per pixel. These estimates are based on a combination of census data with various geospatial covariates, such as land cover, nighttime lights, temperature, roads, buildings, etc. The version used in this study is also adjusted such that country totals correspond to the official UN population estimates.

Machine learning pipeline

Basic training set-up

For our neural network, we applied a widely used state-of-the-art architecture for semantic image segmentation – the DeepLabV3 system[42] with a ResNet-50 backbone[43]. For any image input, this model generates an output of the same size, where every pixel contains a value between 0 and 1, indicating the probability of this pixel belonging to an informal settlement. At every training step, the neural network receives a batch of satellite image tiles of a given size, and for every one of them produces these probability maps, which are then compared to the binary ground truth tiles belonging to the same locations. Over many training iterations, the model learns to segment informal settlements by minimizing the binary cross-entropy between its own outputs and the ground truth. Optimization of the model's parameters is done through the AdamW optimization algorithm[44]. To help the neural network distinguish formal from informal settlements better, we additionally increase the weight of the binary cross-entropy loss function for every pixel that belongs to a formal settlement, whenever this information is also available to us. Finally, we further adjust the weighting of the loss based on the overall ratio of informal settlements in our training images.

Through our analysis, we concluded that it is relatively difficult for our model to generalize to other African cities that have not been seen at training time, even if it was trained in many cities from several countries at the same time. For this reason, we decided to train many different models on different groupings of cities and to gather their predictions for any new city. Such an ensemble of models generally provides more robustness through this averaging effect of utilizing multiple models trained on different data[45].

In Tanzania, where we have recent ground truth data for seven cities (Arusha, Dodoma, Kigoma, Mbeya, Mtwara, Mwanza, and Tanga), we trained seven different models, each of them trained on six of the cities and evaluated on the remaining one after every training epoch.

Leaving one city out of every training process allowed us to validate how well our current model was able to generalize to unseen data, and to save the model at a specific moment in time when this generalization was best. For Kenya, we applied the same procedure for the seven available ground truth maps (Kisumu, Nairobi-Kawangware, Nairobi-Kibera, Nairobi-Mathare, Nairobi-Eastleigh, Nairobi-Korochogo, Nairobi-Viwandani). To balance the large number of informal settlements in our training data from Kenya with more formal settlements, we also included three completely formal locations (Nairobi-Lavington, Nairobi-Muthaiga, Nairobi-Runda) in each training process. In South Africa (Cape Town, Durban, Embalenhle, and Lebohang), we only trained two models, excluding either Embalenhle or Lebohang since we considered the generalization of a model trained without either Cape Town or Durban as not satisfactory. As the last model, we paired the data from Freetown (Sierra Leone), Kampala (Uganda), and Nyala (Sudan) with the already used data from Mtwara (Tanzania), Embalenhle (South Africa), and Kisumu (Kenya). We did this because we found that adding one city from Tanzania, South Africa, and Kenya each improved the performance of this model. For the validation of this model, we used all other cities.

Model adjustments and self-supervised learning

To increase diversity between the models, we also varied the size of the tiles taken from the full satellite images. For all models from Tanzania, we used tile sizes of 512x512 pixels (roughly 26 km^2 tiles), whereas we used 128x128 (1.5 km^2) tiles for all Kenyan models and 256x256 (6.5 km^2) tiles for the South African models as well as for the final model on Freetown, Kampala, Nyala, Mtwara, Embalenhle, and Kisumu. Regardless of the specific tile size, we selected the tiles with random shifts but equally spread across all parts of the images during training. Furthermore, we applied the same pre-processing steps for all cities. All image tiles were normalized by the mean and standard deviation of each spectral band which we computed for more than 2,000 satellite images across sub-Saharan Africa. Moreover, for all ground truth tiles, we set the pixel value to 0 (= no informal settlement) for all pixels affected by cloud coverage.

We further improved the performance of our models significantly by starting the supervised training procedures with neural network weights initialized through a pre-training step. This pre-training step employs a relatively recent paradigm in machine learning, known as self-supervised learning[46]. Self-supervised learning describes methods that don't utilize explicit, human-annotated ground truth information but that automatically create their own supervisory learning signals from unlabeled data. It has been shown that initializing model weights by pre-training them in a self-supervised manner can lead to a sharp increase in downstream performance on supervised tasks[46]. In our case, we modified the Barlow Twins method[47], using our network architecture as the encoder model. The goal of Barlow Twins is to learn latent representations within the deep learning model which lead to uncorrelated features that are invariant to certain specific artificial distortions applied to image inputs. In contrast to the original Barlow Twins method, we didn't apply artificial distortions to natural images but utilized temporal Sentinel-2 satellite images[30]. Concretely, in every pre-training step, we encoded a batch of unlabeled satellite images with our segmentation network that was augmented with three attached fully connected layers. We then also encoded a second batch of satellite images from the exact same locations as those in the first batch but taken at a different point in time. That allowed us to apply the Barlow Twins idea[47] of learning latent image representations with uncorrelated latent features that are also invariant to the differences between corresponding images in the two batches. The underlying idea here was to pre-train our models to become insensitive and possibly invariant to the differences between satellite images from the same location, taken at a different time. This is sensible because most visual differences between the images would either come from seasonal or atmospheric effects (which are unimportant for informal settlements prediction) or discolorations due to pre-processing steps such as the atmospheric correction. On the other hand, assuming that the time difference between the images is not too large, we expected that visual changes due to important structural differences would be comparatively infrequent. Most importantly, we found that initializing our model weights for the supervised training on informal settlements based on this self-supervised pre-training step significantly enhanced our downstream predictions.

Ensemble predictions

After completion of the full training of all models, we aggregated their predictions as motivated above. In this prediction process, any satellite image from a new city was fed through each network after tiling, to match the tile size that the current model was trained with. This means that from left to right, top to bottom, we segmented informal settlements in each tile after the other (with some overlap over the tiles to avoid unwanted effects at the tile borders), until we could assemble these tiles to a full segmentation over the whole image. Once this was done, we first averaged the segmentation maps across all cities in a given country. This was only applicable for Tanzania, Kenya, and South Africa, where we had several models per country. Finally, we then took a weighted average of the final four segmentation maps (one each for Tanzania, Kenya, South Africa, and the final one for Freetown-Kampala-Nyala-Mtwara-Embalenhle-Kisumu) with weights according to their estimated strength based on the amount and quality of their training data. To be precise, we assigned a weight of 0.3 to both the Tanzania and the Kenya model and a weight of 0.2 to each of the other two models. The final raw product for each city in a given year was a raster file at a spatial resolution of 10m per pixel with continuous pixel values ranging from 0 to 1. The higher the pixel value, the higher the predicted probability that this pixel was covered by an informal settlement. These 'probability maps' can readily be used to infer nuanced spatiotemporal patterns of informal settlement locations within cities. A simplified graphical illustration of the entire machine learning pipeline, including training and prediction, is provided in Extended Data Figure 7.

Analysis

Binarization of segmentation maps

Prior to calculating city- and country-level estimates of informal settlement prevalence, we converted the continuous probability maps into binary maps such that each pixel was either 0 (= no informal settlement) or 1 (= informal settlement). Given the broad spatial scope of our study and the non-negligible differences across countries in terms of geographical and in particular morphological features in urban areas, we decided against a uniform threshold value to be applied to all 529 cities. Instead, we applied the following iterative procedure. First, we applied for each city three different intuitive threshold values to the continuous probability map – 1/5, 1/4, and 1/3 – yielding three binary maps per city and year. Based on these maps (in conjunction with the population count data[32]), we calculated three alternative country-level estimates of the share of the urban population living in informal settlements (see Geospatial analysis for more details) for the year 2020. We next compared these estimates to the corresponding estimates provided by UN-Habitat[1]. For each country, we then settled on one threshold value such that the difference between our estimates and the UN-Habitat estimates were minimized (Supplementary Table 2). For countries without UN-Habitat data, we selected the modal threshold value of all neighboring countries. After this calibration, the correlation coefficient between our estimates and the UN-Habitat estimates of 2020 was very large with r=0.79 (Extended Data Fig. 8), and for the majority of countries, the modulus difference between our estimates and the UN-Habitat estimates was smaller than 5 pp (16 countries) or smaller than 10 pp (10 countries) (Extended Data Fig. 9).

Performance evaluation

The performance of machine learning models for binary classification tasks can be evaluated through various accuracy metrics. For our specific task, three metrics are particularly informative. Recall (also Sensitivity or True Positive Rate, TPR), Precision (also Positive Predictive Value, PPV), and the F1 Score, which are calculated as follows:

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

$$PPV = \frac{TP}{TP + FP}$$

$$F1 = 2 \times \frac{PPV \times TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN}$$

Where *T/F/P/N* stand for true/false/positive/negative. Both the TPR and the PPV measure the ability of the model to correctly identify pixels covered by informal settlements (TP) – the TPR in relation to the actual extent of informal settlements in the ground truth (P or TP+FN), and the PPV in relation to all predicted informal settlement pixels (TP+FP). The F1 score is the harmonic mean of TPR and PPV and thus a composite measure of Recall and Precision. Supplementary Table 3 provides these test metrics for all cities with available ground truth data from Kenya, South Africa, and Tanzania, based on the country-specific models. This means that the prediction and corresponding test metrics on, for example, Arusha, Tanzania, were based on a model that included all cities from Tanzania, except Arusha, as training data. Excluding the city of interest is crucial to retrieve informative test metrics, as the goal of our study was to predict informal settlements in cities without any ground truth data. For increased transparency, we also included three additional accuracy measures, namely (overall) Accuracy, Specificity (True Negative Rate, TNR), and Intersection over Union (IoU). Given the limited amount of ground truth data, we generally reach satisfactory accuracy measures. Precision ranged from 32.51% (Kigoma, Tanzania) to 73.06% (Nairobi-Eastleigh, Kenya), Recall from 25.90% (Kigoma, Tanzania) to 97.63% (Nairobi-Mathare, Kenya) and the F1 Score from

28.72% (Kigoma, Tanzania) to 81.30% (Nairobi-Korochogo, Kenya). The corresponding mean (median) across all cities were 59.31% (64.58%) for Precision, 70.45% (72.01%) for Recall, and 62.55% (63.21%) for the F1 Score, respectively. These test statistics were complemented with the Precision-Recall Curve and the Receiver Operating Characteristic (ROC) Curve (Supplementary Fig. 3), for each city. Both identify the ideal binary threshold value that either jointly optimize Precision and Recall or jointly optimize the TPR and FPR.

Lastly, Supplementary Figure 4 visualizes the performance of our predictions within cities, i.e., it shows the distribution of true/false positives/negatives across pixels within cities with ground truth data. From left to right, the panels show 1) the input Sentinel-2 satellite image, 2) the binary ground truth raster, 3) the raw (continuous) prediction map, 4) the binary segmentation map, and 5) the classification of pixels into true positives (green), false positives (red), true negatives (white), and false negatives (blue). The visualizations confirm the findings from the test metrics – our models are generally well-suited to correctly identify informal settlements, yet with varying degrees of precision and sensitivity across cities, according to the quality and complexity of each image to be analyzed.

Geospatial analysis

Based on the binary segmentation maps containing per-pixel information on predicted informal settlement probability, we conducted several geospatial analyses. We calculated 1) at the city level and 2) at the country level the a) share of the urban area covered by informal settlements (*ShA*), b) the share of the urban population living in informal settlements (*ShP*), and c) the total urban population living in informal settlements (*TotP*). The following equations illustrate these calculations:

$$ShA_{c,t} = \left(\sum_{n=1}^{N} I_{bin,c,t,n}\right) \times \frac{1}{N}$$

$$ShP_{c,t} = \left(\sum_{n=1}^{N} I_{bin,c,t,n} \times P_{c,t,n}\right) \times \frac{1}{\sum_{n=1}^{N} P_{c,t,n}}$$

$$TotP_{c,t} = \sum_{n=1}^{N} I_{bin,c,t,n} \times P_{c,t,n}$$

I_{bin} is a pixel-level binary indicator of informal settlement coverage, P is the WorldPop population count estimate per pixel, c stands for city or country, t for time (year), and N is the number of pixels within city or country boundaries (urban area only).

Prior to the calculations, the following preparatory steps were conducted. The WorldPop population count rasters[32] were resampled from their original spatial resolution of 100m to match the 10m resolution of the binary segmentation maps. Resampling was applied such that the sum of the population count in the disaggregated (smaller) pixels of the resampled raster was equal to the population count of the corresponding original pixel congruent to the disaggregated pixels. For all country-level calculations, the Africapolis city polygons[31] were dissolved at the country level, while retaining spatial segregation of individual cities. Similarly, the binary segmentation maps were merged at the country level, while disregarding all pixels outside Africapolis city boundaries.

Software used for machine learning pipeline and analysis

The entire machine learning pipeline was implemented in PyTorch[48,49] and PyTorch Lightning[50]. For the calculations of all model evaluation metrics, we used the *scikit-learn* package[51].

After some preparatory steps in QGIS 3.24.1[41], the geospatial analysis was executed in R 4.3.1[52]. The *sf* package[53] was used for handling shapefiles (city polygons), the *terra* package[54] for handling raster files (segmentation maps and population counts), and the *exactextractr* package[55] for the implementation of the final calculations. Concretely, the package was used to calculate zonal statistics of the binary segmentation maps and population counts within (individual or country-level dissolved) city boundaries. For *ShA* the unweighted mean of the binary segmentation maps was calculated, for *ShP* each pixel of the binary segmentation map was additionally weighted by its corresponding population count, and for *TotP* the total of the population count was calculated, but each pixel was weighted by the binary indicator from the segmentation map.

All descriptive and statistical analyses, as well as all maps (except raster maps), were produced with Stata 17[56].

Limitations

This work should be assessed in full acknowledgment of the data and methodological limitations. Data limitations pertain to the two primary sources of input data for our machine learning pipeline, ground truth data and Sentinel-2 satellite imagery data[30], as well as to the WorldPop population count data[32] used for weighting in the final geospatial analysis. One limiting factor is the amount of reliable ground truth data on informal settlements. With 16 cities from six countries, the availability of ground truth data for the present study is rather moderate yet has the advantages of covering various regions (West, East, and Southern Africa) with different geographical and climatic conditions and significant differences in population size (from 30,000 in Lebohang, South Africa to 5.9M in Nairobi, Kenya; according to Africapolis estimates[31]). These features help ensure appropriate geographical and morphological diversity of the training data. In addition, evaluating the accuracy of our predictions is again limited by the amount of ground truth data, as evaluation statistics used in machine learning can only be calculated for cities with ground truth data. Hence, to complement the common evaluation statistics reliant on ground truth data, we calculated an additional metric that exploits the fact that our final ensemble predictions are weighted averages of predictions based on four ‘country-specific’ models. Specifically, for each city, we calculated the per-pixel standard deviation (SD) of the four different predictions of informal settlement locations (according to the four different models – before aggregating as ensemble prediction). We then calculated city-level (Supplementary Fig. 5) and country-level (Supplementary Fig. 6) means of the SD across predictions. Both across cities and across countries, the mean and median of the aggregate SD were around 0.12 in 2016 and around 0.16 in 2022. These are rather low values compared to the theoretically possible maximum of 0.5, which implies only small variation across predictions from different models. Only 5 (28) cities have a mean SD higher than 0.25 in 2016 (2022) and all countries remain below this threshold in both years. Overall, a higher mean SD across the different models can be interpreted as lower confidence in our ensemble prediction for the corresponding city or country.

Second, for a given city in a specific year, our machine learning pipeline uses all available satellite images with a cloud coverage of less than 15% (“cloud-free”). The more “cloud-free” images are available, the more accurate the predictions, as seasonal changes affecting the visual and spectral appearance of images will be averaged out. The mean (median) number of “cloud-free” images across cities was 49 (36) in 2016 and 49 (34) in 2022. Only 36 (60) cities had less than 10 “cloud-free” images available in 2016 (2022) (Supplementary Fig. 1). This issue is most prevalent in Middle and West African cities in proximity to the coast – caution is warranted when interpreting the predictions for these cities. Nevertheless, even with a small number of images accurate predictions can be made – provided that the quality of the available images is sufficiently high. Aggregation at the country-level further alleviates this caveat – only 2 (3) countries have less than 10 “cloud-free” images on average per city in 2016 (2022) (Supplementary Fig. 1).

Third, WorldPop population count estimates[32] only extend until 2020, yet our analysis covers 2022 as the most recent year. When using population counts as weights, i.e., when calculating the share of, and the total urban population living in informal settlements in 2022, we used the 2020 population count data as an approximation. In absence of more recent population count data, we believe that this two-year difference is acceptable and should not substantially bias our estimates. For the calculation of population shares, only the relative distribution of the population within cities matters, which we assume should not change substantially over two years. Given the positive growth rates of the urban population in all sub-Saharan African countries[2], our estimates of the total population living in informal settlements for 2022 (and the change between 2016 and 2022) will, for most cities, likely be slightly downward biased. In addition, the WorldPop population count data[32] has been criticized for underestimating populations in informal settlements[57–59]. However, it is still better suited to capture populations in informal settlements compared to household surveys which often completely neglect informal settlements, in particular if growth in the urban periphery is unplanned and if sampling frames are not continuously updated.

Methodological limitations are related to the binarization of the “raw” continuous probability maps. Given the geographical and morphological diversity across cities, we started with three different intuitive threshold values and for each country selected the threshold that minimizes the difference between our estimates of the share of the urban population living in informal settlements and those from UN-Habitat[1]. After this calibration, we reach a correlation coefficient of r=0.79 between our and the UN-Habitat estimates for 2020 (Extended Data Fig. 8), with a mean (median) absolute difference of -4 pp (-3 pp). For six of 35 countries with UN-Habitat data, the modulus difference remains larger than 15 pp after calibration (Extended Data Fig. 9). Although speculative, one reason could be geographic and climatic features. In five of these six countries our estimates are markedly smaller than the UN-Habitat estimates – and these countries are heavily dominated by desert and steppe. While it would be possible to introduce additional binarization thresholds, this would increase the complexity of our procedure. More importantly, this would not be a guarantee for increased accuracy as the UN-Habitat data itself is based on census and survey data with their own limitations and varying quality across countries[13–15,17].

Code availability

All code used for the machine learning modeling and data processing pipeline – including downloading and pre-processing of Earth Observation data – is publicly available under https://gitlab.renkulab.io/deeplnafrica/deepLNAfrica/. The repository also includes the continuous probability maps for all 529 cities, as well as code to create binary maps based on threshold values. R code for the geospatial analysis and Stata code for descriptive and statistical analysis (including maps) is available upon request.

Data availability

All data used in this study is open-access and publicly available. For our various ground truth datasets, we provide a link to the respective original data source in the Supplementary Material, Section 1.1. We also advert to cases where we obtained the ground truth data directly from the institutional provider upon request.

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Author contributions

N.B. and K.H. conceptualized the study. K.H., M.V. and E.S. acquired funding. N.B. and S.S. curated the data. S.S. conceptualized and implemented the machine learning pipeline with inputs from M.V. and E.S. N.B. conceptualized and implemented the geospatial analysis with inputs from K.H. N.B. and S.S. prepared tables and figures with inputs from K.H. and M.V. N.B. wrote the first draft of the manuscript, and all authors reviewed and edited the manuscript. All authors discussed the results and contributed to the revision of the final manuscript.

Competing interests

The authors declare no competing interests.

Supplementary information

Supplementary information is available in the online version of the paper.

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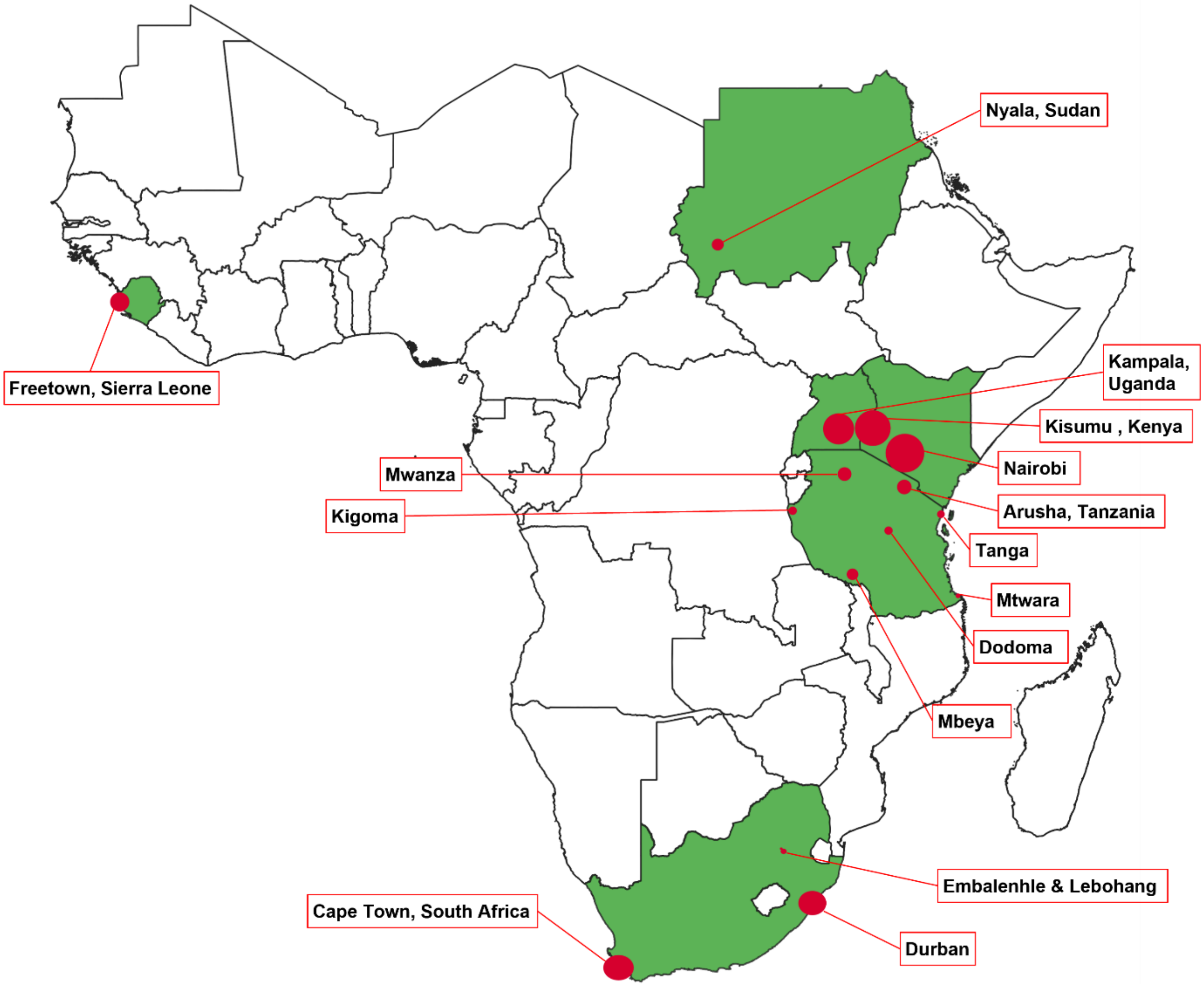
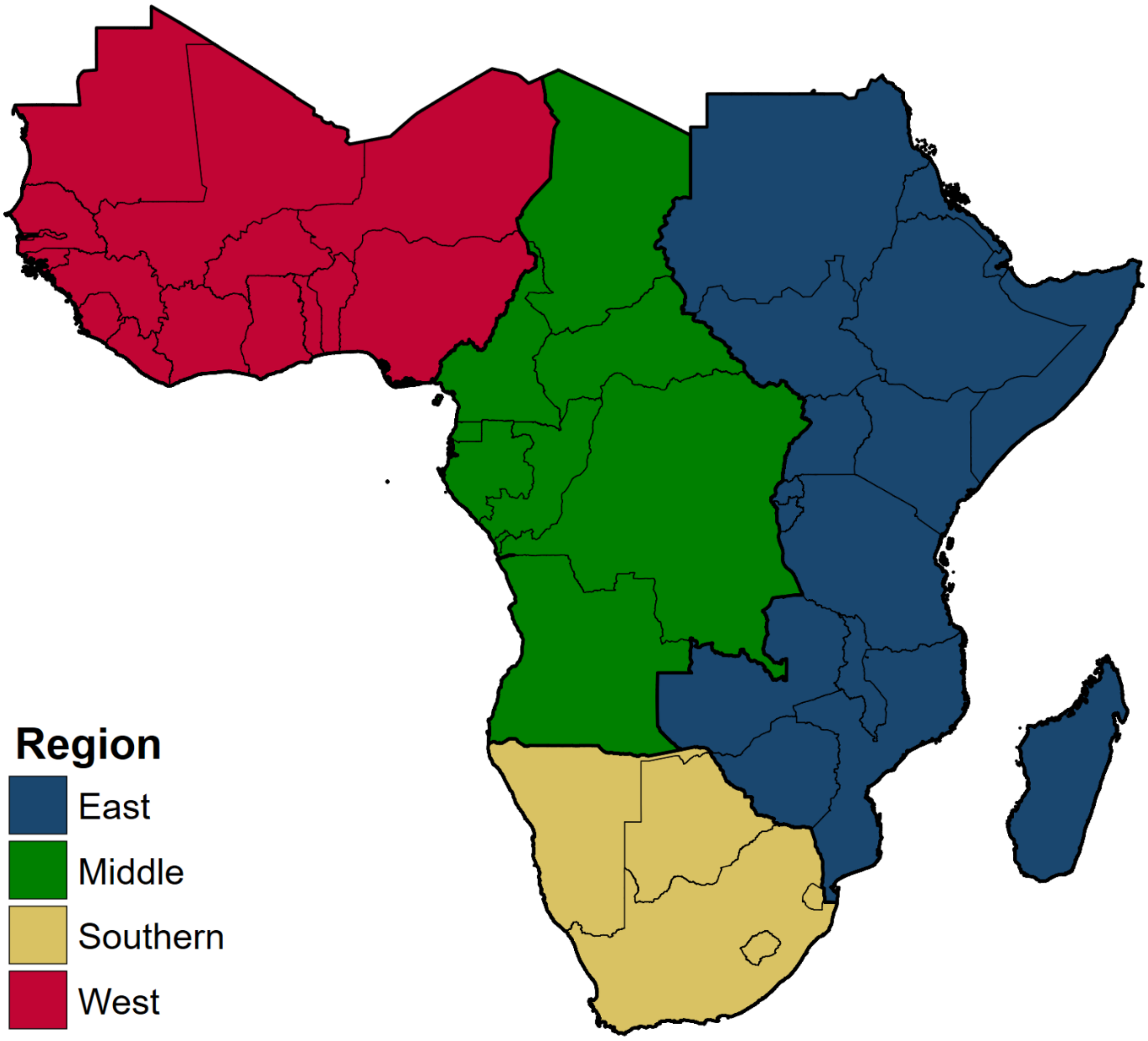
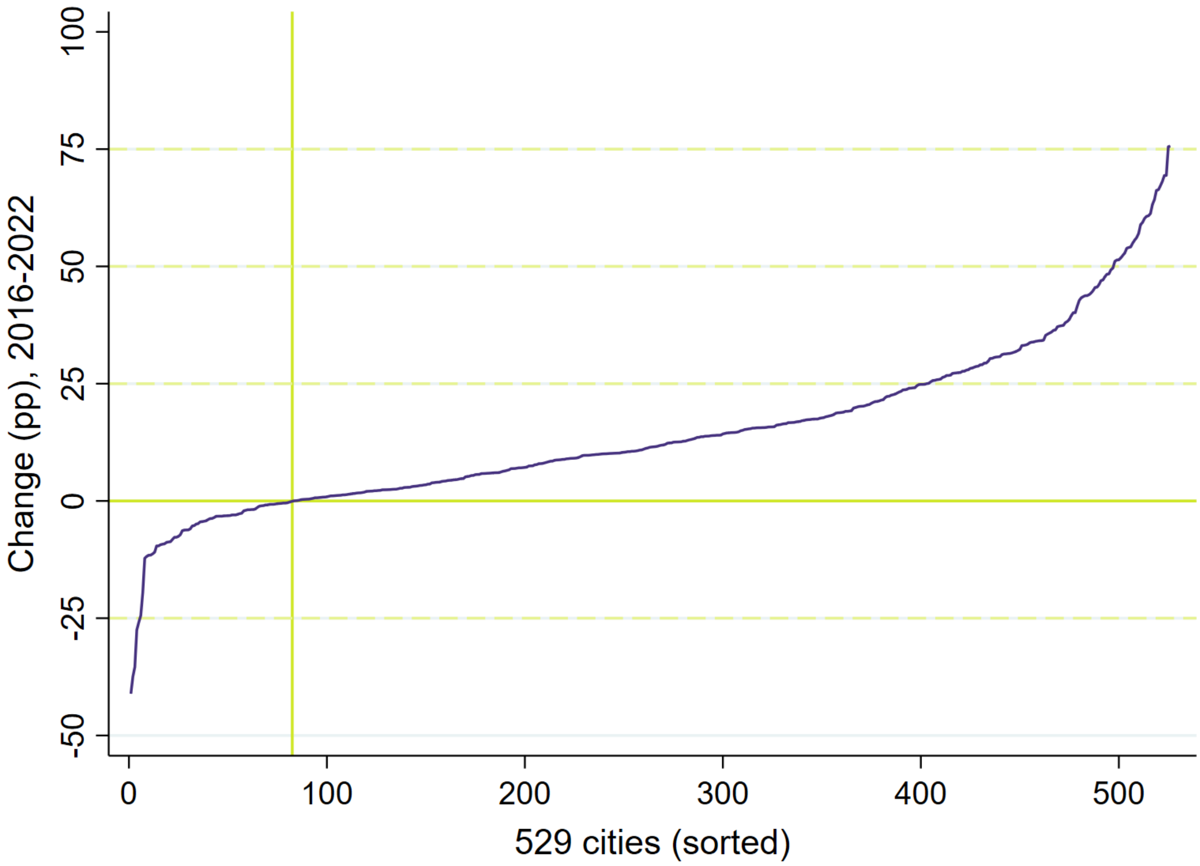
Extended Data



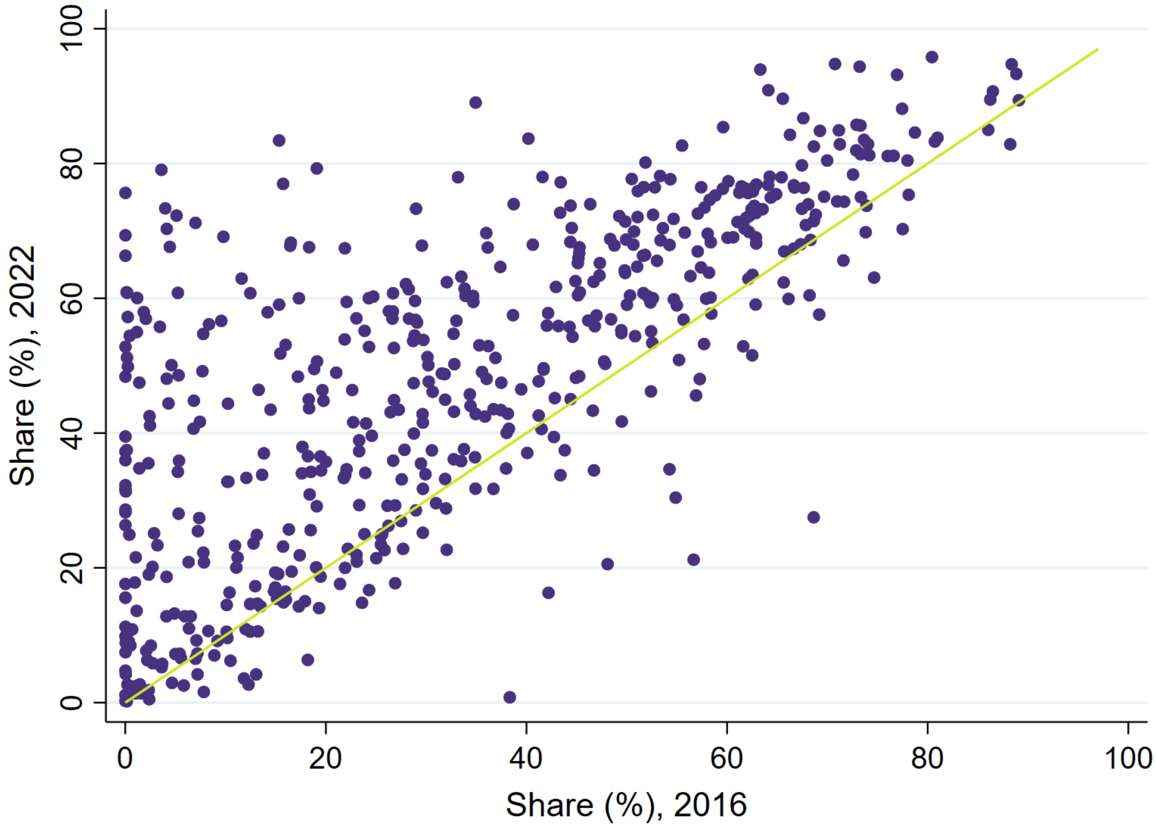
Extended Data Figure 1 | Locations of the 16 cities with ground truth data. The location of cities with ground truth data are mapped by red circles. The circle area is proportional to the cities' total population size (in 2015, according to Africapolis estimates[31]). Countries with cities with ground truth data are filled green, countries without cities with ground truth data are left blank.



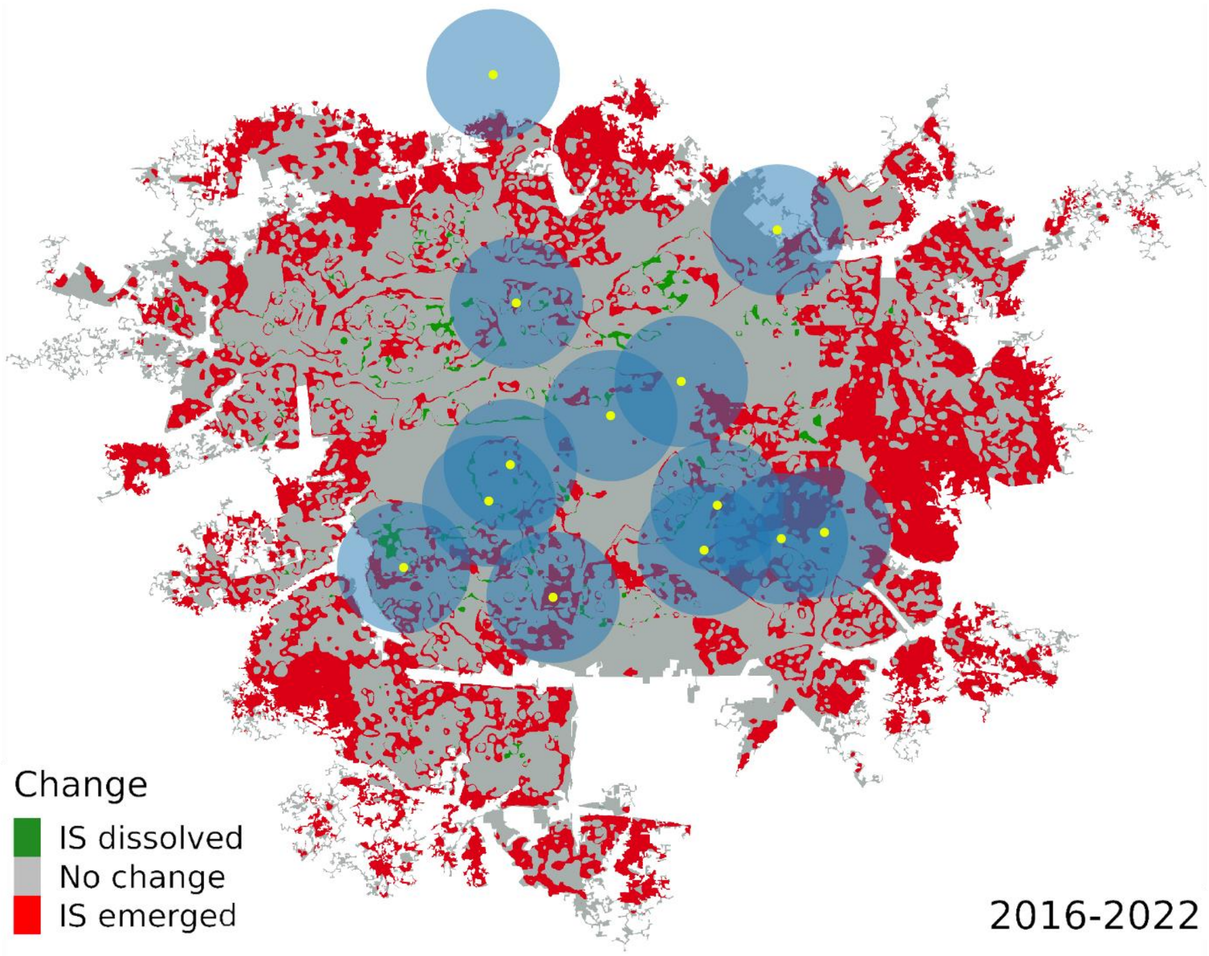
Extended Data Figure 2 | Classification of regions in sub-Saharan Africa. We classified countries as belonging to one four regions in sub-Saharan Africa: East, Middle, Southern, and West Africa. We therefore followed the United Nations (UN) Geoscheme for Africa[60], with the only exception that we included Sudan in East Africa, which the UN classifies as part of North Africa.



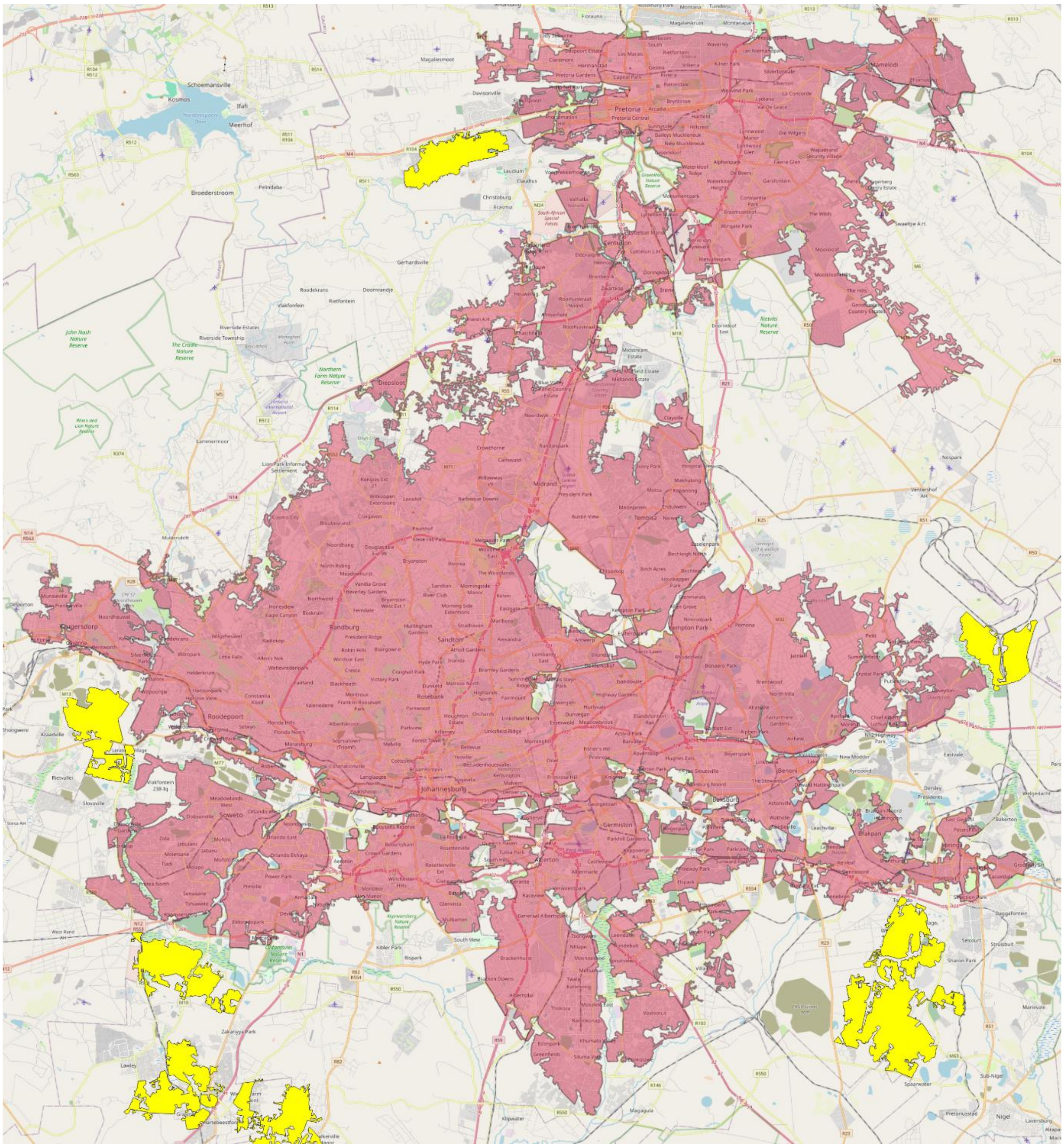
Extended Data Figure 3 | Changes in the share of the urban population living in informal settlements between 2016 and 2022 across 529 cities. Changes are expressed in percentage points (pp). Cities are sorted on the x-axis in increasing order according to the changes between 2016 and 2022.



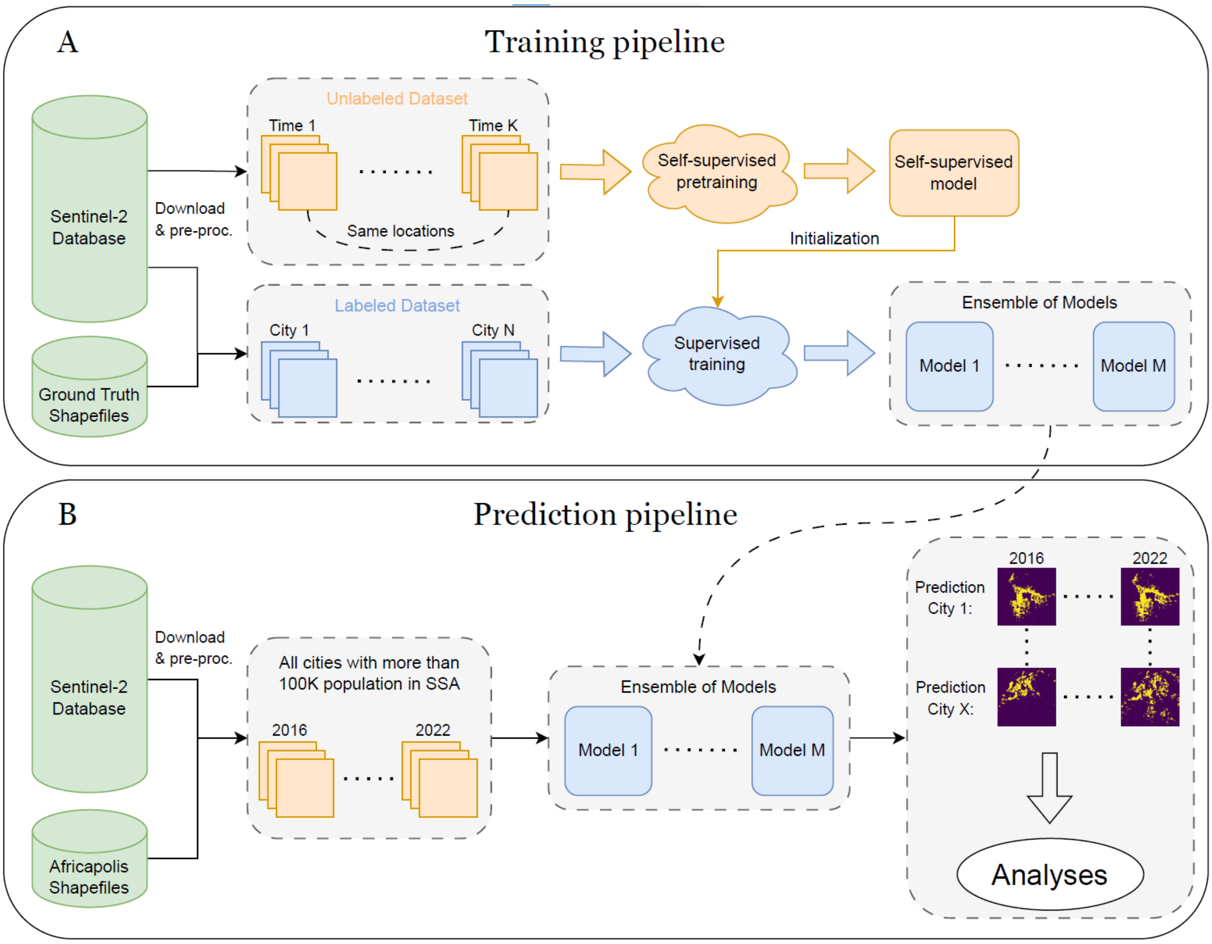
Extended Data Figure 4 | Share of the urban population living in informal settlements – 2016 versus 2022, 529 cities. Cities are depicted by dark purple circles. Circles above the 45-degree-line experienced an increase in the share of the urban population living in informal settlements between 2016 and 2022. Circles below the 45-degree-line experienced a decrease.



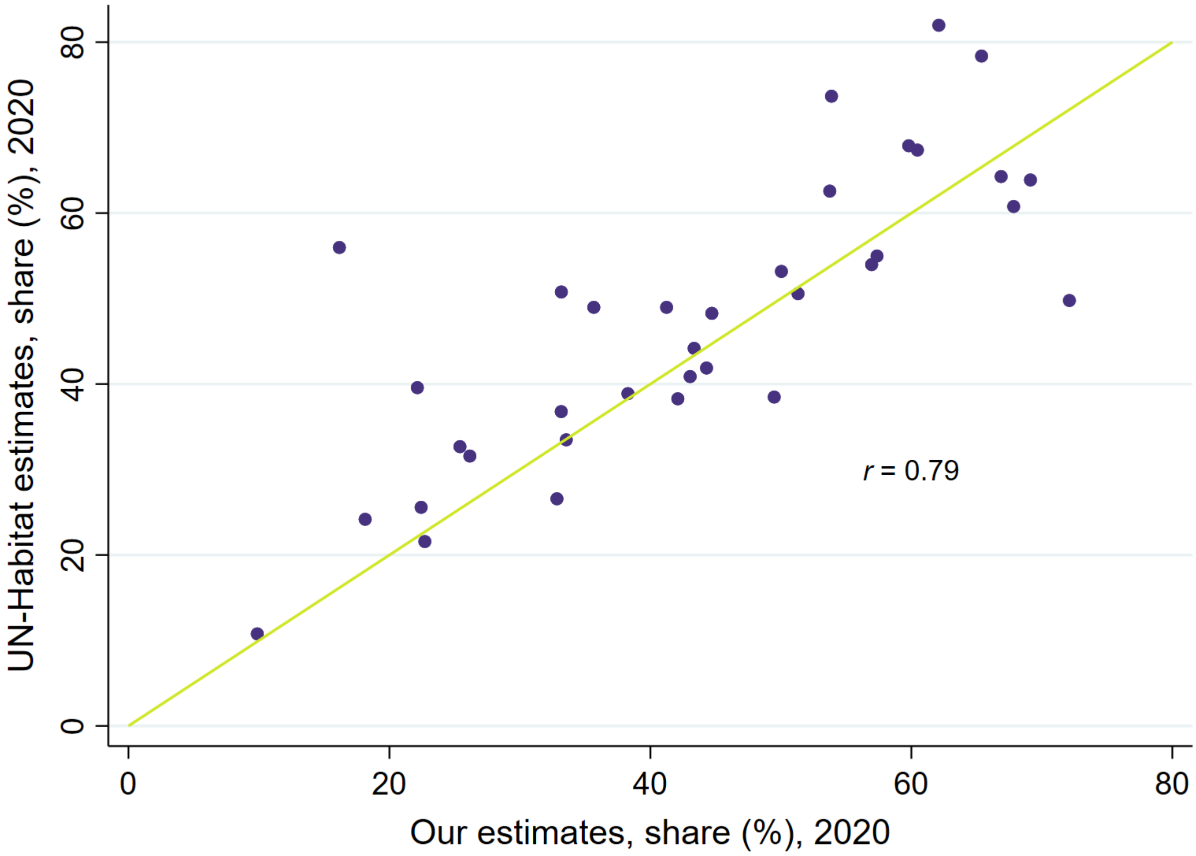
Extended Data Figure 5 | DHS sampling and informal settlement growth in Ouagadougou, Burkina Faso. IS stands for informal settlement. Yellow dots are DHS 2018[38] PSU centroids. Blue-shaded circles indicate 2km random displacement buffer of DHS PSUs. The true PSU centroid can thus be located anywhere within the corresponding blue-shaded circle.



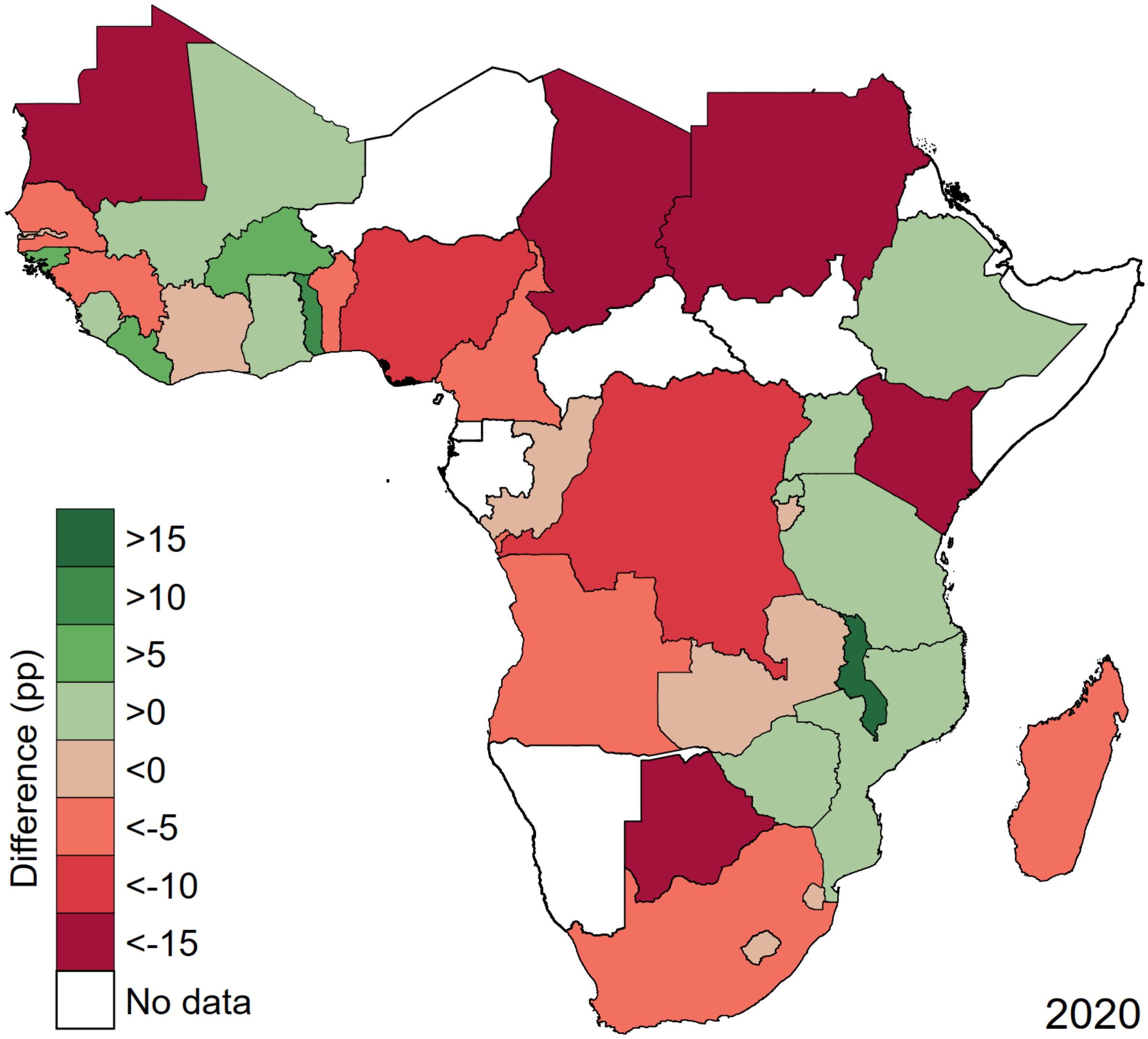
Extended Data Figure 6 | Africapolis polygon of Johannesburg/Pretoria, South Africa. The red shaded polygon illustrates the area and boundaries of the urban agglomeration of Johannesburg and Pretoria, South Africa (including various suburbs), according to Africapolis[31]. Yellow polygons are considered separate cities because their built-up area is more than 200 meters away from the Johannesburg/Pretoria entity. For orientation, the background shows an OpenStreetMap layer of the area[61].



Extended Data Figure 7 | Illustration of training and prediction pipeline. Top panel illustrates training pipeline. Bottom panel illustrates prediction pipeline.



Extended Data Figure 8 | Correlation between our predicted estimates and UN-Habitat estimates – 2020, country-level. Countries are depicted by dark purple circles. Both axes measure the share of the urban population living in informal settlements. Circles above the 45-degree-line indicate higher estimates by UN-Habitat and circles below the 45-degree-line indicate higher estimates by our method. *r* is the correlation coefficient.



Extended Data Figure 9 | Difference between our predicted estimates and UN-Habitat estimates – 2020, country-level. Negative differences (red shades) mean that our estimates are lower than the UN-Habitat estimates[1]. Positive differences (green shades) mean that our estimates are higher than the UN-Habitat estimates. Nine countries have no UN-Habitat data.