International population conference
Brisbane, July 20-24 2025

Predicting poverty in African cities using open source remotely sensed data

Géraldine Duthé[1], Basile Rousse[1,2], Hervé Bassinga[3], Valérie Golaz[1], Arlette Simo-Fotso[1]

[1] Institut national d'études démographiques (INED), France
[2] LIPADE, Université Paris Cité, France
[3] Institut supérieur des sciences de la population (ISSP), Université Joseph Ki Zerbo, Burkina Faso

Short abstract

Due to a lack of regular statistics, little is known about socioeconomic and environmental dynamics of African cities. Recent advances in spatial imaging technologies, along with their growing accessibility, allow for the acquisition of high-resolution temporal and spatial data worldwide and Open source remotely sensed data provide a large variety of measures for many uses. In this study, we aim to explore the relevance of such kind of sources in order to predict the socioeconomic and environmental characteristics of neighborhoods in African cities. To do so, we use buildings detection provided by Google Open Buildings: models have been trained using deep learning to detect buildings from remote sensing images. Confidence scores are also provided for each detection. The higher the score, the more confident the model in its prediction to distinguish buildings. We assume that this score, in urban cities, can help to identify neighborhoods with no clear urban planning, informal housing and poor socioeconomic conditions. We first use census data to explore the correlation at the neighborhood level in Antananarivo and Ouagadougou. We then use data from Demographic Health Surveys in order to test this association on a larger sample of African cities.

Background

In low- and middle-income countries, the rapid urbanization in a context of low economic development has led to the surge of informal housing neighborhoods - slums in the worst case - and more generally to large socioeconomic inequalities. A non-negligible share of urban residents do not benefit from the urban health advantage as it has been demonstrated in Latin America and as it is on debate in African cities. In this context, the burden of adverse environmental conditions, that usually characterize the slums and spontaneous installation areas, appears to cumulate to other socioecononomic burdens (poverty, density…) and dramatically impact on health and mortality. However, due to the lack of reliable statistics, little is known about health and environment at a fine scale in many sub-Saharan African cities.

Objective

Recent advances in spatial imaging technologies, along with their growing accessibility, allow for the acquisition of high-resolution temporal and spatial data worldwide and Open source data provide a large variety of measures for many uses. In this study, we aim to explore the relevance of such kind of sources in order to predict the socioeconomic and environmental characteristics of neighborhoods in African cities.

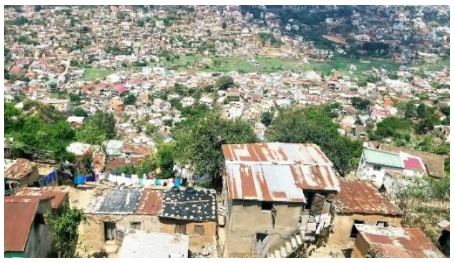
To do so, we use buildings detection provided by Google Open Buildings: models have been trained using deep learning to detect buildings from remote sensing images. Confidence scores are also provided for each detection. The higher the score, the more confident the model in its prediction to distinguish buildings. We assume that this score, in urban cities, can help to identify neighborhoods with no clear urban planning, informal housing and poor socioeconomic conditions. We first use census data to explore the correlation at the neighborhood level in Antananarivo and Ouagadougou. We then use data from Demographic Health surveys in order to test this association on a larger sample of African cities.

Data and method

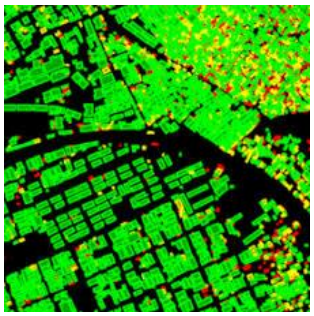
Environment data and indicators

Google Open Buildings: detection of the buildings from deep learning based on satellite images. The model confidence in each detection is also provided. The higher the score, the more confident the model is in its prediction to distinguish between buildings and not buildings.

Satellite



Antananarivo



Google Open Buildings

Socioeconomic data

For Madagascar, the census was carried out in 2018 by INSTAT. Our analysis is based on data from 6 districts of the Antananarivo Urban Community (CUA) and 192 neighbourhoods.

For Burkina Faso, the census was carried out in 2019 by the INSD, and we use data from the 12 arrondissements and 55 sectors of the city of Ouagadougou.

Preliminary results, for Antananarivo and Ouagadougou

Figure 1. Mean confidence of Google Open buildings by neighborhood in Antananarivo (district 1-5)

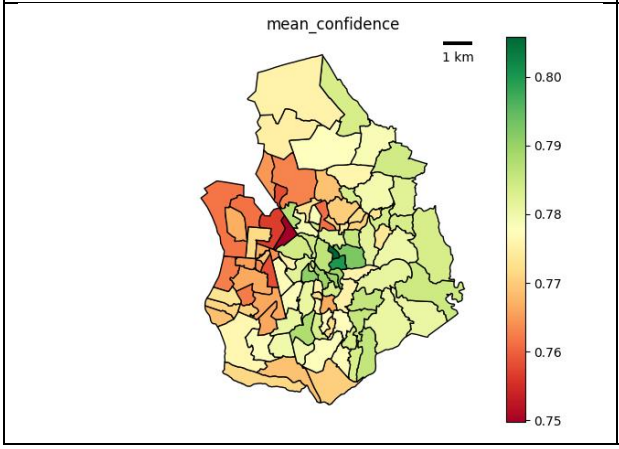


Figure 2. Share of individuals living in a household with the head that has at least secondary education in Antananarivo

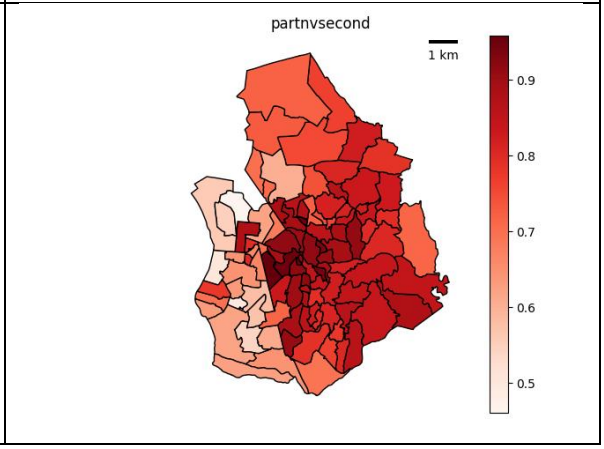


Figure 3. Mean confidence of Google Open buildings by 55 sectors in Ouagadougou

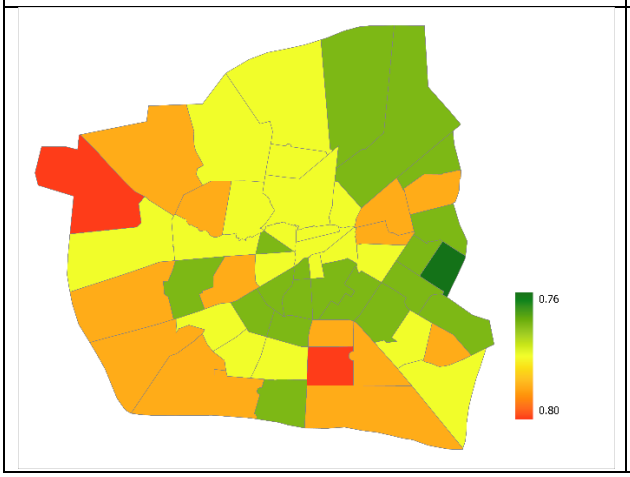


Figure 4. Share of individuals living in a household with the head that has at least secondary education in Ouagadougou

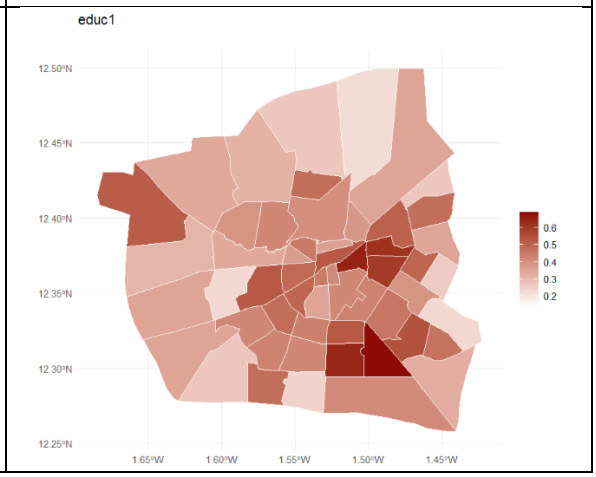
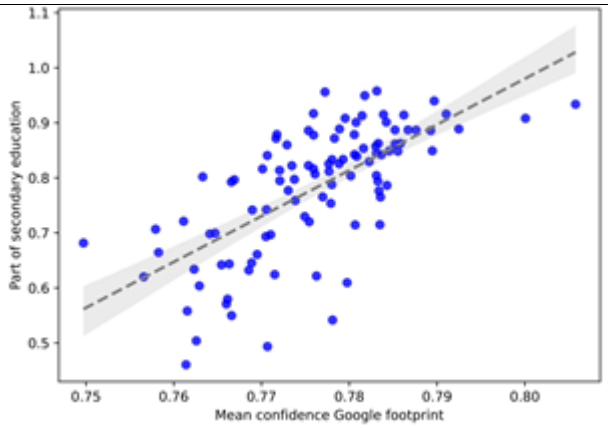
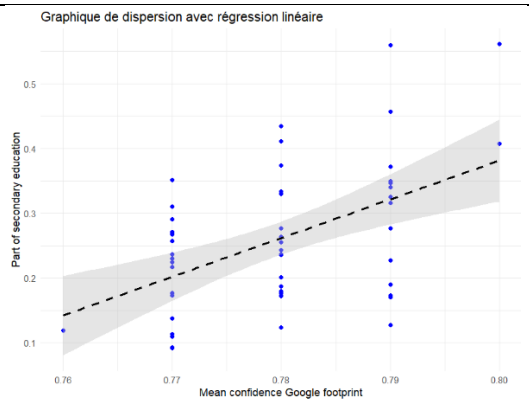


Figure 5. Correlation between the mean confidence of Google footprint and the share of individuals who live in a household with a head having at least a secondary education- Antananarivo	Figure 6. Correlation between the mean confidence of Google footprint and the share of individuals who live in a household with a head having at least a secondary education- Ouagadougou
	

In Antananarivo, we see a strong correlation between the two indicators (r=0.68).

The analysis will be completed with other socioeconomic variables and replicated in Ouagadougou at a finer scale.

We will also use data from Demographic Health surveys in order to test this association on larger sample of African cities, using the geolocalization of the household and the enumeration area.

Limitations

Unfortunately, the information on the construction of the prediction model is very low and cannot be replicated.

Discussion

The mean model's confidence of the Google Open Buildings (i.e., the ability to distinguish in satellite images the buildings) is correlated to socioeconomic level and could be a good proxy for characterizing unfavorable socioeconomic areas and could help to geolocalize informal neighborhoods and slums beyond the administrative borders. Although this information has to be used with caution, it can be useful in absence of regular data.

Acknowledgements

INSTAT Madagascar & INSD Burkina Faso.