☐ Aktualisiert am 11. Jul. 2018



THE DIGITALIZATION OF THE GLOBE: (MACHINE-)LEARNING ABOUT POPULATION IN NEED OF SUPPORT

□ Von gast

☐ Kommentieren

This article is part of our series Congruence and Competition of Norms and Values in the Context of Global Digitalization.

by Michael Nagenborg & Monika Kuffer

The discussion about the interplay between digital technologies and the process of globalization is often focused around the following question: who has access to global information networks and who benefits from digital communication technologies? These are essential questions and it can hardly be denied that they confront us with a series of political and ethical questions. However, we also need to recognize the ongoing digitalization of the globe, a process where more and more people are put on various kinds of maps.

The mapping of populations in various parts of the world does not only happen in the context of military operations and other security-related domains (such as refugee management). Earth observation techniques are also employed, e.g. to map land rights of farmers in rural areas, to control agriculture subsidies, to provide quick support in disaster relief or monitoring the long-term post-disaster recovery, or, more general, enable urban and regional planning in previously unmapped territories. In the following, we will focus on the specific case of 'slum detection' to highlight some of the ethical and political challenges of these developments.

Satellite imageries are currently available at a spatial resolution of up to 30 cm. Such very-high-resolution images allow detecting areas with deprived living conditions due to their morphological characteristics, e.g., small building sizes, lack of public (green) spaces, and the absence of orderly road arrangements. (Kuffer et al., 2016). Recent studies suggest the potential of using machine learning to detect unreported slum settlements.

While improving the living conditions of the 1 billion inhabitants of such settlements (UN-Habitat 2017) is recognized as a significant challenge in the global political area (e.g. as part of the Sustainable Development Goals), research has shown that the official and available data on slum developments is often inconsistent, outdated, and excludes smaller slum settlements (Mahabir et al.

2018). Besides, in countries like India, informal settlements are entitled to upgrading, which creates an incentive for municipalities not to report slum developments (Nolan 2015). Given such findings, using machine learning to allow for automation of slum detection seems to be a reasonable tool shaping pro-poor policies.

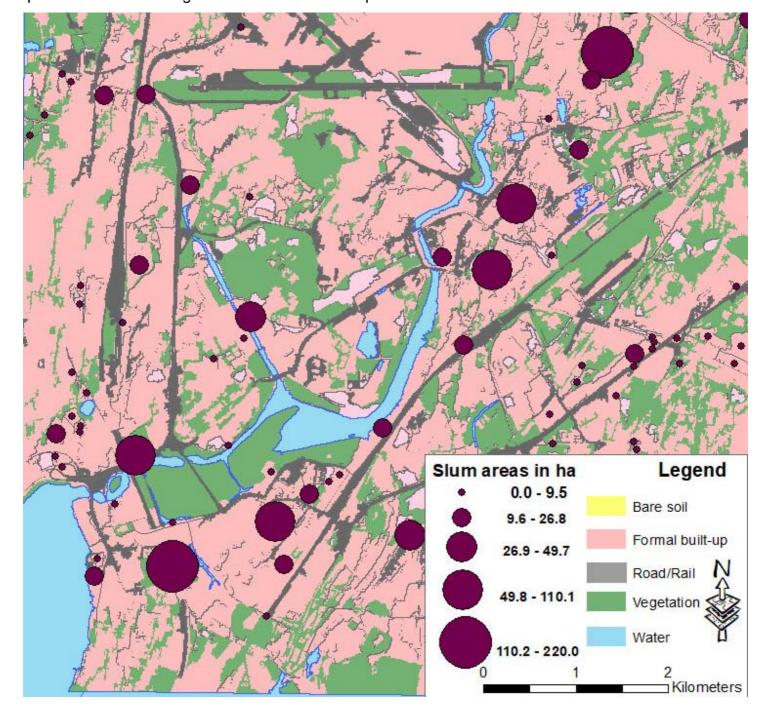
However, the responsible design and use of earth observation technologies ask for careful considerations about the acquisition, processing, and use of the data. In the following, we will focus on the use of the data. We should not neglect fundamental questions such as why the technology is employed for specific areas rather than others. For example, just because the morphological characteristics of slum areas allow for automated detection does not mean that people living in these areas are the poorest people living in the city (Baud et al. 2010). We also need to ask of which locations up-to-date satellite imagery and other data is available and how much the images cost (e.g. very-high-resolution satellite images for an entire city cost easily several thousand Euros). Furthermore, the processing of data requires attention because the current error rate for slum detection is about 10% on the most general level and is likely to increase when looking for more defined characteristics. The quality of the data available and the uncertainty to define slums, of course, also influences the accuracy for the area in question.

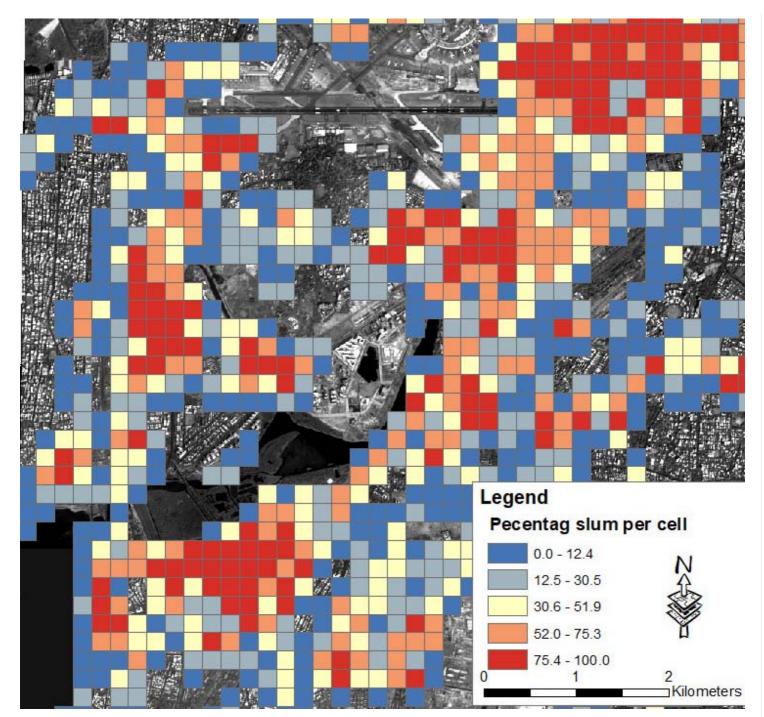
All these considerations should be taken into account when the data is made publicly available. Without knowing how the data has been acquired and processed, it becomes hard, if not impossible, for members of the public to understand and make good use of the maps.

Furthermore, such maps may raise questions about group privacy and identity politics. While 'slum' is a common term in policy documents and is embraced by NGOs such as 'National Slum Dwellers Federation' (NSDF, India), inhabitants of such areas may well reject the label. Furthermore, there might be valid concerns about having one's home identified as being located in a 'slum' when it comes, e.g., to credit score systems or to apply for a job. Inhabitants of such areas may also have a collective interest in not being mapped. As we have seen in the case of mapping land rights, poor farmers may become even more vulnerable to exploitation once they have been put on the map. For slums, examples exist in Nairobi of illegal forced evictions by private investors (Amnesty International UK 2014, Miyandazi 2015, Mukere 2017; see also: Githira 2016), making slum maps publically available could make inhabitants even more vulnerable.

One way to address these tensions is to publish only aggregated data and add additional information layers to the map. For example, the correct identification of slum boundaries is a challenging task. The outcome of the (semi)automatic process will be a map where these boundaries are represented by a neat red line, which seems to suggest a clear inside/outside distinction. A user of such a map may even ask if a specific object (e.g., a small house) is part of a slum or not. However, the purpose here is to render visible unreported slum areas rather than providing detailed information about single streets and houses. Figures 1 and 2 show potential alternatives for making the locations of slums visible without drawing too much attention to irrelevant

details. While it may look odd to lower the level of detail once the data has been processed most accurately, we need to take into account that neither maps nor technologies are neutral tools, and specific alternatives might be better suited for a particular context.





One of the core issues here is that earth observation technologies are "top-down technologies" (in a very literal sense), and the employment of such technologies leaves little room for resistance on the ground level – and there is no inherent technical need to collaborate with the inhabitants in the production of such maps. However, the employment of such technologies only seems reasonable, if automated slum detection becomes part of pro-poor development. The ultimate goal should be to support the inhabitants in finding ways to improve their living conditions.

Given the "top-down" nature of the technologies under consideration, we also need to be aware of the risk to frame "slum dwellers" as a sole object of population management from a distance. Research into the politics of the transition towards sustainable and resilient cities emphasizes the need to recognize the rights of all inhabitants and to understand how slum dwellers build their resilience in an otherwise hostile environment. Thus, the key challenge is this: how we can make responsible use of top-down technologies (in a very literal sense) in bottom-up processes and how

can we support the people on the ground with the help of the ,eyes in the sky'?

Finally, 'automated slum detection' should not be understood as a technological fix for dealing with unreported urban developments. While it is a helpful tool for creating more knowledge about people in need, it does not help us to understand, why authorities fail or are not able to act in accordance with the rights of slum dwellers in the first place.

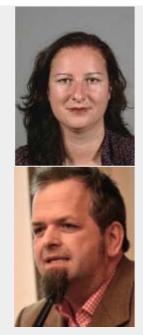
Acknowledgment

The essay is based on the preparatory work for a joint research paper on Earth-Observation and the SDG Slum Indicator.

References

- Amnesty International UK (2014). Kenya: Justice for residents forcibly evicted in City Carton. - Online: https://www.amnesty.org.uk/kenya-justice-residents-forcibly-evicted-city-carton (last access: June 25, 2018)
- Baud, I., Kuffer, M., Pfeffer, K., Sliuzas, R. V., & Karuppannan, S. (2010). Understanding heterogeneity in metropolitan India: The added value of remote sensing data for analyzing sub-standard residential areas. *International Journal of Applied Earth Observation and Geoinformation*, 12(5), 359–374. Online: https://doi.org/10.1016/j.jag.2010.04.008 (last access: June 25, 2018)
- Kuffer, M.; Pfeffer, K.; Sliuzas, R. (2016). Slums from space—15 years of slum mapping using remote sensing. Remote Sensing, Vol. 8, Issue 6, art. 455. Online: https://doi.org/10.3390/rs8060455 (last access: June 25, 2018)
- Mahabir, R., Croitoru, A., Crooks, A., Agouris, P., & Stefanidis, A. (2018). A critical review
 of high and very high-resolution remote sensing approaches for detecting and mapping
 slums: Trends, challenges and emerging opportunities. *Urban Science*, 2(1), 8.
- Miyandazi, V. (2015). Forced Evictions and Demolition of Informal Settlements in Kenya.
 Oxford Human Rights Hub (19th November 2015). Online: http://ohrh.law.ox.ac.uk/forced-evictions-and-demolition-of-informal-settlements-in-kenya/ (last access: June 25, 2018)
- Mukere, K. (2017). Justice Odunga Halts Illegal Eviction of Squatters from KDF Land. Online: https://www.kenyans.co.ke/news/justice-odunga-halts-illegal-eviction-squatters-kdf-land (last access: June 25, 2018)
- Nolan, L.B. (2015). Slum definitions in urban India: Implications for the measurement of health inequalities. *Population and Development Review*, Vol. 41, 59–84.

Monika Kuffer works as lecturer at the Department of Urban and Regional Planning and Geo-Information Management at the University of Twente.



Michael Nagenborg works as Assistant Professor for Philosophy of Technology at the Department of Philosophy at the University of Twente.

Tags: earth observation machine learning mapping poverty slums

SCHREIBE EINEN KOMMENTAR

Deine E-Mail-Adresse wird nicht veröffentlicht.

Kommentar

Name

