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Earth Observation + Morphometrics: towards a systematic understanding of cities in challenging contexts

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Abstract

The ongoing fast and unprecedented urbanisation, strongly affecting cities in the Global South, is casting urban development into challenging dynamics, involving, for example, the construction of new or expansion of existing informal settlements lacking the most basic services. This informal urban development is insufficiently understood due to limited resources, leading to an absence of data to support its urban analysis and, consequently, obstacles to address social equity, sustainability, and resilience through urban planning and design practices. Although the potential of Earth Observation (EO) has widely been recognized for mapping different urban patterns, the surge of big data and data science, along with usually costly high resolution datasets are marginalizing the open science of interpretable urban morphology with the abstract relationship between mapped socioeconomic patterns and image features. In this work, an "EO + Morphometrics" framework is proposed to combine open EO data with open tools for explicit, reliable and consistent measurements of urban form and thus to understand development patterns based on urban morphology. More specifically, a reengineered convolutional neural network is applied to freely available Google Earth imagery to extract building footprints for entire cities. Morphometrics then uses this information to measure hundreds of metrics of the built environment and output homogenous urban form types. This two-step method is applied to a few fast-growing sub-Saharan cities. To test whether specific urban types correspond to socioeconomic patterns, we compare the outcomes with local delineations of informal settlements. Morphological types, characterised by a compact/organic urban fabric, seem to be predominantly contained in the boundaries of informal settlements. We argue that "EO + Morphometrics" paves the way for deriving a generalizable understanding of urban form in challenging contexts. This information can, in turn, be used for further analysis (for example, with socioeconomic data) and inform local planning and interventions.

Keyword: *Earth Observation; morphometrics; urban poverty; informal settlements; deep learning; urban morphology.*

1 What is missing?

Looking through the history of applying Earth Observation (EO) based technology to mapping cities, there is the ambition of mapping every aspect of cities directly from remote sensing images. Starting from delineating physical boundaries of cities (Schneider et al., 2003), to detect socioeconomic patterns such as functional zones of residential, industrial, and commercial, or living status shown as poverty and informal settlements (Cockx et al., 2014; Herold et al., 2003; Kuffer, Pfeffer, & Sliuzas, 2016). From early efforts of Object Based Image Analysis (OBIA) to using abundant image features, such as the Gray Level Co-occurrence Matrix (GLCM) and those automatically derived from deep learning algorithms, high level objects can be detected as the

combination of low level textures like edges, lines and blobs (Kuffer, Pfeffer, Sliuzas, et al., 2016). However, while acknowledging the detection power of EO technology, we also realize that limited discussion can be found regarding the generalizability and interpretability of these applied techniques and workflows. Although essential components of a scientific practice such as input data, induction-deduction loop wired through hypothesized model, and predicted outcomes can be found, this entire workflow is disconnected from human conceptualization of real world objects such as urban elements. Instead, the workflow focuses on abstract pixel patterns and image features, leading to a pure experimental exercise with an isolated practice that has limited practical impacts. Such an abstract relationship between image features and urban patterns does not relate to any practical actions in terms of planning and design of real world urban elements, such as buildings and streets. Ultimately, despite the evolution of techniques for mapping urban patterns, the entire workflow remains largely ad hoc to limited study cases thus lacking generalizability and interpretability (Fig. 1).

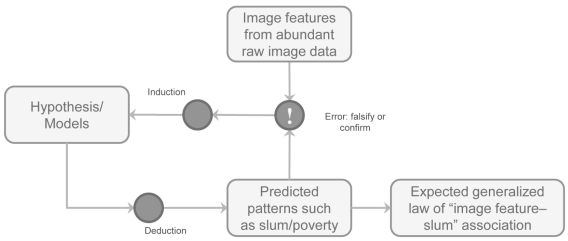

Fig. 1 *The workflow showing the ongoing effort of leveraging image features or raw image data to map urban patterns.*

2 A modified workflow

We suggest that the existing workflow (Fig. 1) can largely be improved in terms of scientific validity and practical scope. Specifically, by simply involving explicit and meaningful quantification of urban elements, such as buildings and streets, before mapping urban patterns (Fig. 2), the mapping of urban patterns can thus be immediately interpreted back into practical context through the quantification of real world urban elements. Although our suggestion is not new as earlier work of mapping urban patterns through the morphology of buildings can be found (Doğrusöz & Aksoy, 2007; Taubenbock et al., 2009), this suggestion as a new component in the workflow can soon magnify the detection power of EO, while boosting the generalizability of studies in urban morphology by taking advantage of the spatial coverage of EO data.

To ensure the replicability of the workflow, we also suggest to rely on freely available RGB satellite images from Google Earth imagery datasets for building extraction, leading to a less data demanding and more replicable practice of applying the detection power of EO.

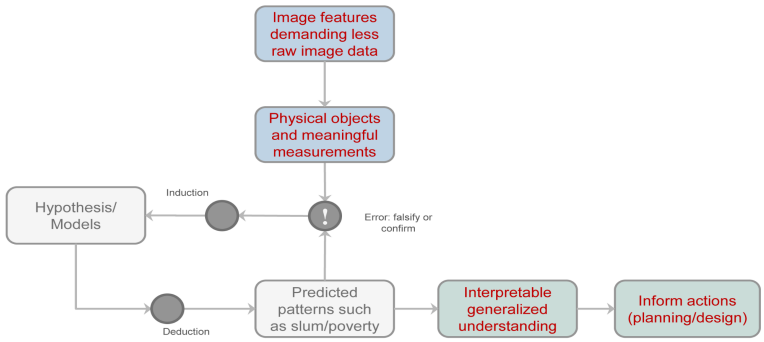

Fig. 2 *Workflow with an added component of explicit quantification of urban objects/elements, which enhances interpretability and reproducibility.*

Implementing the added component in the workflow can be reduced to a 2-step scheme: (1) detecting physical urban elements, and (2) measuring their shapes and relations. In short, we propose "EO + Morphometrics" for mapping urban patterns where a repeatable workflow and interpretable knowledge can be obtained. In the following sections, we will apply this 2-step scheme of "EO + Morphometrics" to investigate the relationship between building morphology and informal settlements with socioeconomic deprivation. The hypothesized model consists of a simple unsupervised clustering algorithm to map and explain the spatial pattern of informal settlements. In section 3, the technical details of the added "EO + Morphometrics" component will be illustrated, followed by the case study of mapping informal settlements in a few sub-Saharan cities in section 4. Further implications of the proposed workflow will be discussed in section 4 and concluded in section 5.

3 The technical component of "EO + Morphometrics"

In this work, we focus on one of the most fundamental elements of urban morphology, buildings (Moudon, 1997). The entire technical component of "EO + Morphometrics" facilitates interpretable scientific practice by using explicit and meaningful measurements of building morphology, aiming to avoid over-engineered and data-intense models along with expensive datasets for replicable open science.

3.1 Free EO data for building extraction

There are many types of free EO based imagery datasets available worldwide, however, as we already decided to focus on buildings, the available datasets narrow down significantly, considering the level of detail required for building extraction. Google Earth images and Bing Satellite Maps are among these few, meeting both requirements of resolution and worldwide coverage.

3.2 Creating maps of building footprints

There is a large number of publications about extracting building footprints or roof outlines from Google Earth images (e.g., Xing et al., 2019). What has not been covered is the limited generalization capability of

existing approaches from sub-city scale to city scales. We set out by adopting the U-Net architecture because it is lightweight (Ronneberger et al., 2015), and fine-tune the detailed structure by replacing the encoder with the ResNet-50 pre-trained on the ImageNet datasets (http://www.image-net.org/), which is good at handling overfitting and vanishing gradient (He et al., 2016). The global open dataset containing labelled building footprints (including data on diverse urban environments) provided by the Wuhan University (http://gpcv.whu.edu.cn/data/building_dataset.html) is used for training our model.

3.3 Measuring the building morphology

For an explicit measurement of the spatial configuration of buildings as typical real world urban elements, we rely on the open source Urban Morphology Measuring Toolkit (Fleischmann, 2019). The tool provides several metrics quantifying forms of buildings and streets in six domains, including dimension, shapes, spatial distribution, intensity, diversity and connectivity. In this work, we only compute 22 metrics for building morphology to illustrate how the entire workflow can capture socioeconomic patterns through urban morphology.

4 Mapping and understanding informal settlements through urban morphology

We apply our workflow at the city level, while also rely on freely available Google Earth images and open source software for generalizability and reproducibility. Three case studies are selected from the sub-Saharan lower-middle-income countries: Nairobi and Kisumu in Kenya, and Ouagadougou in Burkina Faso. All of them well represent the prototype development pattern of fast growing cities with insufficient provision of basic needs, forcing a large fraction of city dwellers to live in informal settlements. For each city, we previously obtained the spatial information of informal settlements delineated as slum boundaries from the local government (Ouagadougou) and a local NGO (Nairobi). Some of these boundaries are not up-to-date, thus current assessment of informal settlements is not meaningful. In addition, without officially produced maps of buildings, a thorough assessment of building maps is not possible. Consequently, all three study cases are examined visually.

We first tested the entire workflow in two cities of Kenya, where more than 56% of urban population in this country lives in informal settlements (Wamukoya et al., 2020). In Nairobi, this number rises to 60-70%. People living in informal settlements are exposed to pollution, overcrowding, poor infrastructure and sanitation, and violence with high levels of vulnerability (APHRC, 2014). Unfortunately, much of this information is masked by aggregated statistics at both national and local levels. Holding the spatial information of informal settlements obtained from local authorities as reference information, we assume such topology can be interpreted by the physical form of cities from the perspective of urban morphology. As mentioned previously, we also expect that investigating the relationship between informal settlements and urban morphology could provide insights into the variations of physical conditions in such areas and could inform the development of guidelines for planning and design strategies.

Taking advantage of data and tools mentioned above, we found that a specific urban type obtained from clustering the 22 metrics of building morphology (lower in Fig. 3) visually resembles the pattern of informal settlements (upper in Fig. 3). There are also other places classified in the same urban type but not labelled as informal settlements, which could be considered as a false positive prediction. However, as discussed earlier, given the fact that the standards of informal settlements can be highly localized, the potentially incomplete survey of atypical informal settlements, the uncertain level of physical manifestation of socioeconomic deprivation within informal settlements, the amount of manifested physical information captured in morphological patterns, as well as potentially different choices of clustering techniques, we tend to stay conservative in assessing how this particular mapped morphological pattern in Fig. 3 intersects with the pattern of informal settlements.

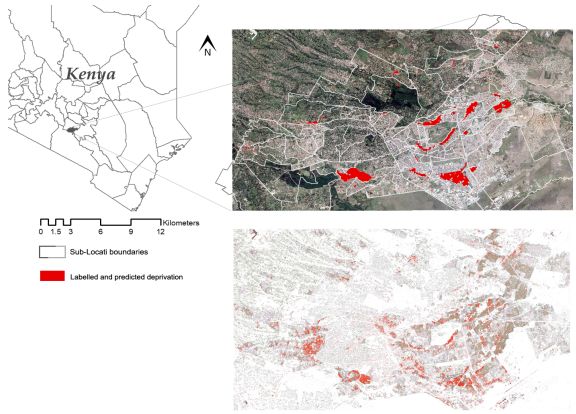

Fig. 3 *In Nairobi, Kenya, the morphological pattern (lower image) is partially resembling the pattern of informal settlements (upper image).*

In another city in Kenya, Kisumu, where more than half of its 0.4 million residents reside in slums (UN-Habitat, 2005), the information regarding the spatial pattern of informal settlements has not been updated timely. While the morphological pattern intersects a large part of the informal settlements pattern (Fig. 4), there are again, like in Nairobi, many places morphologically equivalent to informal settlements (lower in Fig. 4) but not labelled as such (upper in Fig. 4). With the outdated informal settlements pattern, it is even more difficult to assess how such socioeconomic patterns are reflected in morphology.

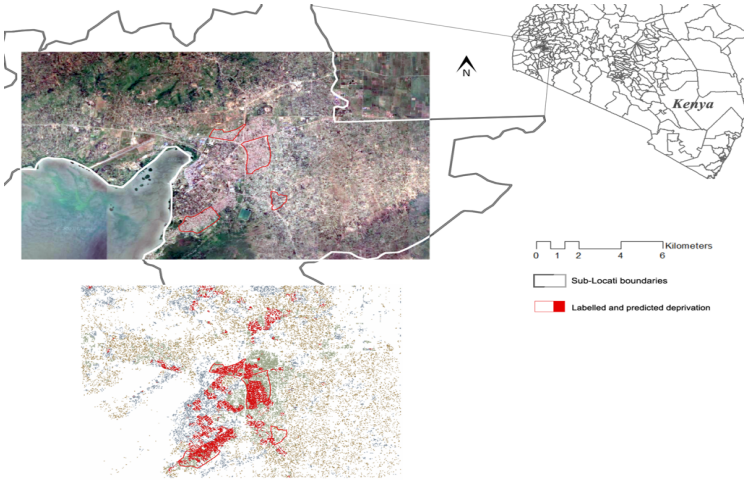

Fig. 4 *In Kisumu, Kenya, the morphological pattern (lower image) is partially resembling the pattern of informal settlements (upper image).*

According to the extremely outdated census of 2003, the population of Ouagadougou, the capital city of Burkina Faso, tripled in only two decades since 1985 (Schug et al., 2018). Such a scale of population increase forced intense growth of unplanned settlements at the city outskirts (Fournet F. et al., 2008). The growth pattern led to two major types of urbanization: planned settlements, referred to as *loties*, and unplanned settlements, known as *non-loties*. The two types of settlements are labelled as red (*non-loties*) and blue (*loties*) in the upper image of Fig. 5, while the morphological patterns are shown in the lower part of Fig. 5. Compared to the cases of Nairobi and Kisumu, the *non-loties* as the reference informal settlements pattern seems less likely to be captured by the morphological patterns (lower in Fig. 5). Without additional background or prior knowledge for the assessment of how the morphological pattern intersects with the target socioeconomic pattern, we can at least visually acknowledge that morphology can still explain informal settlements in different urban contexts.

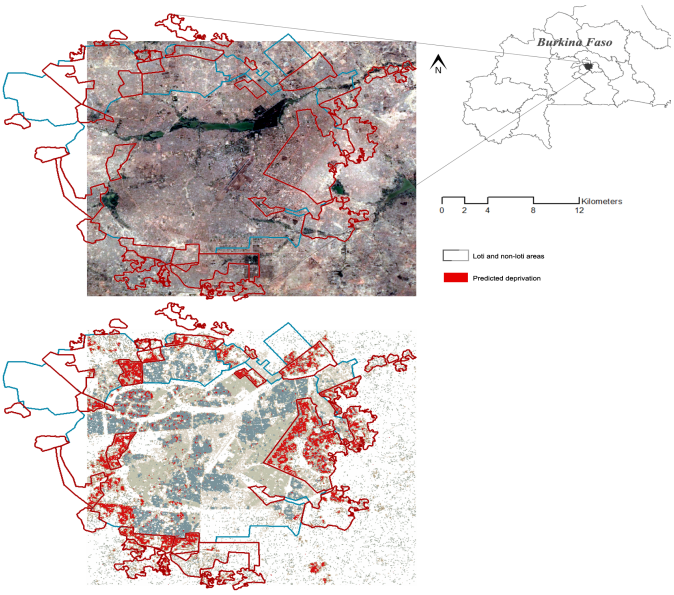

Fig. 5 *In Ouagadougou, Burkina Faso, the morphological pattern (lower image) is partially resembling the pattern of informal settlements (upper image), where planned settlements are known as loties (blue), and unplanned settlements as non-loties (red) in the local urban context.*

Only four metrics are examined as a simple illustration for interpretable morphological patterns. Given the diverse appearance of the informal settlements in all study areas, the boxplots in Fig. 6 nicely represent how certain metrics contribute to morphological patterns. For instance, given all informal settlements are occupied by less aligned buildings, the case in Kisumu shows that the building alignment is more deviated from the level of formal areas (Fig. 6(b)). It certainly indicates socioeconomic pattern is influenced, and probably giving rise to certain urban form, which might further inform practical actions for achieving sustainable development through improving urban forms.

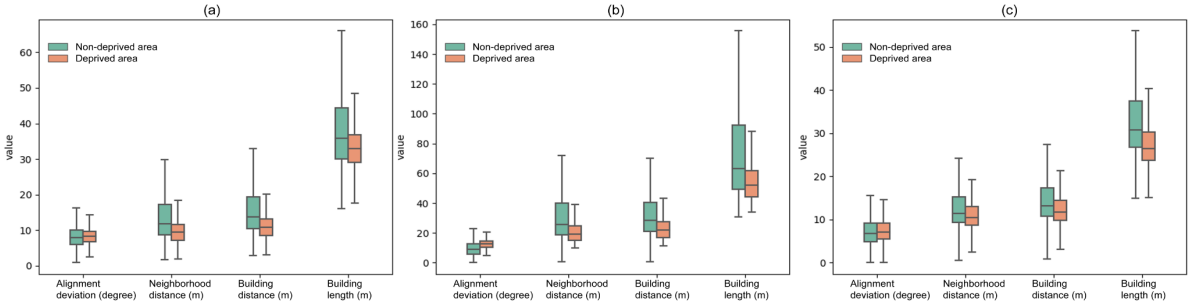

Fig. 6 *Sample morphological metrics comparison between formal and informal settlements in (a) Nairobi, (b) Kisumu, and (c) Ouagadougou.*

5 Final remarks

What has been presented in this work is only a small fragment of a larger research endeavour linking different disciplines and techniques, with the ultimate goal of informing improvements. We summarize and discuss a few critical points which may influence the scientific validity of mapping urban patterns.

5.1 The scope and scientific significance of EO

The scope of EO within this work is limited to the extraction of urban elements, not using the full potential of EO (e.g., mapping socioeconomic patterns directly). However, this limitation reduces the complexity of the EO based model, as the mapping of physical elements stays within the scope of EO. Stretching the scope of EO to “see” aspects more than the physical ones ultimately means exploring image characteristics as proxies to represent the target patterns to be mapped. Such exhaustive mining of proxies would inevitably lead to less interpretable results, let alone the fact that many proxies were abstract image features.

5.2 The implication of measuring physical urban characteristics

Interpretable metrics, as presented in this work that capture socioeconomic patterns, possess the potential to inform planning interventions aimed to improve and transform such patterns. While it can be difficult,

integrating metrics into code-based planning and design guidelines are highly recommended. Some of the metrics covered in this work can be considered as action enabled metrics such as floor area ratio, building density, as well as orientation, which can already be found in implemented urban design guidelines. Other metrics, although interpretable and intuitively understandable in the context of urban form, are less informative for urban planning and design practitioners such as building alignment and variance of the alignment. Given the potential of interpretable metrics, further research should identify those most efficiently acted upon. In the current state, it remains an open question: What needs to be measured to reflect processes in the urban system so that interventions can be derived and implemented to improve it?

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