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Research Paper

EO + Morphometrics: Understanding cities through urban morphology at large scale

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HIGHLIGHTS

- A workflow is provided for understanding urban patterns based upon meaningful measurements of urban form elements.
- Interpretable urban patterns are derived through publicly accessible data and tools ensuring workflow scientific validity.
- EO has a shifted but important role for the potential of interpreting socioeconomic patterns through urban forms.

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ABSTRACT

Earth Observation (EO)-based mapping of cities has great potential to detect patterns beyond the physical ones. However, EO combined with the surge of machine learning techniques to map non-physical, such as socioeconomic, aspects directly, goes to the expense of reproducibility and interpretability, hence scientific validity. In this paper, we suggest shifting the focus from the direct detection of socioeconomic status from raw images through image features, to the mapping of interpretable urban morphology of basic urban elements as an intermediate step, to which socioeconomic patterns can then be related. This shift is profound, in that, rather than abstract image features, it allows to capture the morphology of real urban objects, such as buildings and streets, and use this to then interpret other patterns, including socioeconomic ones. Because socioeconomic patterns are not derived from raw image data, the mapping of these patterns is less data demanding and more replicable. Specifically, we propose a 2-step approach: (1) extraction of fundamental urban elements from satellite imagery, and (2) derivation of meaningful urban morphological patterns from the extracted elements. We refer to this 2-step approach as “EO + Morphometrics”. Technically, EO consists of applying deep learning through a reengineered U-Net shaped convolutional neural network to publicly accessible Google Earth imagery for building extraction. Methods of urban morphometrics are then applied to these buildings to compute semantically explicit and interpretable metrics of urban form. Finally, clustering is applied to these metrics to obtain morphological patterns, or urban types. The “EO + Morphometrics” approach is applied to the city of Nairobi, Kenya, where 15 different urban types are identified. To test whether this outcome meaningfully describes current urbanization patterns, we verified whether selected types matched locally designated informal settlements. We observe that four urban types, characterized by compact and organic urban form, were recurrent in such settlements. The proposed “EO + Morphometrics” approach paves the way for the large-scale identification of interpretable urban form patterns and study of associated dynamics across any region in the world.

1. Introducing a shift in the workflow

Through the history of Earth Observation (EO)-based technology for mapping cities, the ambition of mapping every aspect of cities directly from remotely sensed images is dominant, spanning from delineating the physical growth of cities (Bhatta, 2010; Reba & Seto, 2020), to

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detecting several socioeconomic patterns, such as employment (Rahman et al., 2019), and human activities represented as land use and functional zones (Herold et al., 2002; Miller & Small, 2003), or poverty and deprived areas (Sliuzas & Kuffer, 2008). Indirectly using EO-based information for mapping socioeconomic patterns such as income, health, education and housing can also be found as auxiliary GIS data and further derivation of metrics are needed (Sandborn & Engstrom, 2016; Sapena et al., 2021). EO-based mapping of non-physical urban patterns is supported by two fundamental assumptions: (1) such patterns can be manifested through the physical appearances of urban elements on images (Taubenbock et al., 2009), and (2) these physical appearances are encoded as shared image features of pixels and segments used for mapping urban patterns (Benediktsson et al., 2003).

Practices in the EO community based on these assumptions have major limitations: the high level of human supervision required for either setting classification rules or feature selection leads to transferability issues due to the fact that rules, image features, and models are case-specific. For instance, early effort of using the Object Based Image Analysis (OBIA) to map socioeconomic patterns, such as deprivation via identifying informal settlements (Hofmann et al., 2008), required predefined rules of pixel segmentation and aggregation as guidelines to "supervise" computers in mapping real world objects. These rules suffered from limited transferability due to the diverse physical forms of deprived settlements (Kuffer et al., 2018). Same limitation applies to the use of image features. Although relatively consistent conventions of deriving image feature within moving windows (Benediktsson et al., 2003), and with predefined metrics such as the Gray Level Co-occurrence Matrix (GLCM) have been applied to mapping neighborhoods (Graesser et al., 2012; Hall-Beyer, 2017), limited discussion can be found about consistently identifying shared image features or rules that represent established patterns. This is true especially for socioeconomic patterns that are often partially represented by physical characteristics. For instance, areas without land tenure security, sanitation and water supply could both appear formal and informal (Taubenböck et al., 2018). To overcome this limitation many studies had to rely on expensive multispectral datasets for image feature mining, leading to less replicable and more data demanding workflows (Kuffer et al., 2018). With the growing demand of mapping accuracy by combining image features and machine learning techniques (Wieland & Pittore, 2014), the use of features is even more implicit. Recent developments, such as Convolutional Neural Networks (CNN), allow to automatically learn image features that capture socioeconomic patterns (Persello & Stein, 2017; LeCun & Yoshua Bengio, 2015; Nordhaus & Chen, 2015; Yeh et al., 2020). The standard workflow remains largely unchanged in seeking image features for relating pixel patterns directly to urban patterns (Fig. 1). As long as the models are developed and trained *ad-hoc* for study cases (Mahabir et al., 2018; Tong et al., 2020), the automatically learnt features can again be context specific to certain cases (Wang et al., 2019). Although there are indeed recently published works claiming the mapping of urban types at global level, such as the Local Climate Zones (Zhu et al., 2022), these works are normally presented

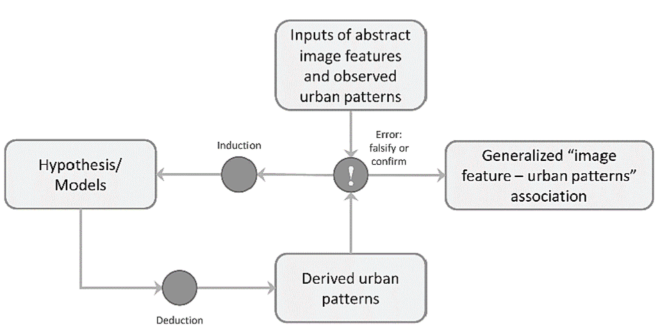

Fig. 1. The standard workflow: urban patterns such as socioeconomic status mapped directly from EO data by using image features.

again by only highlighting patterns of sample study areas, and collecting site specific data as a primary solution to train their model is a known issue (Demuzere et al., 2019). We thus argue that the scientific validity of the existing workflow is limited as it lacks transferability and is difficult to replicate despite the evolution of techniques for mapping urban patterns.

Apart from the issue of transferability, we also realize that the standard workflow of using pixel patterns and image features leads to limited interpretability of derived urban patterns. Stretching the detection power of EO to map urban patterns other than physical ones, such as those pertinent to socioeconomic status, leaves the interpretation of mapped urban patterns restrained by the association between abstract image features or pixel patterns, and the mapped pattern (Fig. 1). The standard workflow is disconnected from the practical context. Thus it does not support reliable and replicable interpretations. For rigorous scientific practice, it has been suggested that the model hypothesis should be informed by real world status, while derived outcomes could further inform practical actions (Box, 1976). Compared to modeling in urban planning and statistical analysis practice (Batty, 2017), by focusing on abstract pixel patterns and image features only the workflow remains disconnected from the human experience of fundamental urban elements such as buildings and streets (Moudon, 1997), and can thus be considered a sectorial practice with limited practical impacts. Although socioeconomic patterns such as deprivation maps can be of practical relevance, they can hardly inform actions such as planning and design practices, without understanding the relation between the socioeconomic patterns and fundamental urban elements. With the surge of big data and data science, the induction-deduction loop of seeking image features is becoming a more isolated test bed, where explaining urban patterns is dominated by abstract knowledge within the world of 2-dimensional pixels as opposed to real world objects and processes. Consequently, existing mapping activities leave a fundamental question unanswered: *to what extent can socioeconomic patterns be captured and explained from information on the built environment obtained from images?*

Acknowledging the power of EO for detecting patterns directly from imagery data, we suggest that the standard workflow can be improved in terms of transferability or replicability, and interpretability while maintaining the detection power of EO. To do so, we further suggest using publicly accessible data for the mapping or extraction of urban elements at large scale to consistently produce reliable, objective and replicable delineation of the elements, so that measurements are derived for real urban objects rather than abstract image features. On these it will then be possible to base the study on interpretation of socioeconomic phenomena, such as land use types, socioeconomic groups (e.g. working groups), poverty or level of deprivation, by established measurements of physical forms of urban objects. More recent experiments, including those obtaining 3 dimensional information of built environment from EO for large scale morphological structure mapping (Li et al., 2020; Taubenböck et al., 2017), have already shown possibilities of deriving meaningful urban morphological characters before looking into socioeconomic phenomena. We also realized that morphological characters can be more specific than only having general ones such as density and height at national or continental scale. Our proposal (Fig. 2) focuses on deriving physical urban elements, such as buildings and streets conforming to the human conceptualization of the physical world, with meaningful morphological measurements of forms of their geometry and spatial relationships, before mapping urban patterns. The interpretation of real world urban form components has been the focus of the urban morphology discipline for more than a century. Researchers in urban morphology explored the relationship between socioeconomic processes and the generation of specific urban form patterns, in terms of building and street configuration (Conzen, 1960; Dibble et al., 2019; Larkham, 2006; Moudon, 1997; Whitehand, 2007; Venerandi et al., 2018). Almost in parallel, there are also city models developed for characterizing city forms in cultural regions such as Europe, Latin America, Africa, Japan

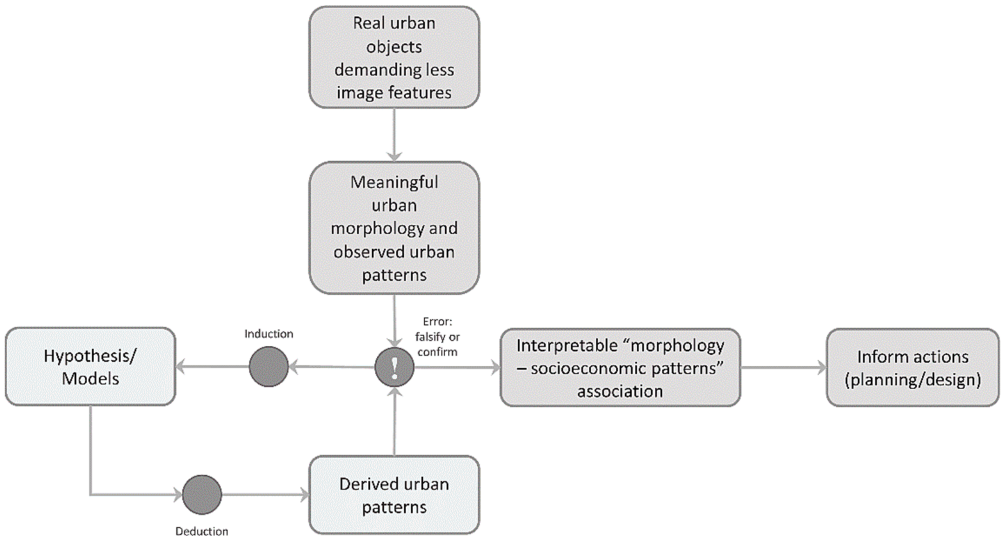

Fig. 2. Proposed workflow: urban patterns are mapped from meaningful metrics of real-world physical objects (urban form elements). Major shifts in both inputs and outputs are shaded with darker gray.

and China, which focused on historical development of cities (Ehlers, 2011). Urban form is thus quantified through meaningful measurements of urban elements rather than exhaustively seeking abstract image features, and can subsequently be related to non-physical patterns about other aspects of cities such as socioeconomic status. Creating the final maps of urban patterns based on measurements of these urban elements reconnects the workflow to the practical context, thus the predicted outcomes are straightforwardly interpretable and can inform practical actions including urban planning and design operated upon the urban elements.

Obviously, the proposed workflow is powerful but relies on the availability of consistent input data and therefore is still limited in general application, hence the potential of linking it to advances in EO. Many studies have already presented the possibility of extracting buildings from publicly accessible regular RGB satellite imagery, such as Google Earth images (Han et al., 2021; Ji et al., 2019; Vakalopoulou et al., 2015; Xing et al., 2019; Xu et al., 2018), leading to a less data demanding and more replicable EO-based practice. Ultimately, the revised workflow maintains the convention of using physical information through the EO technology as in Fig. 1, but the scientific validity of the workflow in terms of transferability and interpretability would be maintained.

The proposed workflow focuses especially on (1) EO based detection of physical urban elements from available satellite imagery, which is then for (2) the measurement of configuration of such elements via metrics rooted in the urban morphology discipline. We consider the added components of deriving physical urban elements along with meaningful measurements as the major shift in the workflow, and tag them briefly as "EO + Morphometrics" approach. In the following sections, we will exemplify the approach through explaining deprivation – a socioeconomic urban pattern – by the form of buildings. Referring to our proposed workflow, objects and meaningful measurements are narrowed down to buildings and building form, respectively. The proposed model will be a simple unsupervised clustering algorithm to map and explain the spatial pattern of deprivation. In section 2, the technical detail of our conceptual workflow "EO + Morphometrics" will be illustrated, followed in section 3 by the illustration or application of the workflow to the study case of mapping deprivation in Nairobi, Kenya. Further implications of the proposed workflow will be discussed in section 4, and concluded in section 5.

2. The technical components of "EO + Morphometrics"

As part of the proposed "EO + Morphometrics" approach, EO is applied to extract fundamental urban form elements from publicly accessible data, while morphometrics subsequently generates an abundant numerical description of the same basic elements. In particular, among the several aspects of urban form (Wentz et al., 2018), we focus on one of the most fundamental elements in urban morphology – buildings (Moudon, 1997). Building plots will be delineated based upon the buildings. Other urban elements such as streets or open spaces are more difficult to define especially in informally developed areas, and using inconsistently defined or incomplete street information will not be beneficial for our interpretation.

2.1. Open EO data for building extraction

There are many types of publicly accessible EO-based imagery datasets available worldwide. However, considering building extraction and the image specifications required for the purpose, the range of viable datasets narrows down significantly: Google Earth images[1] and Bing Satellite Maps are among those few datasets offering both appropriate resolution and worldwide coverage. Google Earth images usually have a resolution of 0.6–1.2 m depending on the source sensors, which is normally considered sufficient for building extraction. Hence, despite of the limited data options, we have accepted a typical trade-off in open data and open science: lower quality data in exchange for wider availability and accessibility. Thus we work with Google Earth because images are publicly accessible, have global coverage and are frequently updated for our study area. This data can be downloaded in multiple ways. Google Earth Pro[2] provides direct image download at its highest resolution. Third party open tools such as SAS.PLANET[3] help acquiring data from the Google Earth portal. Since our study case is one city, the amount of data downloaded does not qualify as "mass data download", thus does not violate the data usage guidelines.

[1] Google Earth use guidelines: https://www.google.com/permissions/geoguidelines/.
[2] https://www.google.com/earth/versions/.
[3] https://www.sasgis.org/sasplaneta/.

2.2. Creating building footprint maps

As mentioned in section 1, the extraction of building footprints from Google Earth images has already attracted significant scientific interest. However, inherent limitations to scaling up from intra-city level to larger scales have been hardly discussed. On the one hand, it is difficult to capture the diversity of urban form around the world. Sometimes, it is difficult to scale up a building extraction model even within the same city as planned areas are very different from informal settlements. On the other hand, in the case of machine learning-based building extraction, many of the proposed models seem to be very complicated so that could be flexibly fitted to data, hence, with a risk of being over-engineered. Given the limited amount of data available in many sub-optimal study areas, the consequence of a small training dataset together with over-engineered models is overfitting and reduced generalization in the context of machine learning (Yuan, 2018).

In the proposed workflow, building extraction aims at two concurrent objectives: (1) to improve the scalability of the model, while (2) ensure extraction accuracy for measuring building form. Such objectives can be achieved by leveraging the power of a simply modified existing deep convolutional neural networks (CNN). The CNN is an extension of neural networks into higher dimensions so that it can take multi-dimensional arrays as opposed to a vector, hence, it can be applied to images for building extraction. Recent advancement in CNN architectures for building footprint mapping show that: (1) there is a good consistency in adopting general model architectures which follows the encoder-decoder structured CNN, such as the U-Net (Ronneberger et al., 2015), and (2) variation in more detailed structure of the encoder or decoder is large, which retains the diversity of how models, for example the U-Net, can be constructed. In consideration of its lightweight nature, we set out by adopting the U-Net architecture and fine-tuned its detailed structure by replacing the encoder part of the model. The rationale of experimenting with the encoder structure is that representational features, at different levels of detail, are extracted from this part of the U-Net. We use part of the renowned ResNet-50 pre-trained on the ImageNet datasets[4] as our encoder, as the residual network is good at handling overfitting and vanishing gradient (He et al., 2016). We did not use the entire ResNet-50 because we only wanted to take advantage of the pre-trained model to extract lower-level features of edges so that higher-level ones such as building shapes can be properly captured from the images. Using part of the ResNet-50 is also beneficial for keeping the entire model lightweight (Fig. 3). Once the pre-trained part is integrated in the U-Net, the learnt low-level features are transferred into the U-Net and the model must be trained only to learn some high-level abstract features, such as rectangular shapes, to map the buildings on the image. Similar idea of modifying the U-Net with an enhanced power of learning low level feature has already been adopted and compared with baseline U-Net for mapping different land surface objects (Cao & Zhang, 2020; Wang et al., 2019; Ye et al., 2020).

To train our model, we rely on an open data repository – the global dataset containing labeled building footprints provided by the Wuhan University.[5] The labeled global dataset also covers different building structures from different cities around the world. Although it is impossible to adequately represent the entire diversity of buildings, this is beneficial for training a generalized model to recognize buildings with varying shape, size and density. Specifically, we experiment with different types of building labels as shown in Fig. 4. For example, buildings labeled explicitly with their edges (Fig. 4(d)). For the interested readers, we provide all details about our entire model openly on Kaggle.[6]

The extracted building footprints from the Google Earth images are raster data showing the probability of pixels being building footprints. Two further steps are needed to obtain the final product: (1) building identification and (2) polygonization. Although accuracy estimation is the conventional way to identify a threshold to convert the pixel probability raster to binary map of buildings, these accuracy metrics are not completely applicable to cities with many densely built informal settlements. Any random outcome of model would always intersect with the actual buildings on the ground producing a true positive estimation (Wang et al., 2022). This forces us to manually adjust a threshold while visually interpret the corresponding binary building map patterns in both formal and informal areas. We manually selected a threshold above the third quartile of the predicted pixel value to generate a binary image showing buildings and non-buildings ready for boundary extraction. Then building boundaries are obtained by converting the raster data to vector polygons through the use of the *OpenCV*[7] library able to identify pixels belonging to the building blobs.

2.3. Measuring the building morphology

Our measurement of the building morphology follows the morphometric approach, which delivers a systematic numerical characterization of urban form (Dibble et al., 2019). We apply a subset of methods for the identification of urban patterns proposed by Fleischmann et al. (2021), i.e., selecting only those morphometric characters (23 of 72 characters, Table 1) that can be derived from building footprints extracted in the previous step and a morphological tessellation. There are indeed metrics regarding the third dimension of buildings and also about the morphological configuration of streets, yet not applicable to our analysis due to the lack of information about streets as well as building heights. The tessellation is a spatial unit generated using a Voronoi-based spatial partitioning technique (Fleischmann et al., 2020). The morphometric characters use *momepy*, an open-source toolkit for urban morphometrics (Fleischmann, 2019), a part of the Python Spatial Analysis Library (*PySAL*) (Rey et al., 2021; Rey & Anselin, 2007).

Following the original method, each of the initial characters has been analyzed within its spatial context using 4 contextual characters – interquartile mean to get a general tendency, interquartile range to get a spread of values, interdecile Theil index to understand local inequality of distribution of values and Simpson diversity index to capture variety of values within the city-wide context. All contextual characters were computed within the context defined as 10 topological steps on morphological tessellation, compared to 3 in the original method. That is to accommodate for imprecision of EO-based building footprints. Thus, $23 \times 4 = 92$ characters are computed for the context of each building footprint.

Buildings are then classified through an unsupervised clustering operation in a 96-dimensional feature space. Thanks to the spatially autocorrelated nature of contextual characters, we can apply scalable K-Means clustering to all the buildings in the study area and obtain the urban types classification over the entire city, where each morphological cluster involves buildings with similar morphology. The clustering of all buildings in the high dimensional feature space is defined by the metrics along with a chosen number of clusters. This choice is informed by the clustergram method (Schonlau, 2002), which shows a diagram informing how elements (buildings in this case) belong to clusters as the number of clusters increase. And each cluster center is weighted by the first PCA loading of the metrics about the buildings. Thus the clusters are properly represented by the centers. These urban types are ultimately compared with the spatial patterns of socioeconomic status, in particular deprived areas or slums, to examine the building morphology within deprivation. The detailed information is provided in the next section. Given the built form of deprivation as a strong indicator of durable housing as well as an important physical expression of poverty, the value

[4] https://www.image-net.org/.

[5] https://gpcv.whu.edu.cn/data/building_dataset.html.

[6] https://www.kaggle.com/jonwang4/buildingenome-gpu-demo.

[7] https://github.com/opencv/opencv.

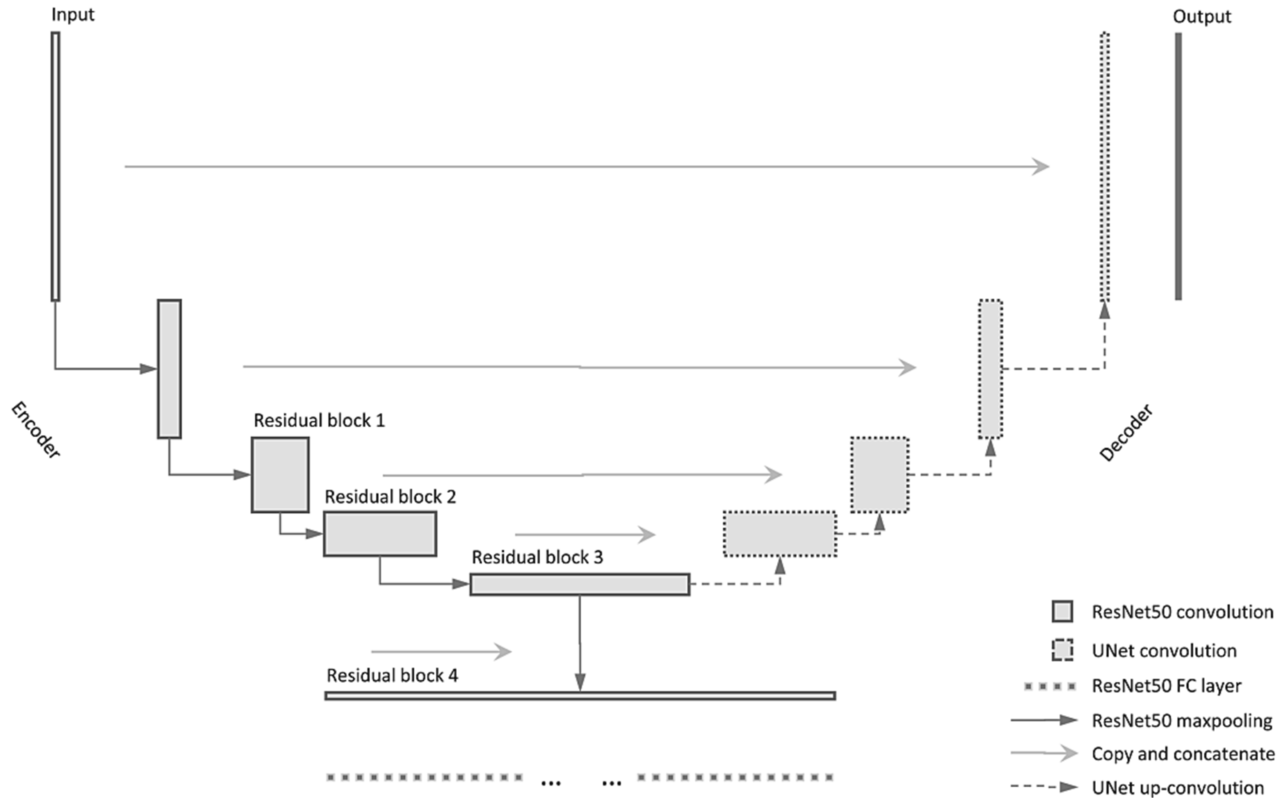

Fig. 3. Model architecture modified from the U-Net with ResNet-50 as the encoder.

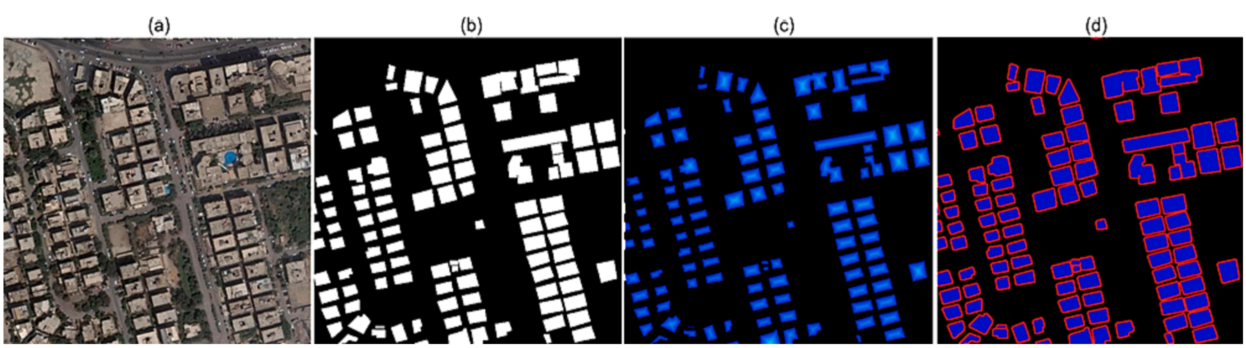

Fig. 4. Labeling for model training. (a) Original RGB image, (b) binary labels, (c) heatmap labels, and (d) edge-roof labels.

of our "EO + Morphometrics" approach could readily be manifested.

3. Mapping and understanding deprivation in Nairobi, Kenya

3.1. Deprivation and morphological diversity in Nairobi, Kenya

We applied the proposed workflow to the city of Nairobi, Kenya, a country where more than 56 % of urban population in 2014 lived in deprived areas (Wamukoya et al., 2020). In Nairobi city, this number rises to 60–70 %. People living in deprivation typically face a high level of vulnerability due to poor housing conditions, infrastructure, services, hazards, contamination, health conditions, and security (APHRC, 2014). The majority of deprived areas are found in the Eastern part of Nairobi, which goes back to the British colonial zoning (e.g., Master Plan of 1948). Furthermore, deprived areas are commonly located along major infrastructure (e.g., railways, main roads) and in flood prone zones. Deprived areas are dominated by high built-up and population densities (Kraff et al., 2019). As a consequence, the majority of Nairobi's urban inhabitants concentrate within around 5 % of the total built-up area of Nairobi (Mutisya & Yarime, 2011). Most people in deprived areas rent houses and pay a substantial amount of their income for (sub-standard) housing and services (e.g., paved bathrooms and toilets). Housing structures are diverse, e.g., the elongated structures (buildings) visible on satellite images are subdivided into small subunits that are rented. Areas are diverse in terms of functions, they are often a mix of residential, businesses and (self-helped) services. Unfortunately, detailed information regarding the formation, location, environmental characteristics and relocation patterns of these deprived areas is largely masked by the fact that statistics at national and city level are aggregated.

We use spatial information about a number of deprived neighborhoods sourced from local NGOs and community groups as a reference to explore whether socioeconomic conditions are reflected by the urban form. However, this layer is not a complete representation of all deprived areas in Nairobi and has several boundary uncertainties. As a starting resource, we use a publicly accessible Google Earth image including all main built-up areas of Nairobi (upper Fig. 5). The Google Earth image is a mosaic of very high resolution satellite images captured

Table 1
Selected morphometric characters measured to characterize and detect patterns of urban form. Implementation details are available in the documentation of *momepy* (docs.momepy.org) and in the supplementary material of published work (Fleischmann et al., 2021).

index	element	level	context	category
area	building	S	building	dimension
perimeter	building	S	building	dimension
circular compactness	building	S	building	shape
corners	building	S	building	shape
squareness	building	S	building	shape
equivalent rectangular index	building	S	building	shape
elongation	building	S	building	shape
centroid - corner distance deviation	building	S	building	shape
centroid - corner mean distance	building	S	building	shape
solar orientation	building	S	building	distribution
cell alignment	building	S	building	distribution
longest axis length	tessellation cell	S	tessellation cell	dimension
area	tessellation cell	S	tessellation cell	dimension
circular compactness	tessellation cell	S	tessellation cell	shape
equivalent rectangular index	tessellation cell	S	tessellation cell	shape
solar orientation	tessellation cell	S	tessellation cell	distribution
coverage area ratio	tessellation cell	S	tessellation cell	intensity
alignment	neighbouring buildings	M	neighbouring cells	distribution
mean distance	neighbouring buildings	M	neighbouring cells	distribution
weighted neighbours	tessellation cell	M	neighbouring cells	distribution
area covered	neighbouring cells	M	neighbouring cells	dimension
mean inter-building distance	neighbouring buildings	L	cell queen neighbours 3	distribution
building adjacency	neighbouring buildings	L	cell queen neighbours 3	distribution

very recently by different sensor platform such as the WorldView 1, 2 and occasionally 3. The built environment is highly diverse within the city as illustrated in a selection of sample areas displayed from street view (lower Fig. 5), as well as zoomed-in aerial views.

3.2. Building footprints in Nairobi, Kenya

When training our modified U-Net[8] for building extraction, we achieved a training accuracy of 95.25 % along with a validation accuracy of 93.79 % on the Wuhan University global building dataset. We then directly applied the trained model to the Google Earth imagery of Nairobi. Despite some on-going efforts of automatically mapping buildings in Nairobi, such as the recent release of the Google Open Buildings,[9] there is hardly reliable ground truth data for validating the mapped result. Yet, the resulting map can still be examined visually as shown in Fig. 6.

We obtained 506,435 mapped buildings in total. The buildings manifest urbanization in Nairobi as built-up areas, with higher built-up density towards the southeastern part of the city (Fig. 6(a)). We also selected five areas within the city for closer examination. One of the least properly mapped areas is that at the outskirts of the city, characterized by scattered households built amongst the croplands (Fig. 6(b)). Here, due to the very similar spectral representation and spatial characteristics in Google Earth RGB, the rectangular shaped crop plots with bare and dry soil are easily misrecognized as building on the image. As a result, a lot of false positive predictions of buildings occur (white circle). Model performance issues are also found in areas of very high built-up densities (Fig. 6(d)). The roofs are closely in contact with, attached to, or even overlapped with each other, making distinctions very challenging even by visual interpretation. As a result, some of the mapped building polygons are only very rough approximations of the building roofs. Nevertheless, they still retain patterns on the image for potential morphological characterization. Three other areas with different building density and amounts of vegetation cover are also shown (Fig. 6 (c), Fig. 6(e), and Fig. 6(f)), which show better model performances compared to the previous areas. With relatively clear contrast between the building and its surroundings, the building edges are captured properly making for improved roof delineation.

3.3. Building morphology of Nairobi, Kenya

The clustering of all the 506,435 buildings in the high dimensional feature space into a chosen number of clusters is informed by the clustergram as shown in Fig. 7. The diagram shows that the data of buildings are represented by different clusters as the number of clusters grows along with the additional metrics of goodness of clustering. The diagrams suggest several potential solutions from more to less conservative splits. Starting with classifying all the buildings into 2 or 3 types, the splits are all clean as seen in the clustergram. Further classifying the buildings into 4 types disjoints buildings from their original types and shifts them into new types, which means that 4 types lead to unstable split. The instability can be observed especially with 10 and 20 types, where buildings are disjointed and rejoined across different types. In contrast the splits are relatively “clean” when buildings are classified around 5, 6, 7 and 15 types, which is also suggested by metrics such as the Davies-Bouldin score (Davies & Bouldin, 1979). The score simply measures on average how compact each cluster is while stays different and far apart from other clusters in the feature space. The lower the score the better the clustering. In this work, we are interested in a more detailed version of clustering with the consideration of the diversity of Nairobi’s built forms, leading to a 15-cluster solution as illustrated by a vertical yellow line and supported primarily by the clustergram and Davies-Bouldin score.

To accommodate for potential overfitting, we further apply a method that minimizes variance as opposed to distance in feature space, the Ward’s hierarchical clustering, to our 15 clusters based on their centroids to derive the basis for the taxonomy of types. The taxonomic tree, shown on Fig. 8, detects three clusters (9, 11, 14) as outliers and identifies the similarity between all the other types. The result is then color-coded based on such a similarity and shown in Fig. 8 and mapped in Fig. 9. Some general patterns are already preeminent as most of the medium to high-density residential areas are concentrated to the eastern part of the city. These areas are mainly highlighted intentionally by blue toned types of 5, 10, 12 and 13. Many such areas fall within the delineated deprivation boundaries that identify designated informally built deprived areas, along with more organized, low-rise dense residentials of type 8. Moving towards the western part of the city, the urban form is mainly characterized by low-density residential forms classified as types 0 and 4. There are also densely packed residentials to the farther western part of the city again largely identified by types 12 and 13. On both the western and eastern edges of the study area, we observe sparsely distributed households over croplands, mainly captured by types 1 and 2. Some of the low-density residential areas intertwined with the well vegetated public open space such parks are also picked up in the western part of the city by type 6. Looking back to Fig. 5 and Fig. 6, the sparse households over croplands (type 1 and 2), nicely vegetated single-family houses (0, 4), densely packed slum households (5, 8, 10, 12, 13), high-density mid (5, 10, 12, 13) and low-rises (8) are all properly

[8] https://www.kaggle.com/jonwang4/buildingenome-gpu-demo.
[9] https://sites.research.google/open-buildings/#explore.

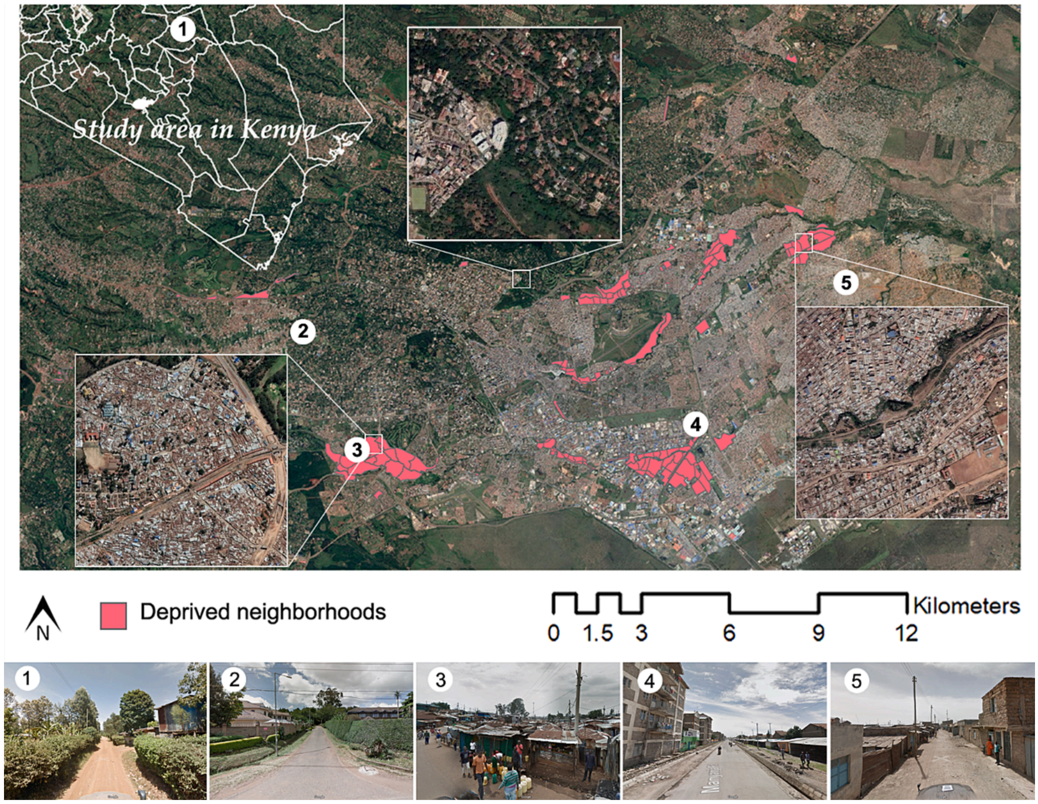

Fig. 5. The study case of Nairobi, Kenia: city plan (Google Earth) and morphological diversity (Google Street View). Three zoomed-in snippets are also provided to highlight the diverse built forms in two deprived areas contrasting with a formally built areas with business and residential constructions.

differentiated at least by type. Overall, the clustering shows a strong East-West divide of the city, which can be traced back to the town planning (racial segregation) during the British colonial period that split the city into the European zone (West), the Asian zone (Central-East) and few African zones (East).

Zooming into the designated deprived neighborhoods identified by black boundaries (Fig. 9), they mostly seem occupied by types 5, 8, 10, 12 and 13, though by no means exclusively since they also emerge outside those boundaries.

Fig. 10 illustrates the relationship between clustered buildings within the slum boundaries and outside of them as a distribution of each type. Although none of the clusters is equal or unique to slums, clusters 5, 8, 12 and 13 contain a vast majority of slum areas. While the designated boundaries are only samples, hence are not expected to comprehensively cover all deprived areas in Nairobi, other types hardly contribute anything at all to urban forms in deprived areas. This indicates that while the urban forms of deprivation are diverse and multifold, they also possess a certain level of distinctive coherence among all urban forms of Nairobi. This conclusion is also consistent with ongoing discussions about multidimensional deprivation (Abascal et al., 2022), where on one side physical characteristics only partially manifest the facets of deprivation, and on the other informal/unplanned settlements may in fact be populated by a diverse set of social groups. In the end, socioeconomic phenomena of deprivation and informality in urban development seem not reducible to the same visible built expression in space. On the contrary, the combined degrees of diversity and consistency in their visible urban form expression, as found in and supported by previous studies (Engstrom et al., 2022; Taubenböck et al., 2018), seems to reflect the complexity of social, economic and legal aspects intertwined in making urban "slums".

The divide of the urban types is most visible at the level of meaningful morphological metrics. We can then extract numerical evidence of the average values that each metric takes in any type. In Fig. 11, we observe that types most represented in deprived areas (5, 8, 12 and 13) are characterized by densely packed buildings, described by both high covered area ratio and related low mean inter-building distance than those in other types. It is worth noting that cluster 3, although not identified as a slum often, shows a similar morphometric profile to those that are seen as slums. Again, as shown in Fig. 11 that cluster 3 is especially similar with 5, 8, 12 and 13 in area of plot in terms of tessellation cell and inter-building distance. The numerical nature of the proposed taxonomy shows the potential to directly inform a new generation of large-scale evidence-based urban planning and design coding systems.

A further attempt of naming the clusters is shown below in Table 2. While each of urban types is described by several morphological metrics, naming the urban types will inevitably compress the information about the multitude morphological character. However, using the key metrics shown in Fig. 11 and combining cluster relationships in Fig. 8, the proxy names for the clusters shown below will help to summarize the strength of the morphological metrics in interpreting urban patterns. For instance, again, buildings in cluster 5, 8, 12 and 13 are all smaller and denser compared to the other clusters highlighting distinctively different built forms of deprived areas in Nairobi. And orientation is less useful for distinguishing deprivation from other areas as both aligned and less aligned built forms can be observed in cluster 5 and 8.

4. Implications and road map ahead

The proposed "EO + Morphometrics" workflow shows the potential to generate taxonomies of urban form at scale never before achieved that are based on humanly discernible entities and measurements, which could potentially pave the way for entirely new types of urban analysis. Further implications of this approach are worth discussing.

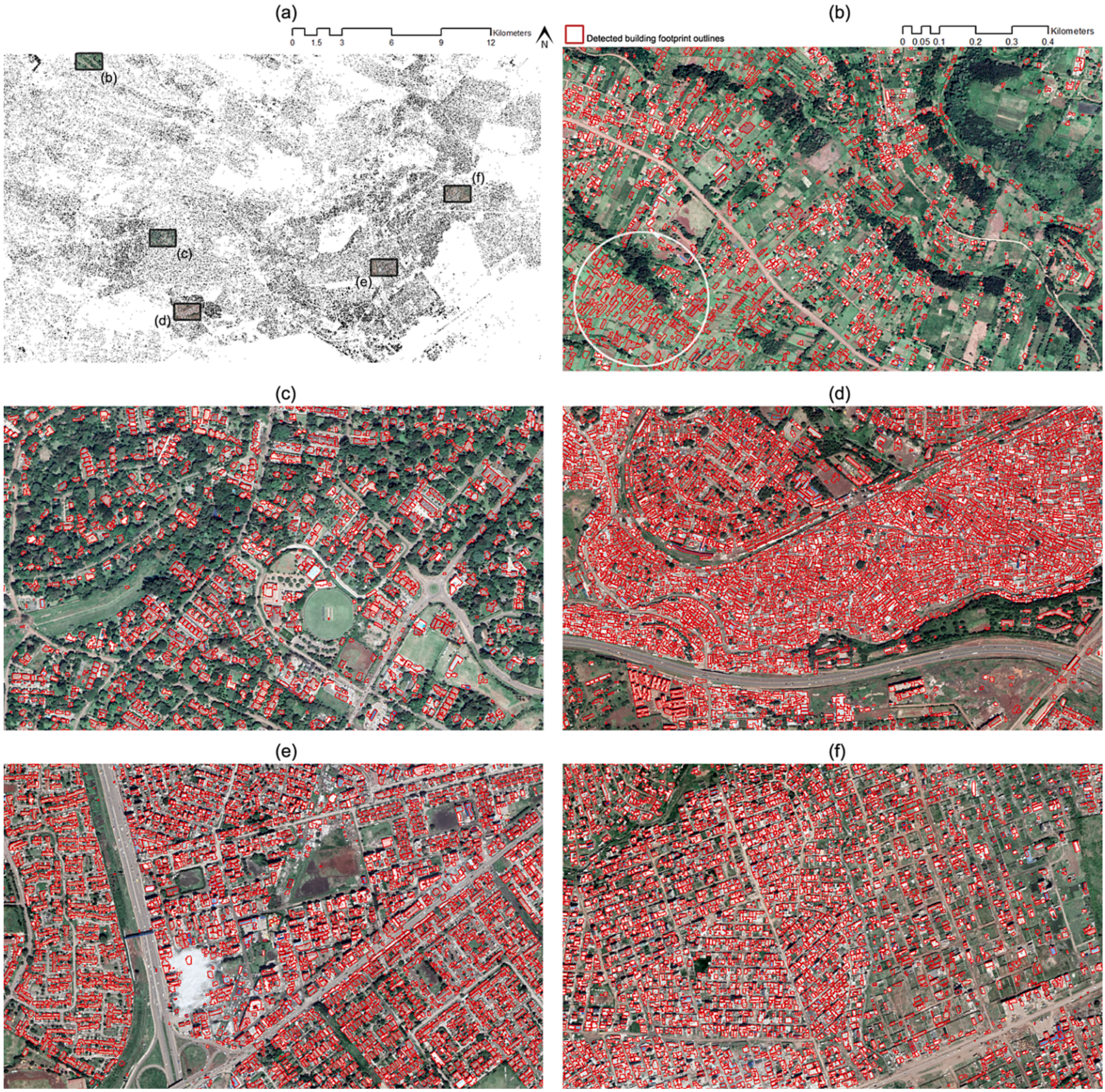

Fig. 6. Building footprints overview and zoomed-in samples (same as in Fig. 5) of extracted building footprints, Nairobi, Kenya.

4.1. The level of observation and the role of the EO

The levels of observation would determine the objects and patterns that can be measured and analyzed (Woodcock & Strahler, 1987), for instance, urban development has been investigated at the scale of the whole city in terms of city size and shapes (Batty, 2008, 2012). From an urban morphology perspective, urbanization patterns, manifested as built-up areas, can be observed at the smaller scale through the detailed measurement of meaningful urban elements such as buildings and streets (Dibble et al., 2019). In this regard, the role of EO is defined in terms of mapping fundamental urban form elements for subsequent numerical description. This seems narrowing down EO's role in directly mapping non-physical patterns. However, at a closer inspection, the role of EO is actually magnified, while being allowed to expand the detailed study to much wider areas and scales, in terms of scientific significance. As shown in section 3.3, where homogeneous urban types are extracted from building footprints and directly linked to provide information that has potential to inform urban planning and design.

The efficacy of EO in mapping non-physical aspects of cities is limited for a number of reasons explained earlier in the paper. Stretching the scope of EO to "see" aspects more than the physical, ultimately leads to exploring image characteristics as proxies of target patterns to be mapped. Such exhaustive mining of proxies is inevitably conducive to increasingly moving away from interpretable real-world results, let alone making sense of abstract image features. The proposed workflow shows that EO is both efficient and effective when used to produce detailed and objective descriptions of urban settlements, to then interrogate with other realms of urban morphology and morphometrics, for

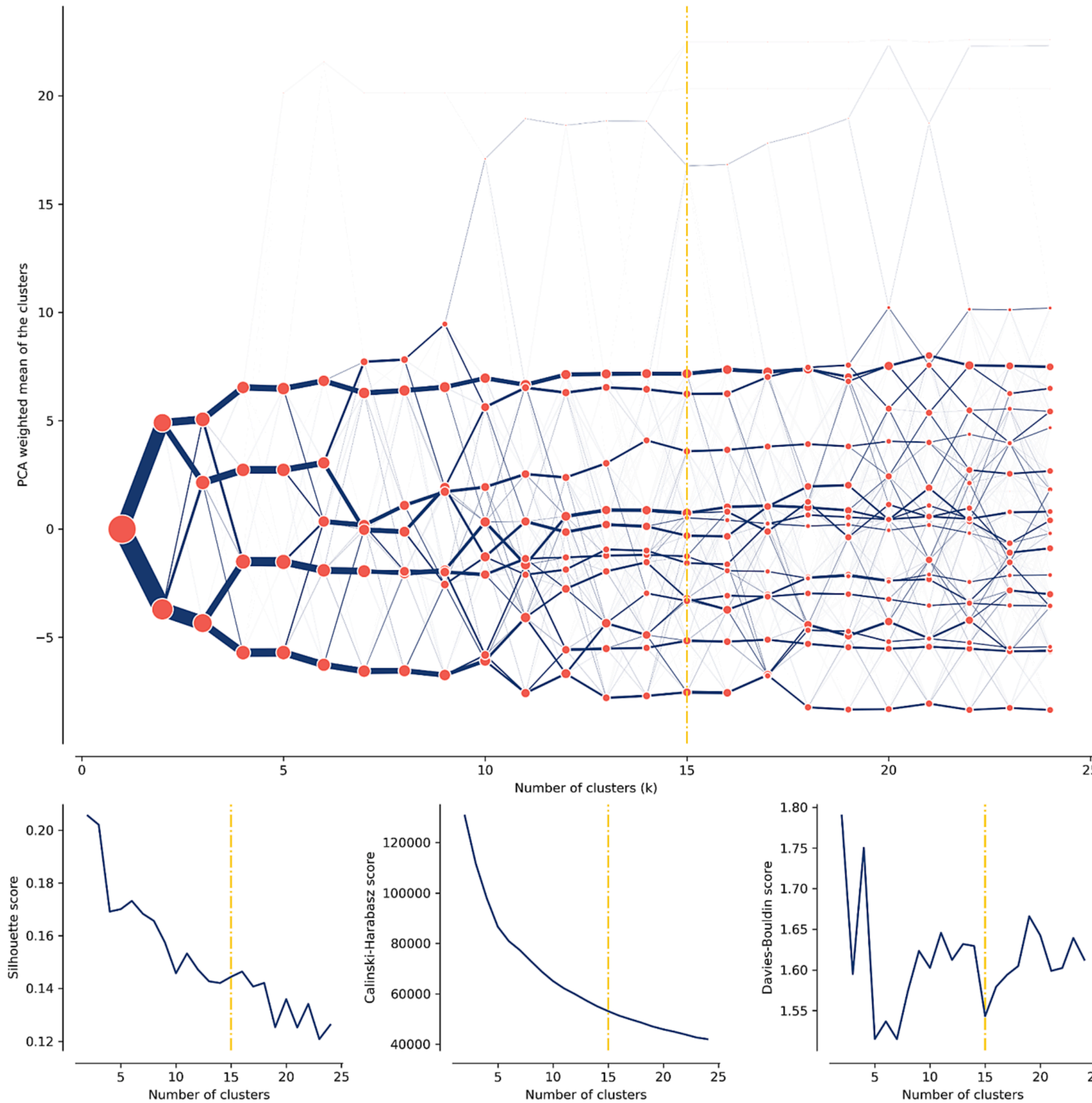

Fig. 7. Clustergram and relevant metrics of a goodness of fit (Silhouette score, Calinski-Harabazs score, Davies-Bouldin score) for different numbers of clusters.

the interpretation of a broad range of urban phenomena.

4.2. Enriching and applying metrics for physical urban characteristics

Deriving meaningful metrics for the description of urban form elements such as buildings has implications at many levels. Science-wise, meaningful metrics improve scientific validity in the practice of modeling urban patterns from image data within an induction-deduction loop (Fig. 2). While the "burden" of deriving meaningful metrics is shifted out of the scope of EO, that does not imply it would disappear. Instead, interpretation requires more explicitly measuring urban elements in ways which make practical sense. In fact, putting humans back into the loop of induction-deduction to foster interpretability has been actively discussed in big data and data science (Scheider et al., 2017). In the artificial intelligence community, there is growing interest in interpretable machine learning, which encourages connections between machine-extracted knowledge and human understanding (Doshi-Velez & Kim, 2017).

At the practical level, meaningful metrics studied in relation to socioeconomic performance can complement and support urban planning and design coding systems. Current planning and design codes may insufficiently inform the socioeconomic or environmental performance of urban places (Buckner Inniss, 2011). Although there are indeed active discussion about relating urban forms and socioeconomic pattern, especially on the topic of urban sprawl and compactness (Ewing et al., 2002; Frenkel & Ashkenazi, 2008; Gielen et al., 2018), many of the measurements are only applicable at the city scale with other indicators about population and employment. And those measurements at small

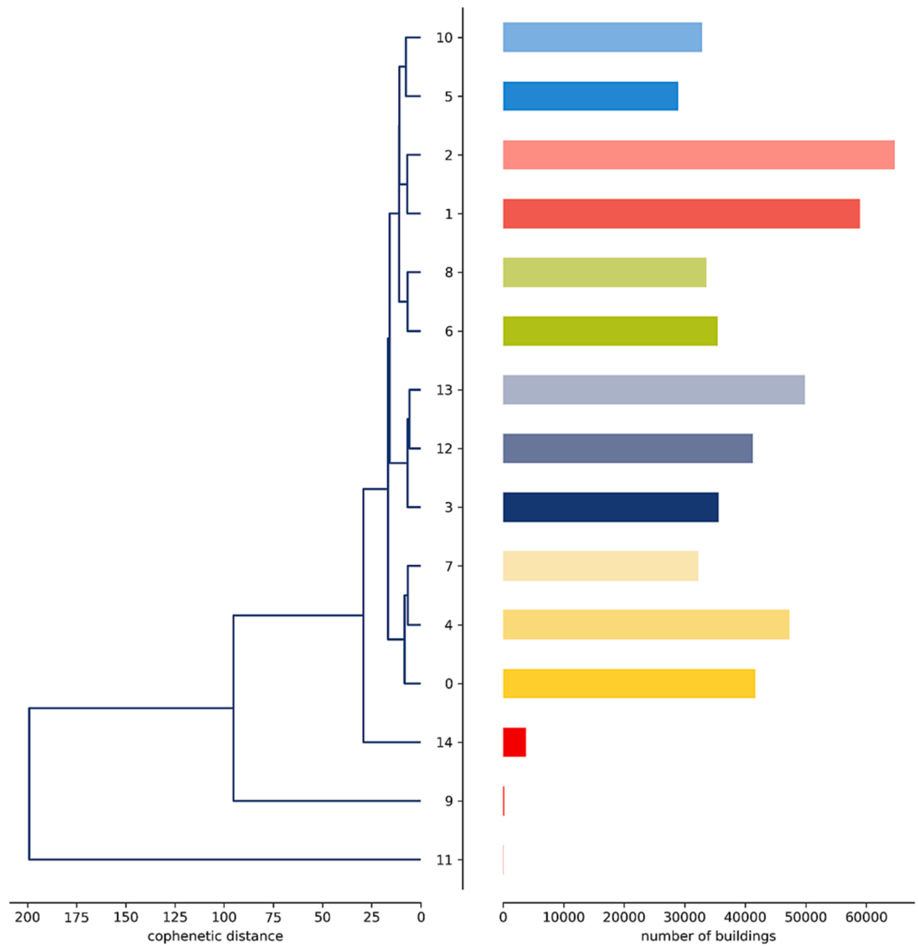

Fig. 8. Taxonomic tree showing the similarity between clusters represented by cophenetic distance and a number of buildings assigned to each cluster. From both the tree and counts, we can identify clusters 11, 9, and 14 as outliers caused by data quality issues described above and exclude them from the further analysis. The color-coding is representing natural groups of classes into higher-order taxa.

scale of neighborhoods and buildings are also needed to inform actions. Thus, interpretable metrics such as those presented in the proposed workflow possess the potential to directly inform new development practices that would impact more reliably local socioeconomic processes. Some of the metrics proposed, such as floor area ratio, building density, and orientation, can be considered "action-enabling metrics", in that they are already widely used in existing design codes, though without the support of rigorous extra-large scale evidence from the ground. Other metrics, although interpretable and intuitively understandable in the context of urban form, are less informative for practitioners in urban planning and design. Nevertheless, they might inform not only socioeconomic patterns, but also environmental or ecological patterns (Wamsler et al., 2013). For example, sky view factor (SVF), building volume density, and building proximity are few among those metrics capturing urban climatic patterns such as ventilation and heat (Xu et al., 2017). These metrics emphasize the potential impact of our ongoing research in real-world policy and practice.

There is no one-size-fits-all rule about what elements of urban form should be measured to best capture processes of change in urban form and design practices. For instance, in the study of sustainable urban development, several metrics have been used in published literature regarding urban sprawl and compactness (Kotharkar et al., 2014; Tsai, 2005), yet the measured forms were not necessarily informing sustainability (Echenique et al., 2012). Then, what should be measured? We see this as a question to be answered in the long run. Furthermore, different perspectives determine how measured metrics can be related to the practical context. Simply treating urban forms as either the consequence of urbanization, or the driving force shaping one of many potential subsequent urban processes can be misleading. For example, while the demand for public space and transportation defines and is defined by patterns of buildings and streets, these patterns also form "street canyons" which are sensitive to urban ecology due to thermal performance (Ali-Toudert & Mayer, 2006). Such interconnected processes may push many of the existing climate mitigation guidelines regarding street and building patterns towards the overoptimistic side. Simply using metrics regarding building and streets to inform climate adaptation should not ignore potential impacts on their fundamental functionality of commuting.

4.3. Open science for mapping urban dynamics

Combining re-framed EO and meaningful urban form metrics generates a mapping synthesis that is scientific and open. Specifically, scientific means a replicable practice that starts with observations, conforms to the human conceptualization of real-world objects such as urban form elements, where meaningful observations can be fed into the loop of induction-deduction, and finally leads to interpretable results that further inform practical action. This entire workflow conforms to George Box's model of "data analysis in scientific investigations" (Box, 1976). More importantly, the shifted scope of EO also reduces the demand of data, as the "burden" of deriving metrics is shifted away from the application of EO to raw image data. Hence, over-engineered machine learning techniques and expensive data can be avoided. Interpretable and replicable mapping practice, along with publicly accessible

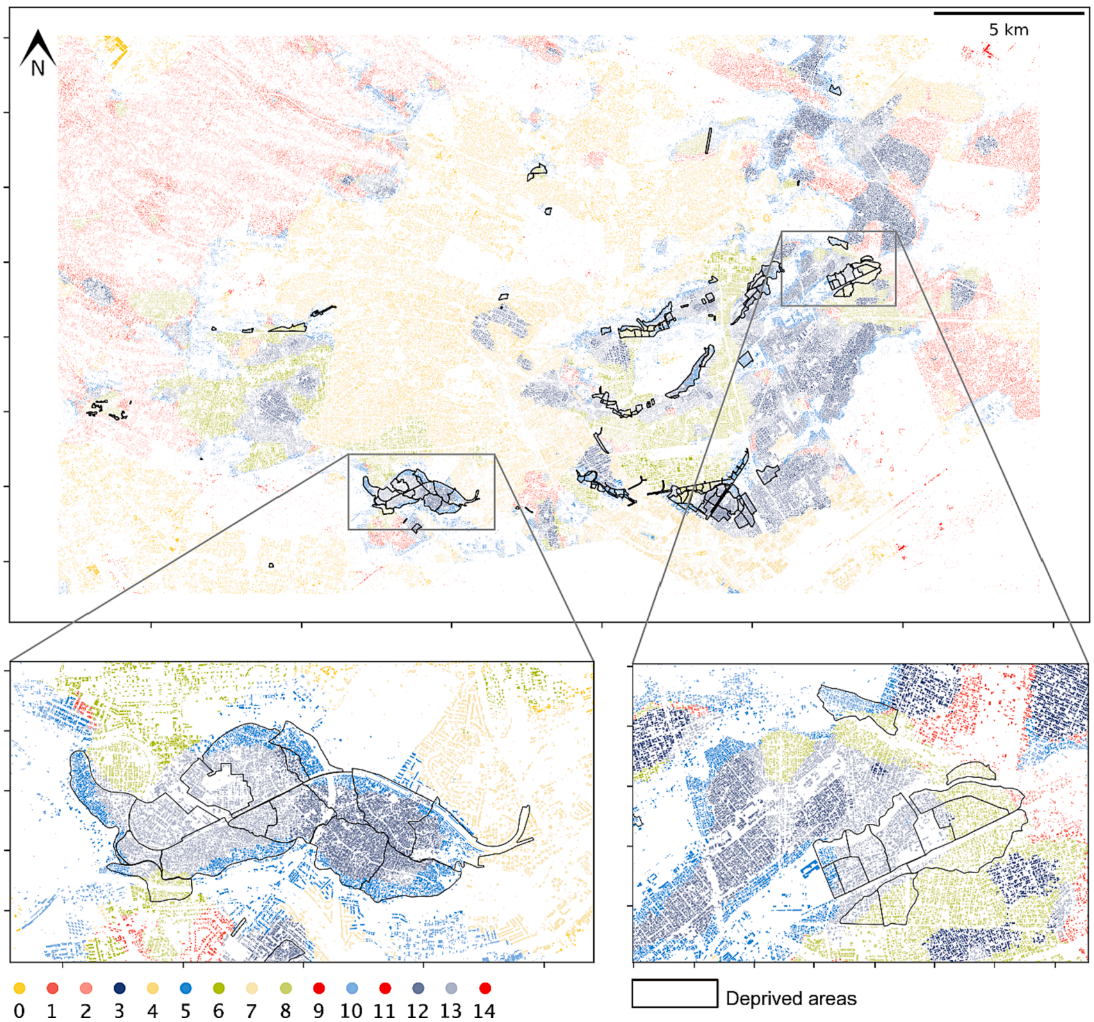

Fig. 9. Building clusters with different urban types of Nairobi, Kenya (above), and zoom-in of types in Kibera, one of the largest slums in Africa (lower left), and Biafra (lower right).

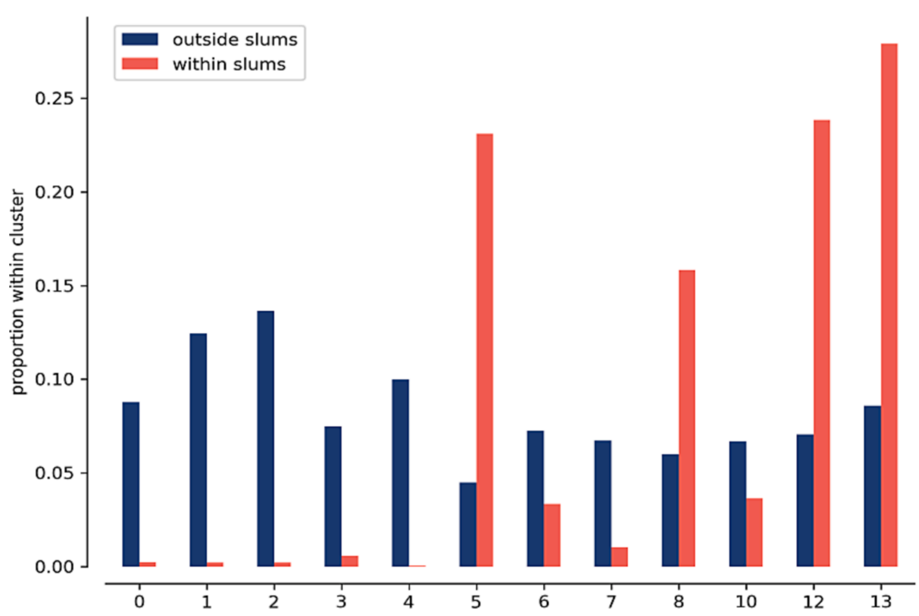

Fig. 10. Distribution of buildings identified within our outside slums into individual clusters as a ratio of a total count of buildings in each (within or outside) type. We can see that only a few clusters contain a notable number of buildings within slums.

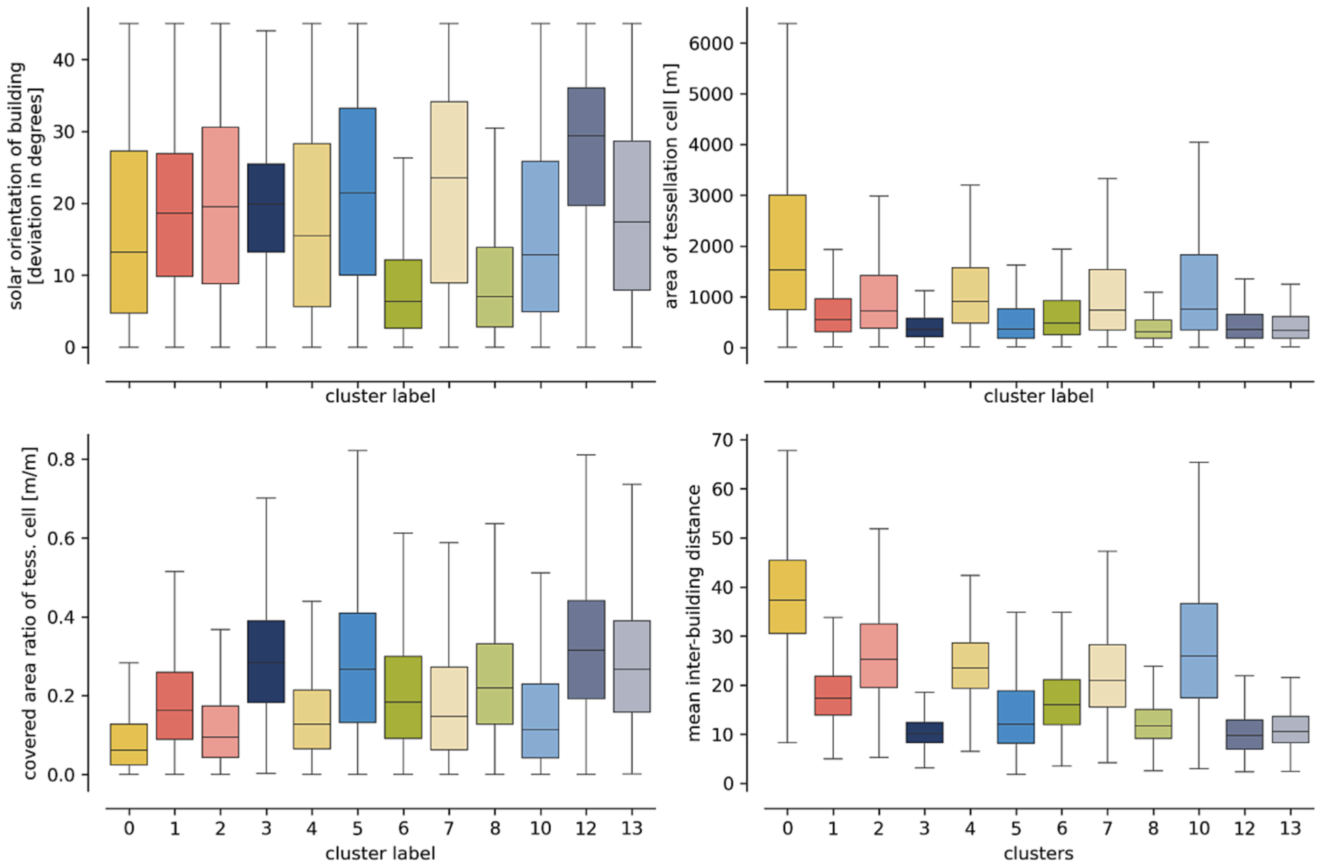

Fig. 11. Distribution of values of four sample metrics across urban types. Solar orientation of buildings is among a group of characters unable to distinguish slum and non-slum clusters. However, area of tessellation cells, covered area ratio or mean inter-building distance show notable differences and help us understand what makes slum structures typical.

Table 2
Proxy names of urban types based upon key morphological indicators. The order of the cluster label is consistent with the information in Fig. 8.

Cluster label	Cluster proxy names
10	small-area, median-dense, non-oriented
5	small-area, median-dense, non-oriented
2	median-area, sparse, less-oriented
1	median-area, sparse, less-oriented
8	small-area, median-dense, oriented
6	small-area, median-dense, oriented
13	small-area, dense, less-oriented
12	small-area, dense, less-oriented
3	small-area, dense, less-oriented
7	large-area, sparse, non-oriented
4	large-area, sparse, non-oriented
0	large-area, sparse, non-oriented
14	outliers
9	outliers
11	outliers

data, as shown in this work, pave the way to an open science of real-world urban patterns and applications. However, what cannot be neglected in front of open science are ethical and political issues as long as mapping technology can hardly be considered as neural (Bennett et al., 2022), especially in the situation of mapping socioeconomic status. Producing maps that are publicly open will inevitably encounter ethical and political issues. For instance, socioeconomic groups mapped as in poverty are with the risk of been stigmatized and loosing privacy as already been vulnerable (Kuffer et al., 2018). Then there should be a great deal of consideration towards the trade-off between open science and level of details been exposed.

4.4. The road map of "EO + Morphometrics"

Along the pathway of an open science for mapping and understanding urban patterns, we identify the following priorities both technically and methodologically:

- Improving the precision in detection of building footprints as current problems of falsely detected buildings in croplands, imprecisely captured building footprint outlines, and especially in some densely built areas the derived building polygons only roughly resembled the patterns of shapes (Wang et al., 2022);
- Exploring the potential of EO in extracting information capturing more realistic 3-dimensional characteristics, and urban form elements other than buildings, such as street networks mapping with its inherent challenge of defining streets especially in informal areas, and obtaining street information from freely available open imagery data source or GIS map services;
- Enriching the set of meaningful and ontologically clean metrics that can characterize socioeconomic and environmental processes, and inform urban policies;
- Developing a systematic and consistent selection technique to identify the optimal number of urban types, as the one proposed and used in this paper is based on a heuristic technique thus variations in this number may result in inconsistent urban types;
- Explore the potential of consistently representing urban morphological types across different regions and along time possibly by combing supervised clustering, so that the role of same urban morphological types at different places and times can be studied (e.g. in the process of slum evolution or gentrification);

- Modeling the relationship between morphological metrics and urban patterns about and beyond the socioeconomic one;
- Investigating the interpretation of morphological metrics further in the context of both urban morphology and complexity systems, so that effective transfer of knowledge between morphometric analysis and real-world policy and practice is maximized.

5. Conclusion

In this work, we presented the workflow, technical specifications and case study application of the proposed "EO + Morphometrics" approach. Combining the strength of EO-based technology and GIS-based morphometrics, this approach supports a scientific understanding of urbanization through explicit measurements of meaningful urban form elements. The validity of the approach is demonstrated in the study case of Nairobi, Kenya, where 15 urban types captured the significant diversity of forms visible on the ground. In particular, the combined coherence and diversity of the urban form in designated deprived areas are also well picked-up. Several implications come forward from the successful implementation of the proposed workflow. The role of the EO and that of meaningful metrics of urban form have been thoroughly discussed. In the future, we would expect improvements in EO's capacity to mapping basic urban elements and deriving more metrics for interpreting urbanization into the practical context of planning and design. Ultimately, we are moving towards an open science of urban morphology.

CRediT authorship contribution statement

Jiong Wang: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Martin Fleischmann:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Alessandro Venerandi:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Ombretta Romice:** Writing – review & editing. **Monika Kuffer:** Writing – review & editing. **Sergio Porta:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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