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The dynamics of poor urban areas - analyzing morphologic transformations across the globe using Earth observation data

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ABSTRACT

The urban environment is in constant motion, mostly through construction but also through destruction of urban elements. While formal development is a process with long planning periods and thus the built landscape appears static, informal or spontaneous settlements seem to be subject to high dynamics in their ever unfinished urban form. However, the dynamics and morphological characteristics of physical transformation in such settlements of urban poverty have been hardly empirically studied on a global scale or temporal consistent foundation. This paper aims at filling this gap by using Earth observation data to provide a temporal analysis of built-up transformation over a period of ~7 years in 16 documented manifestations of urban poverty. This work applies visual image interpretation using very high resolution optical satellite data in combination with in-situ- and Google Street View images to derive 3D city models. We measure physical spatial structures through six spatial morphologic variables - *number of buildings, size, height, orientation, heterogeneity* and *density*. Our temporal assessment reveals inter- as well intra-urban differences and we find different, yet generally high morphologic dynamic across study sites. This is expressed in manifold ways: from demolished and reconstructed areas to such where changes appeared within the given structures. Geographically, we find advanced dynamics among our sample specifically in areas of the global south. At the same time, we observe a high spatial variability of morphological transformations within the studied areas. Despite partly high morphologic dynamics, spatial patterns of building alignments, streets and open spaces remain predominantly constant.

1. Introduction and background

"*All entities move and nothing remains still*" the Greek philosopher Heraclitus postulated. With regard to humankind's history urban morphology has always changed over time. Since ancient history, cities arose and fell over centuries. These dynamics are triggered by transformations in the natural environment or by changing societal conditions. While we might think the built urban landscape is static, time gnaws at its physical form – be it through reconstruction, new construction or destruction. Especially spontaneous settlements, squatter settlements, slums, ghettos and other manifestations of urban poverty are considered dynamic forms of structural changes (Mahabir et al., 2016). These developments in the built environment affect building morphologies and their patterns (Rubenstein, 2011), such as the underlying street order or the size and arrangement of open spaces. As an example, there are dramatic morphological transformations from the complex building alignment of a gecekondu settlement in 2009 to a planned building arrangement in Ankara, Turkey in 2017 (Fig. 1.).

There is a massive urban transformation across the globe triggered by rural-urban migration (Davis, 2006), new globalizing markets (Sassen, 1996), climate change (UN-Habitat, 2013), or economic crisis and wars (Castles et al., 2013). Significant effects emerge in cities across the globe, by means of e.g. informal-, spontaneous- and squatter settlements, slums (UN-Habitat, 2015a), ethnically segregated enclaves (Wacquant & Howe, 2008), social succession processes (Hoffmeyer-Zlotnik, 1976), ghettos (Stehle, 2006), and other manifestations of urban poverty. Especially these urban areas related to poverty are presumed to be highly dynamic in relation to other parts of the urban society (Kuffer et al., 2016; Patel et al., 2018).

Until now, there is an innumerable variety of physical appearances of urban poverty across the world. Taubenböck et al. (2018) reveal a large assortment of such morphologic forms containing 'slums' or 'informal settlements', among many others. However, geodata documenting their built-up environment - and particularly their temporal evolution - have hardly been retrieved in high resolution and/or large-area coverage. Thus, a call for a data revolution, to systematically

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Fig. 1. Karaağaç/Altıağaç (Ankara, Turkey), extensive change in the built-up environment between 02.07.2009 (top) and 21.02.2017 (bottom); ©Google Earth 2019.

gather digital information on different spatial levels has been declared (UN-Habitat, 2015a). To respond to this demand, it is one crucial step to systematically examine the morphology of these areas. Yet, their high dynamics can only be investigated by bridging the gap from static to multitemporal measurement. In the recent past, Earth Observation (EO) has proven to be an important tool for capturing these areas relating to morphology and temporal dynamics. Remote sensing studies so far rely on different methodological approaches (e.g. pixel- or object-based, machine learning, visual image interpretation), as well as different spatial scales (e.g. urban region, city, settlement or individual buildings), see Kuffer et al. (2016) for an overview. There are different approaches for a highly detailed building level detection in such areas: The representation of slums in Level-of Detail-1 city models in 3D using LiDAR or unmanned aerial vehicles (e.g. Gevaert et al., 2016; Temba et al., 2015), however, remains scarce. Only very few studies have focused on a systematic 3D documentation of areas of urban poverty (Taubenböck & Kraff, 2014, 2015). Most change detection studies do describe the growth of poor urban areas (e.g. Badmos et al., 2018), yet very high resolution (VHR) data are scarcely applied due to e.g. imperfect automated approaches or missing local knowledge (Mahabir et al., 2018).

The main objective of this paper is to gain a better understanding of the morphologic dynamics at the high spatial resolution LoD-1 city models in these areas representing urban poverty. Therefore, it is essential to classify, quantitatively characterize and visualize transformations of these particular settlements. The foundation of this panel study consists of data from 16 areas, each covering 2 time steps over a period of approximately 7 years. Aiming at a global representation, we put value on a well distributed area selection across four continents with unlike physical and cultural criteria. The *spatial selection* includes further criteria as formality status, minimum number of buildings, among others. For details on the study site selection we refer to Section 3.1. We developed 3D building models by using VHR optical satellite data (e.g. Quickbird, WorldView) of approximately 0.5 m geometric resolution for two time steps.

For the assessment of building height, we integrate in-situ surveys as well as geotagged photography and a literature survey. In order to capture the morphology of the built environment in all dimensions, we use spatial variables and characterize morphological changes by indicators for the *building morphology* and the *pattern of the settlement*. With it, we aim to address the following research questions:

(1) Are there variable dynamics of morphological change across the selected areas of urban poverty over a 7-year time period?
(2) How dynamic is the built-up urban spatiotemporal change within areas of urban poverty?

The remainder of this article is organized as follows: Section 2 reviews the state of the art on poor urban areas in the context of EO and urban geography. Section 3 introduces the selected study areas and the literature survey in the frame of the applied data and methodology. Furthermore, the methodological workflow and the spatial variables for analyzing the morphology are presented. Section 4 comprises the results of the temporal transformation of the urban morphology. In Section 5 we discuss the results in the geographical context of urban poverty research. Finally, Section 6 serves as an outlook and concludes this study.

2. State of the art: mapping dynamics of poor urban areas by EO

For monitoring and mapping areas of the urban poor, EO has been increasingly applied in recent years. Most current studies focus on the development of automated methods with optical data (e.g. Hofmann et al., 2008; Kuffer & Barros, 2011) or SAR data (e.g. Wurm et al., 2017). Detecting poverty areas with frequently unclear textural patterns, pixel-based methods (Baud et al., 2010; Bruzzone & Bovolo, 2013) have been often replaced by object-based methods, especially with regard to multi-temporal objects (Tewkesbury et al., 2015). Still, manual visual image interpretation (MVII) is used to explore delineating formal from informal at the high spatial level of individual buildings (Baud et al., 2010; Taubenböck & Kraff, 2014), or for describing the nature of their structural patterns (Taubenböck et al., 2018). Automated processes still do not offer the demanded accurate data quality and availability (UN-Habitat, 2015a) as e.g. very high level of 3D detail in these often complex, high dense areas. However, only few scientific approaches use MVII, especially being subject to LoD-1 roof extraction (Kuffer et al., 2016). With regard to the nature of the homogeneous textures as they appear in the images of these areas, automated methodologies have weaknesses in the derivation of individual buildings, yet the methodology of MVII offers more reliable precision (Baud et al., 2010; Kuffer et al., 2016; Mahabir et al., 2018).

- Nevertheless, there is still a lack of a consistent and structured approach in EO and urban geography to systematically map the physical environment in space and time:
- Relating to *space*, firstly, there are different scales that are tackled, as e.g. classifications are presented on city scale (Kit & Lüdeke, 2013), for single slum case studies (Veljanovski et al., 2012) or on a single area (Leichtle et al., 2017). Secondly, there is socioeconomic segregation. Many qualitative models and indices have been introduced to solely spatially distinguish urban population groups. There is e.g. a correlation between urbanization and wealth (Glaeser, 2011; Taubenböck et al., 2019), a remarkable linkage between socioeconomic information and remote sensing (Baud et al., 2010; Taubenböck et al., 2009) or spatial ethnical delineation patterns discovered by e.g. Hanslmaier & Kaiser (2017). Arrangements of the 'urban social space' (Shevky & Bell, 1955) on city level or 'social topography' on single building level had been realized punctually in 1980 already (von Frieling, 1980). Still qualitative but more precisely, Lloyd (1979) differentiates between 'slums of hope' and 'slums of despair'. Davis (2006) introduced a very generic slum typology differentiating between 'formal status' and intra-urban 'location'. UN-Habitat (2003) additionally took into account 'size', 'age' and a first hint to 'temporal dynamics'. Kohli et al. (2012) postulated a first quantitative yet still generic 'slum ontology', based on the pioneer ontology work of Hofmann et al. (2008). Subsequently, Taubenböck et al. (2018) established a quantitative, empirical global categorization of 'morphologic types' of urban poverty. Furthermore, a methodological feasibility of correlations between poverty and remotely sensed morphologic slums were proven (Wurm & Taubenböck, 2018).
- Relating to *temporal* change, the above-mentioned studies serve as basis and legitimate the necessity for measuring time transitions in a generic and adoptable method. Kuffer et al. (2016) summarized EO's progress after 15 years of slum mapping by highlighting that "*spatiotemporal information on slums is scarce at the city scale*". In fact, not even the city scale is representative for single slums, as an empirical mean of slum sizes amounts 126 × 126 meters (cp. Friesen et al., 2018). In the context of computational simulation, e.g. 'agent based' models were applied to measure temporal change of slums' fragmentation pattern on city scale (Barros & Sobreira, 2002) or models to predict informal settlements growth (Roy et al., 2014). Recently techniques of 'Machine/Deep Learning' have been adapted for slum detection and delineation from other (urban) landscapes (e.g. Wurm et al., 2019, 2019) and also with a multitemporal concept (Liu et al., 2019; Pratomo et al., 2018); however, with a focus on classifications

at district level. On the geometric level of individual buildings, new approaches use e.g. unmanned aerial vehicles (Gevaert et al., 2016), yet generally multi-temporal morphologic transformations have hardly been addressed (except e.g. Bruzzone & Bovolo, 2013). Thus, multi-temporal EO-based studies beyond case-study character of slums are still generally scarce due to the complexity of these structures, accuracy issues of existing techniques and poor availability of consistent VHR datasets (Hofmann et al., 2015).

3. Data and methodology

In this section we first (Section 3.1) introduce the literature survey and selection of globally distributed study sites. Subsequently, (Section 3.2) the methodological concept for capturing data, the spatial variables for measuring the temporal transformation and the morphologic classification are introduced. Finally, (Section 3.3) the methodologic workflow will present the concept in detail, illustrating obstacles and uncertainties.

3.1. Literature survey and study site selection

Neither a global slum compendium, nor any other kind of repository does exist that contains all poor urban forms worldwide. This is primarily due to the fact that the necessary (geo)data are mostly neither existing nor – if they exist – are consistent. The latter is due to many different established definitions and approaches towards poor urban areas (Gilbert, 2007; Nuissl & Heinrichs, 2013) and due to different methods in delineating these areas. Hence, we rely on a literature survey to provide a representative sample of a large diversity of poor urban areas across the globe. Our study comprises inner-city areas where poverty has been documented in literature. These types can e.g. be slums or ghettos but also other areas with different physical conditions. Hence, we avoid typological limitations and remain with the term “poor urban area”. Suburban and rural areas as well as overnight makeshift shelters are disregarded in our concept as we focus on established constructions only.

In general, the measurement can be applied as a multidimensional approach. Next to the indicator of economic poverty, poor urban areas also feature a lack of education, health and living standards, as expressed e.g. by the Multidimensional Poverty Index (MPI). In our study, however, we do not explicitly follow selected dimensions or any other kind of index-based poverty measurement. Instead, we only rely on literature (cf. appendix), that assures all study areas documented as poor urban areas. However, for each area we offer further information about shelter and infrastructure conditions, formality status, crowding or topographical accessibility.

For the selection of our 16 study sites, we used scientific search engines (google scholar, scopus, jstor, openlibrary and sapub) and as search items we put generally used terms as e.g. ‘slum’, ‘ghetto’ or ‘informal settlement’, ‘deprived area’ or ‘squatter settlement’ as well as local terms linking to poor urban areas, as e.g. ‘favela’, ‘township’, ‘chawl’, ‘urban village’, ‘gecekondu’ and many more. We systematically verify each area to be in line with our *spatial selection* at both time steps and guarantee different geographic aspects (e.g. population, surrounding environment, infrastructural conditions). We searched in titles, abstracts and entire articles, mostly in English, occasionally in other languages. Next to ISI-referenced articles we scarcely used conference papers, grey literature and newspaper articles, not limited to any dates, yet the EO data range from 2002 until 2017.

The *spatial selection* for the study sites comprises the following criteria: a) documented in literature as poor urban area; b) global distribution, covering different continents and cultures; c) an accumulation of at least 1000 buildings is required construing as settlement; d) sites are chosen from different topographic locations and e) with dissimilar formality status, that is formal or informal and not of spontaneous character (not constructed overnight, cp. appendix). With our selection we f) depend on the availability of VHR imagery, i.e. multimodal and -temporal data sources, and we rely on established criteria, suggested by Taubenböck et al. (2018). Furthermore, we choose g) for each site a temporal interval between t_1 and t_2 of approximately 7 years within a total time frame between 2002 and 2017. Based on these criteria, we selected 16 sites each with 2 time steps, resulting in 32 3-D models, where we cover four areas per continent (except Australia) for a global distribution: Cairo, Lagos, Nairobi and Cape Town from Africa; Rio de Janeiro, Lima, New York and Philadelphia from North- and South- America; Shenzhen, Mumbai, Ulaanbaatar and Ankara from Asia; and London, Évry, Athens and Bucharest from Europe.

3.2. Methodological conceptualization

In order to document the physical built-up environment of an area and its temporal transition (t_1 and t_2), we capture its physical appearance using three spatial levels:

- Level-3 (L3): We classify single buildings at *building level* (LoD-1).
- Level-2 (L2): Aggregation of these geoinformation from L3 to the *building block level* to capture the pattern of the morphologic appearance.
- Level-1 (L1): Additional aggregation of geoinformation from L2 + L3 to analyze the physical appearance of the area at the *entire district level.*

We use spatial variables on these level (cp. Fig. 2) to systematically retrieve the structural appearance of the poverty areas: *1) number of buildings; 2) building's size; 3) building height; 4) building orientation; 5) building density; 6) heterogeneity*.

Finally, to convey the morphologic classification between t_1 and t_2, we analyze the dynamics by i) the total *number of buildings*; ii) the building morphology from the variables *size* and *height* and iii) the pattern of the settlement from the variables *orientation*, *heterogeneity* and *density*.

3.3. Methodological workflow and uncertainties

For an overview, the conceptualization and the workflow are visualized in Fig. 2.The workflow comprises consecutive steps for each study site and its temporal datasets t_1 and t_2: **(1)** Capturing buildings and blocks; **(2)** computation of the spatial variables capturing the morphology and the patterns of the area; **(3)** calculating and measuring morphologic transitions over time and **(4)** comparing inter-and intra-urban results.

(1) Capturing buildings and blocks: We use multi-temporal VHR optical satellite data (e.g. Quickbird, WorldView) with geometric resolutions of up to 0.46 m (pan sharpened). We choose morphologically representative regions (ROI) for each area, since the sites' full extents often range in vast km^2 scopes. The ROIs portrait all kinds of structures, e.g. open spaces, dense built-up zones, different building types and similar street networks. We digitize a single building roof as one polygon (L3) and we depict the construction's ground floor in m^2. Mapping is done by cognitive perception via MVII which as a method offers many advantages: For instance, the interpreter uses tools and scales in a steady manner, follows a consistent approach and a standardized digitization protocol (based on Taubenböck et al., 2018 and Kuffer et al., 2016). In this way, one is able to capture vertices of more complex and angular roof shapes and to distinguish the often homogenous textural patterns in the satellite data. Especially with regard to temporal changes, the interpreter is more resilient to disturbing factors than automated implementations (Kinkeldey et al., 2015) as e.g. deviating viewing geometries, mostly imprecise geometric matching of multimodal and -temporal image sources, clouds, cast shadows or stereoscopic effects with displacement of buildings (Leichtle et al., 2017). For instance, sensor's viewing angles occasionally differ between t_1 and t_2

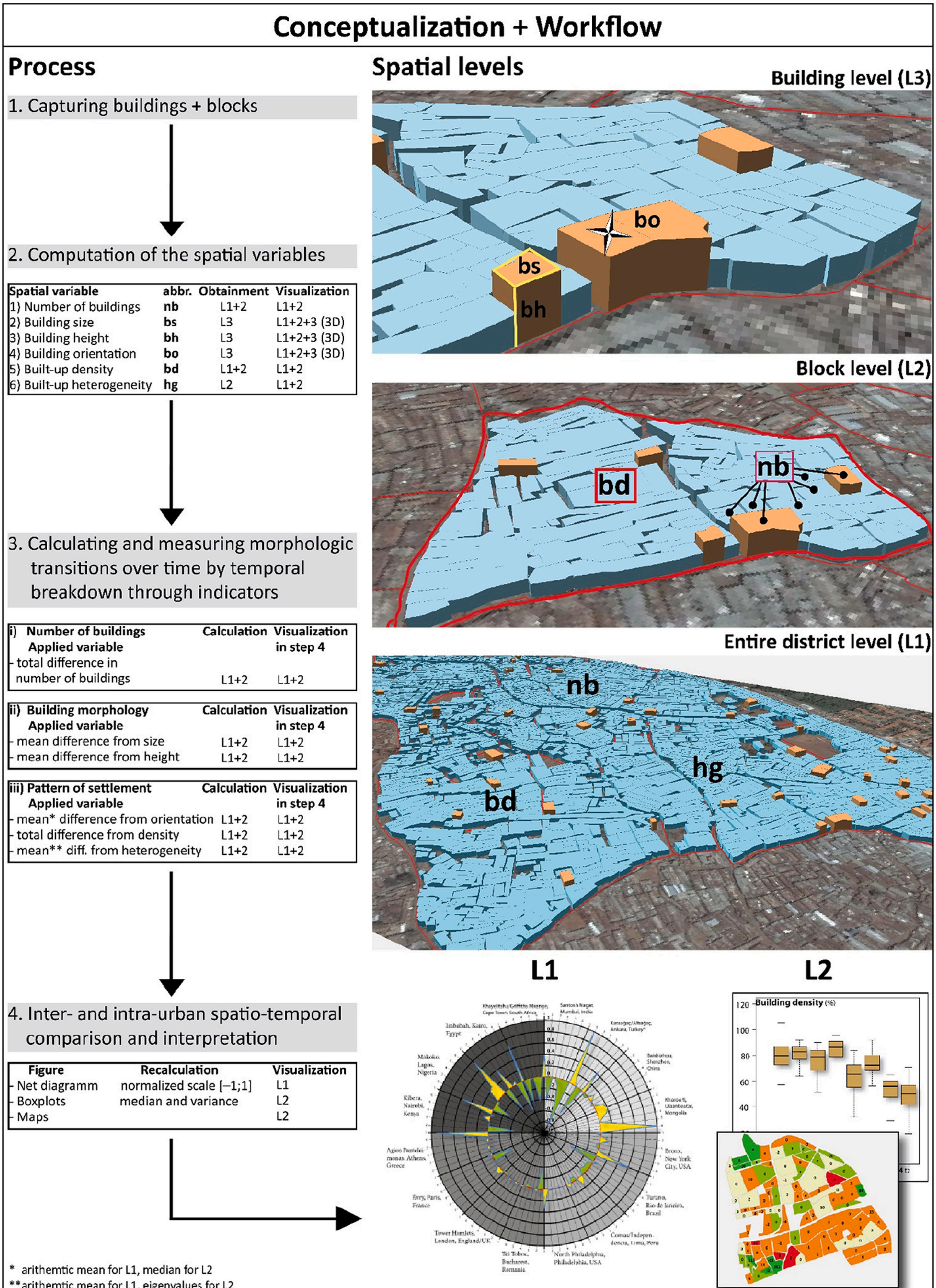

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Fig. 2. Methodological conceptualization presented by the example of Kibera in Nairobi: The workflow contains three spatial levels from mapping buildings to calculating the spatial variables and analyzing temporal morphologic changes.

and might influence radial offsets and buildings' orientation in a misleading way. However, digitizing polygons generally is a difficult task in the context of complex urban poor areas (cp. Kohli et al., 2016) and, in this study, depends on one experienced digitizer only. The digitization of vertices has been consistently done at a detailed, spatial scale of 1:1000. Manual digitization is very time consuming. For the ground floor mapping (roof extraction) of buildings, we registered 8–10 h for an area with 2000 polygons including creation of building blocks. Overall, our dataset contains 119,317 polygons, that is approximately 480–600 h for the sole digitization without assigning building height information. In all cases we were able to produce proper building heights, scaled by their story. In 8 of 16 areas google street view images were available and we were able to count the stories of most single buildings. We assigned the building height to the corresponding building footprints for the particular time step. For the other time step and in areas were no street view information was available (Comas/Independencia, Turano, Griffiths Mxenge, Kibera, Makoko, Imbabah, Baishizhou and Santosh Nagar), we estimated buildings' heights interpretation of the satellite imagery based on shadows, the respective viewing angle, etc. Prior studies (Kraff, 2011; Taubenböck & Kraff, 2014) verified an accuracy with an error quote < 9% only: an error we assess as tolerable. Finally, we rely on in-situ knowledge of the architecture gathered by observations in poverty areas and combined additional geotagged photography. The blocks (L2) serve as spatial reference units for capturing the morphologic pattern of the built environment. The delineation of blocks is primarily based on the network of streets, pathways and intersections and, if not available, realized by homogenous areas in terms of impervious surfaces versus open spaces.

(2) Computation of the spatial variables capturing the morphology and the patterns: 1) The *number of buildings* as counted polygons demonstrate the quantity of building changes; 2) the *size of the buildings* is calculated in m^2 and 3) the *height of the buildings* operationalized as number of floors is derived from a combination of images, in-situ observations and estimations. The latter two variables serve to classify the morphology at individual building level; 4) for calculation of the *building's orientation* we use the longitudinal side of the particular building structure and the difference in orientation to its nearest neighbor. This feature aims at receiving an estimate about structural alignment and order with a scale [0;1] where 0 presents order and 1 presents chaos. 5) The *building density* (%) is computed as ratio of the accumulated building ground floors to the reference units of block areas as well as to the entire district area. In this vein, we retrieve values that contrast open spaces to high density patterns. 6) The *heterogeneity* of the pattern is calculated as each block's building density, set in relation to its particular neighboring blocks' densities. The outcome shows the homogeneity by estimating its block-density fluctuation across the entire area. A higher value represents more heterogeneity. For further details on the mathematical background about the variables, we refer to Taubenböck et al. (2018) and concerning the heterogeneity we refer to Taubenböck & Kraff (2014).

(3) Measuring morphologic transitions over time on the spatial scales L1 and/or L2: Our multi-temporal analysis contains the indicators (i) total number of buildings with its total difference (at L1 and L2) and (ii) the building morphology as differences of the arithmetic means of the variables *size* and *height* (L1 + L2). (iii) The pattern of the settlement as differences of arithmetic means from the variables *orientation* and *heterogeneity* for L1, respectively differences of medians (*orientation) and heterogeneity*'s block-values (eigenvalue) for L2. Additionally, total differences from the variable *density* (L1 + L2) are calculated. From it, we subtract and calculate the development of the obtained differences on the correspondent spatial levels for t_1 and t_2.

(4) We visualize the *inter-urban* morphologic transformations using a radar chart (L1) with the temporal development of all variables in a normalized scale between [−1;1]. We illustrate the *intra-urban* (L2) dynamics by boxplots that display medians and quartiles of the calculated L2 values of the spatial variables. Furthermore, we map spatio-temporal developments of all variables (L2) exemplified for selected areas.

4. Results and interpretation

In this section, we first (Section 4.1) visualize selected areas over time and briefly describe the dynamics in morphology and pattern in a qualitative manner. As a second, more detailed step (Section 4.2), we analyze the dynamics in a quantitative way: We measure morphologic transitions and finally compare inter-and intra-urban differences.

4.1. Qualitative inspection of morphologic dynamics

Ground figure plans (Fig. 3) serve as a qualitative way to visualize morphologic similarities and disparities across time and study sites. A first visual inspection reveals a large variety of morphologic dynamics within our temporal interval of ~7 years: from quasi none to crucial changes. Karaağaç/Altıağaç, Ankara (cp. Fig. 3, no.12), as example, reveals a radical morphologic transformation. A designed new settlement development consisting of large single buildings in low density replaces a prior complex, denser and informally grown pattern. Another example for high dynamics is Makoko, Lagos (no.03). The area shows an extreme densification where (water)street patterns seeming to be the only remaining free space. We also find sites with merely marginal morphologic transformations. Specifically, North America and Europe are examples of a rather static pattern as demonstrated by e.g. North Philadelphia (no.08) and Tower Hamlets in London (no.13). In between this obvious contrast there exist low and high visible transformations as building reorganizations lead to a cityscape that keeps its ordered structure, illustrated by Imbaba in Cairo (no.01); we also see spatial inhomogeneous structural reorganizations within areas such as in Khoroo 9, Ulaanbaatar. There densifications in the east is contrasted by dispersion to the west (no.11). This first overview already displays large differences of morphologic dynamics for areas of the urban poor.

4.2. Quantitative analysis

In this chapter we quantitatively measure the morphologic transitions by a temporal breakdown analysis using the indicators i), ii) and iii) as described in Section 3.3.

4.2.1. Global view: inter-urban morphologic dynamics

Across the globe we find the following key points, referring to research question 1 and visualized by a radar-chart (Fig. 4):

1. **The most significant type of temporal change is identified at the level of individual buildings:** We find highest dynamics in a changing *number of buildings* (cp. Fig. 4) with mostly rising tendencies up to a maximum of +76.9%. This clearly reveals on-going immense morphologic dynamics. Generally, the *number of buildings* seems to negatively correlate with the *building sizes*. That is, rising building numbers often lead to shrinking dimensions (m^2) of *buildings*. This effect can be observed in all studied sites across the globe (e.g. Santosh Nagar, Turano, Tei Toboc, Kibera). However, more specifically, we find different morphologic dynamics between continents. Particularly African, Asian and South American areas feature higher dynamics in contrast to North America and Europe, where we find relatively minor changes in *the number of buildings* (e.g. North Philadelphia −0.2%, Tower Hamlets

Regions in alphabetical order by continents, countries, cities and areas
All areas visualized on the right page, boldly marked areas above

Africa	t1 vs t2
01. Imbaba, Cairo, Egypt	**2004 vs 2011**
02. Kibera, Nairobi, Kenya	2006 vs 2014
03. Makoko, Lagos, Nigeria	**2008 vs 2015**
04. Griffiths Mxenge, Cape Town, South Africa	2005 vs 2012

America	t1 vs t2
05. Turano, Rio de Janeiro, Brazil	**2002 vs 2009**
06. Comas/Independencia, Lima, Peru	2009 vs 2016
07. Bronx, New York City, USA	2009 vs 2016
08. North Philadelphia, Philadelphia, USA	**2010 vs 2017**

Asia	t1 vs t2
09. Baishizhou, Shenzhen, China	2008 vs 2015
10. Santosh Nagar, Mumbai, India	2003 vs 2010
11. Khoroo 9, Ulaanbaatar, Mongolia	**2007 vs 2014**
12. Karaağaç/Altıağaç, Ankara, Turkey	**2009 vs 2017**

Europe	t1 vs t2
13. Tower Hamlets, London, England/UK	**2008 vs 2015**
14. Le Pyramide, Évry, France	2005 vs 2011
15. Agios Panteleimonas, Athens, Greece	2008 vs 2016
16. Tei Toboc, Bucharest, Romania	**2005 vs 2012**

Fig. 3. Eight selected examples of ground figure plans of poor urban areas at time t_1 and t_2.

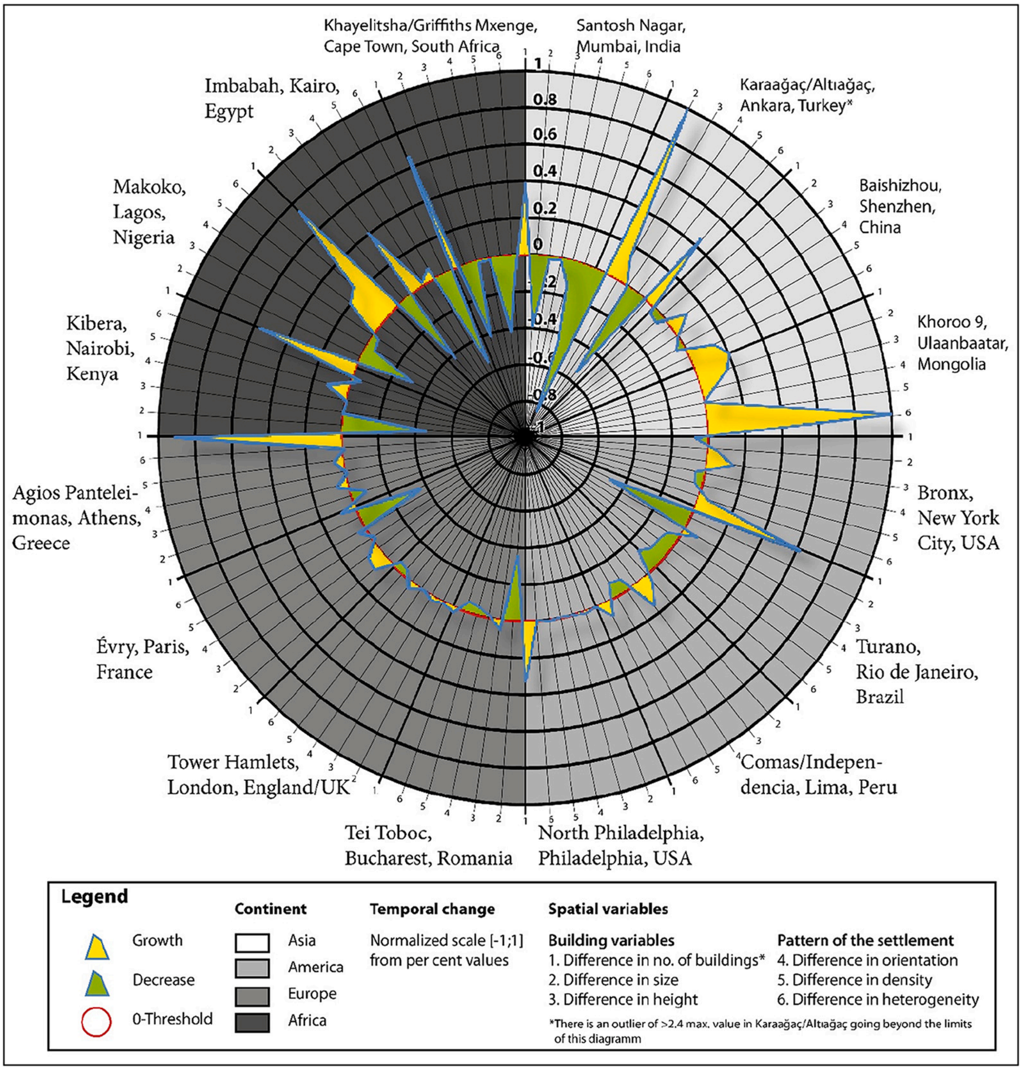

Fig. 4. Radar chart of the selected areas with inter-urban dynamics via spatial variables for buildings and the pattern.

+2.4%) as well as in the *building size*. Due to the formal tenure, we assume rather legally binding land-use plans and less informal developments. However, there is a remarkable constant among our study sites: *building heights* are constantly rising. On average buildings grow about 7%, apart from outlier Imbabah (+34.4%) and apart from Europe showing relatively little variances and growth rates.

2. **The general morphologic pattern remains stable:** The high change rates of the single building morphology is not given for all spatial variables: Building *orientations*, defining the geometric *pattern of the settlement*, feature only very few changes as most values constantly range between + and - 1% over time. Even if we find nearly all sites of our sample transforming to a more ordered building arrangement across the globe, the *orientation* does not demonstrate remarkable transformations in relation. A prior cross-sectional study (Taubenböck et al., 2018) has already proven rather aligned building structures. In the temporal contextat the spatial level of the individual building, *number* of buildings and *size* change significantly (built, rebuilt, demolished), but their *orientation* remains stable (split buildings keep orientation). Thus, on the spatial level of the entire settlement the *pattern* quantitatively illuminates what ground figure plans (Fig. 3) have already shown in a qualitative way: Many settlement *patterns* with their building alignments, open spaces and street networks appear scarcely transformed. In contrast, the variable *building density* demonstrates more significant transformations. Again, African and Asian areas show highest (Makoko +17.1%, Ulaanbaatar 28.7%) and American and European areas reflect least dynamics, (Philadelphia +0.3%), yet still variations (e.g. Tei Toboc −3.6% vs. Agios Panteleimonas +4.6%) appear. The variable *heterogeneity* serves as a legitimate proxy for pattern inconsistency. It mirrors the *density* fluctuations and findings that African and Asian areas show highest transformations, as Fig. 4 demonstrates for instance in the case of Ulaanbaatar (83.9%). Even though, the *heterogeneity* index ranges between 7.6 (homogenous) and 26.7 (heterogeneous) and despite high dynamics (%) (Fig. 4), the global mean decreases from 17.1 (t_1) to only 16.8 (t_2) across all areas. We find that the appearance of the organic structural cityscape remains stable.

We find two outliers with a *density* maximum decrease of −45.6% (Ankara) versus +28.3% rise (Ulaanbaatar) and hereby reflect very high transformation rates, in this case for areas in Asia.

4.2.2. Local view: intra-urban morphologic dynamics

With regard to research question 2 we illuminate the morphologic dynamics by comparing the intra-urban changes, visualized by boxplots (Fig. 5) and a map of Kibera and Tower Hamlets (Fig. 6). Across the globe we find the following key points:

1. Within our study sites we find a high spatial disparity of morphologic changes: For most variables we find high variances (represented by interquartile ranges) within sites as for instance for the *number of buildings* per block. In 12 cases results reveal a highly

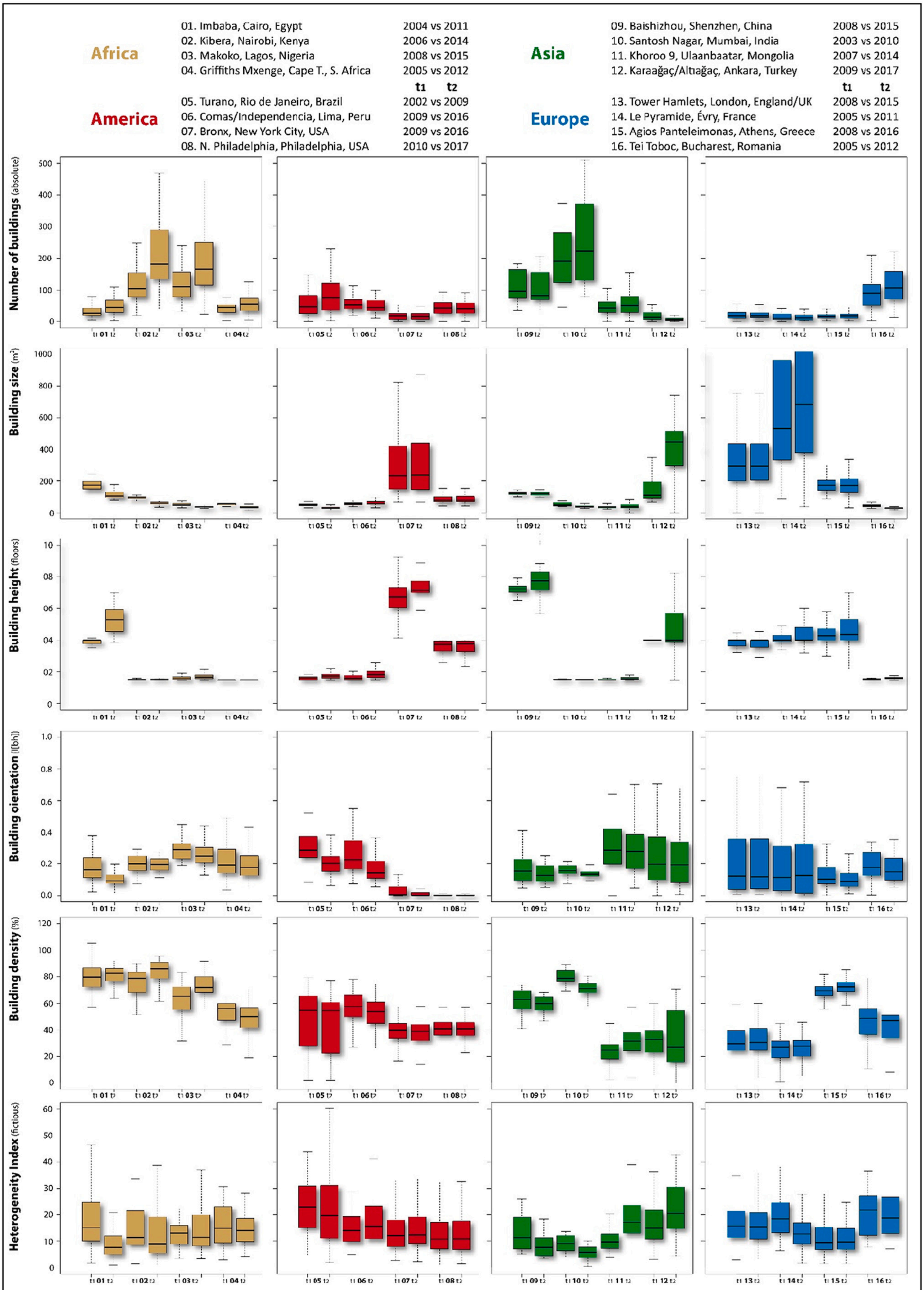

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Fig. 5. Boxplots demonstrate the six spatial variables measuring temporal changes of the 16 selected Arrival Cities.

dynamic changing spatial distribution of (mostly) rising as well as decreasing values (Fig. 5, e.g. no.02,05,10,16). The *building morphology* is furthermore affected by *size* and *height:* Generally, transformations in *sizes of buildings* are significant, sometimes extreme (e.g. no.12), yet intra-urban variances often remain stable (e.g. no.02,07,13).

And, for *building heights* we find the least transformations, as many areas show only few variations. Furthermore, there does not seem to be a correlation, hence a change in building size does not implicate a change in stories or vice versa.

Focusing on the *pattern of the settlement*: Though being spatially disparate across building blocks (especially *density*), we experience a more ordered and homogenous building alignment over time as presented by the *building orientation*. We find a definite and clear trend where 13 cases feature decreasing median values and ranges. Thus, the built-up structures lose complexity leading to a homogenous building alignment across blocks over time. This finding underlines prior results from pattern analysis on the aggregated small-scale level 1 (cp. 4.2.1). Additionally, the *heterogeneity's* block-values confirm this change: It displays significant decreasing values (10 cases), indicating transformations to a more homogenous *pattern of the settlement*.

2. We find fewer intra-urban dynamics for our samples in Europe and North America: There are poor urban areas all across the globe but their visual appearance and morphology is very different. A 'favela' in Rio de Janeiro looks totally different than a 'ghetto' in New York City and a 'township' in Cape Town seems very different to a 'banlieu' in Paris. Different morphologic appearances and transformation might depend on different cultural and environmental outward influences (cp.1). Based on our sample we find an intra-urban continental divide indicated by several spatial variables (Fig. 5). We find this result for the individual *building morphology* as well as for the *pattern of the settlement.* The intra-urban analysis allows for a more tangible change allocation as demonstrated by Fig. 6. We exemplify the 'North-South polarization' of our findings for Kibera and Tower Hamlets: Kibera shows more discordant distributions across the blocks whereas Tower Hamlets demonstrates less dynamics (cp. Fig. 6a + c). Here, the spatial scale reveals its important role as the block level illustrates higher fluctuations of the spatial variables from one block to the other, especially in Kibera (cp. b). However, we also find significant tendencies of growing *heights* and less ordered building alignments of insular blocks in between Tower Hamlet's rather even block values (cp. b + d).

5. Discussion

If you re-visit a slum, favela, informal settlement or any other kind of urban poor area after several years, you may find that the physical environment has changed fundamentally: New buildings may have arisen, others split, streets appeared or vanished, density changed. But it's just as well possible that you may find streets, corners and building blocks at the same place as before. Especially for slums the common narrative is that these are the most dynamic settlement areas around the globe. However, this paper clearly reveals that any generalization is oversimplifying, and in large parts even distorting the truth to falsity. For our 16 sites, which do not contain such areas created overnight, tendencies are identified that generally confirm the common narrative: We find higher morphologic dynamics in the southern hemisphere in slum areas. However, we also specifically find that, although the change in building numbers is often comparatively high, the general spatial pattern of the settlement often remains stable. Additionally, we could also reveal that every site has an own context with its own path-dependencies that shape morphologic dynamics very heterogeneously.

There is an international political demand to improve the life of millions, suffering bad tenure conditions. Exploring and understanding the nature of morphologic transformations is thus of high relevance. The scientific community requests a better perception, unconventional urban city models and to fill the gap of a missing systematic ontology in urban poverty research. EO is capable of measuring urban spatio-temporal changes and to fill this gap. It contributes to the monitoring of the built-up environment even though the highly detailed exploration is challenging. This is due to the variety behind the physical appearance of poverty by its diverse forms. EO data are crucial for classifying these often neglected and less documented areas, especially at a high resolution of 3D-building levels. The sites used in this study are presented in LoD-1 and allow for a high detailed representation of the urban morphology and its change over time; however, with 16 areas we cannot claim results representing dynamics worldwide. Furthermore, with EO data we can only prove physical, morphologic transformations. However, we disclose whether morphologic changes in poor urban areas result from informal, organic, natural built-up processes or from planned interventions (cp. appendix).

In this study we detected morphologic dynamics at very high resolution. Thus, we need to take into account related methodological challenges: The classical MVII offers higher accuracies than automated techniques (Baud et al., 2010). However, this method is cost-intensive in the matter of time and a broad basic population on LoD-1 is difficult to deploy. It also explains why only 15% of scientific methods in this domain are subject to single building level (Kuffer et al., 2016). In comparison to automated processes, however, the interpreter precisely captures single polygons by extracting roofs or distinguishes between pitched roofs and pathways. Nevertheless, the MVII is subject to high uncertainties (Pratomo et al., 2017). Interpreter's behavior has been proven to influence the manual interpretation (Kohli et al., 2016). This includes for instance usage of window extents and source image material as e.g. geometric resolution or vegetation covering the objects of interest. Thus, a totally unbiased digitization is not possible (Hurskainen & Pellikka, 2004), potentially influencing the number of polygons or its size and shape. Since the interpreter's capturing behavior highly depends on image quality, it might influence any results sensitively to a yet unknown effect. Beyond the quantified assessment of the accuracy of the building height, we must assume here, as discussed in the literature, that the visual image interpretation is very accurate - without us being able to quantify this here, since there is no 'ground-truth' reference data on these areas. One might rely for comparison on OpenStreetMap (OSM), serving as a legitimate and accepted basemap for studies. We compared some of our datasets with OSM (e.g. Évry and Tower Hamlets) where they exist. However, OSM contains for instance aliasing artifacts or merged terrace buildings by mistake. Other obstacle are limited historical remote sensing datasets, that restrict the aim for a profound spatiotemporal ontology without high geometric resolution. An objective evaluation of the accuracy of our produced data sets is thus impossible to generate. In general, however, the derived data base is among the highest quality that can be produced by humans from MVII. A further step aiming at deviations among digitizers is necessary to illuminate insecurities and ought to be explored in another study. These uncertainties naturally result in consequential errors that are difficult to assess.

We observe that morphological changes are often reflected in the *number of buildings*. Despite an often, large increase, we find the *density* of buildings does not increase proportionally, but rather that buildings are reduced in *size*. With it, our study confirms the expectations of high spatial dynamics in such areas and we are able to verify research question no.1: We find highly variable dynamics of morphological change across the selected study sites over time on a high spatial level of detail (L3). With respect to research question no.2, we reveal dissimilar dynamics of intra-urban spatiotemporal change (L2). We find a lot of areas that prove significant changes at all three indicators i) total number of buildings; ii) the building morphology and iii) the pattern of

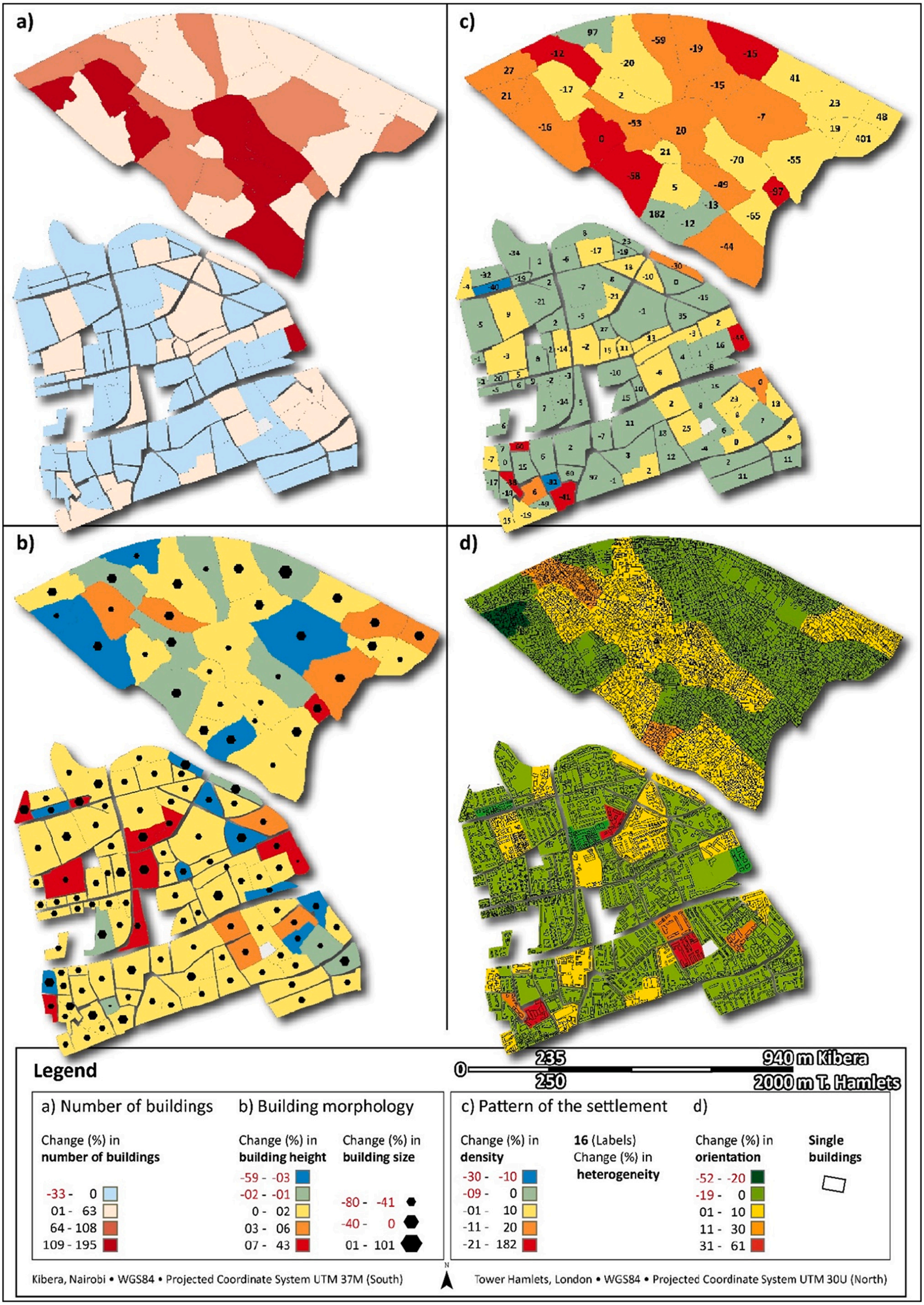

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Fig. 6. Intra-urban temporal change for ROI Kibera, Nairobi and Tower Hamlets, London.

settlement. Among our sample, we find especially areas in Africa, Asia and South America feature significant morphologic dynamics. Contradicting these expectations, we find especially in North America and Europe areas of the urban poor with a generally formal character. They feature significantly less morphologic transformations and remain rather static. Globally, in respect of both research questions the overall organic pattern, defined by major streets, pathways, open areas, etc., remain in most cases comparatively stable. We understand the pattern resulting from LoD-1 building variables whereat topological street analysis or planning approaches as e.g. 'reblocking' (cp. Brelsford et al., 2018; UN-Habitat, 2012) remain unconsidered in this study.

At the end, our sample only provides a principle tendency that cannot reflect all local individual cases. However, we are able to proof some general propositions: As mentioned in Section 1, there is a serious lack of affordable housing in cities due to the massive urban transformation (De Soto, 2000; Woetzel et al., 2014). Thus, urban poor areas are subject to high dynamics (Kuffer et al., 2016, b; Patel et al., 2018). On a global perspective the 'World Atlas of Slum Evolution' (UN-Habitat, 2015b) basically illustrates a substantial transformation of urban slum population of two decades. Furthermore, the 'Slum Almanac' expresses more detailed a rise of 16,500 people per day in urban slums in the southern hemisphere and in the urban northern hemisphere a significant increase of poverty where people cannot afford rents. This dynamic is expressed for instance in high densities, with only fragmented unoccupied patches (UN-Habitat, 2016). Also, density changes due to extensive new building constructions in Kibera are claimed by Veljanovski et al. (2012). And, as matter of fact of slum upgrading, Olthuis et al. (2015) assert building expansions inside the sea in Makoko – these findings are in line with our results. In contradiction to our results, Rubenstein (2011) proposes 'filtering' processes in poor American areas due to subdivided smaller building units. We find decreasing building sizes but not in America where a little rise is measured.

To respond to the demand to gain a systematic and multi-temporal global ontology of poor urban areas, the temporal factor multiplies the already challenging task for a comprehensive holistic detection. There is proof of concept for correlations between urban poverty and morphologic slums derived from EO-data (Sandborn & Engstrom, 2016; Wurm & Taubenböck, 2018) as well as for correlations between urbanization and wealth (Glaeser, 2011; Taubenböck et al., 2019). Wurm et al. (2019, 2019) also proof a relation between citizen's subjective perception and the city structure. However, in this study we do not interpret our explorative physical results for a societal or planning application. At that point where EO reaches its limits, a linkage between the achieved approach to socioeconomic and political indicators/ domains is mandatory to fully understand the geographic context. This is where in-situ observations and expert interviews are necessary to connect 'point-blank' field survey-derived data with such obtained by 'remote' sensing to accomplish a holistic and absolutely valid geographic approach. Only in this way a tangible application for decision makers, spatial planners or development cooperation is possible.

The remaining question is what influences the urban morphologic dynamics in such different ways? Not necessarily but possibly superimposing factors are the pressure of rural-urban migrants, the cultural background and related behavioral norms, the societal and political acceptance as well as possible intervention strategies, the jurisdictional shelter security by law play, among other issues, crucial roles here. The literature survey helps to understand local realities. Nevertheless, due to local interdependencies it does not always assure a valid statement. One example is the case of Ankara Karaağaç/Altıağaç that reveals the consequence of a national spatial planning program called *"Altıağaç-Karaağaç-Hüseyingazi urban regeneration project"* (İdel, 2018), where Gecekondus were replaced by high-rise buildings (cp. Fig. 1) In another case of Santosh Nagar (Mumbai), we know that the area's status is informal and assume that existing dynamics (rising building fluctuation, decrease in density) are connected to the political informal shelter status that dwellers face who arrived in Mumbai after 1995 (Risbud, 2003). The case of Griffiths Mxenge (Cape Town), which as a planned area with formal structures (City of Cape Town, 2011) is different as it still shows significant morphologic changes. However, with a high probability one can assume that the nowadays formal status of land tenure in industrialized areas as in Tower Hamlets or Le Pyramide, influences the very low dynamic morphologic patterns significantly, as ownership is more transparent, partially subsidized and the real estates (though partially deteriorated as e.g. in Athens) with access to a working infrastructure are more anchored in legally binding land-use plans.

6. Conclusion and outlook

Migration has always been a key factor for the accumulation of settlements and it will probably stay a continuous phenomenon. Being the first place to go for the poor, slums and ghettos have been playing a central role in the development of the urban built-up environment in human history. As contemporary new forms of urban poverty have shown, these areas will continue influencing city developments to a large degree in the future. It is of crucial importance to better observe and understand this phenomenon over time.

The increasing availability of VHR EO data with offers new capabilities to spatiotemporally analyze the morphologic appearance of urban poverty. This explorative work confirms inter- and intra-urban spatiotemporal morphologic dynamics of globally distributed selected areas. With it, we empirically confirm observations from other studies that the built environment of the urban poor is subject to high morphologic transformation (Kuffer et al., 2016, b) and we add new empirical findings that a large variety of dynamics is existent. Furthermore, we contribute to the scientific demand for a systematic temporal change comparison across the globe at the level of 3D city models. Based on a first systemized slum ontology (Kohli et al., 2012) and a further empirical 'Arrival City' classification (Taubenböck et al., 2018), we propose a methodology to systematically monitor the changes of poor urban areas.

Due to the challenges for deriving LoD-1 models over time in such complex urban environments, these results base on a sample of study sites that is comparatively small and generalization is not admissible. We suggest setting up a broader LoD-1 geodata acquisition containing a larger basic population that allows a broader global quantitative temporal classification across the world. Furthermore, we used a time interval of approximately seven years for two time steps. A higher frequency and a longer time frame, with many time steps would illuminate an even more detailed area development, such as a 'life cycle'. We know that next to poor urban area's individual character, they globally share morphologic characteristics as e.g. high densities or small building sizes (cp. Taubenböck et al., 2018). Our findings about their temporal dynamics should be compared to those of formal areas to receive a better understanding of urban transition. For future analysis, mentioned data barriers might decrease. However, a methodology for highly detailed capturing of 3D models for large areas in such complex built-up environments ought to be found. Also, our analysis only considered areas where morphological alterations had taken place. Conversely, this means that we have not documented areas where a fundamental change has taken place. But this happens all the time, either by creating new settlements at previous undeveloped land, or by destroying existing settlements, as visualized in the example of Raj Ghat (cp. Fig. 7) in Delhi. This example shows how for a big event - the 'Commonwealth Games' - the poorest city dwellers have to give way. Giving these people

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Fig. 7. Raj Ghat (Delhi, India), extensive change in the built-up environment between 02.03.2004 (top) and 08.03.2012 (bottom); ©Google Earth 2019.

a voice through systematic documentation is also a task for remote sensing.

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Declaration of competing interest

None.

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References

Badmos, O. S., Rienow, A., Callo-Concha, D., Greve, K., & Jürgens, C. (2018). Urban development in West Africa—Monitoring and intensity analysis of slum growth in Lagos: Linking pattern and process. *Remote Sensing, 10*(7), 1044.

Barros, J., & Sobreira, F. (2002). *City of slums: Self-organisation across scales*.

Baud, I., Kuffer, M., Pfeffer, K., Sliuzas, R. V., & Karuppannan, S. (2010). Understanding heterogeneity in metropolitan India: The added value of remote RensingData for analyzing sub-standard residential areas. *International Journal of Applied Earth Observation and Geoinformation, 12*(5), 359–374.

Brelsford, C., Martin, T., Hand, J., & Bettencourt, L. M. (2018). Toward cities without slums: Topology and the spatial evolution of neighborhoods. *Science Advances, 4*(8) eaar4644.

Bruzzone, L., & Bovolo, F. (2013). A novel framework for the design of change-detection-systems for very-high-resolution remote sensing images. *Proceedings of the IEEE, 101*, 609–630.

Castles, S., De Haas, H., & Miller, M. J. (2013). *The age of migration: International population movements in the modern world.* Macmillan International Higher Education.

Davis, M. (2006). *Planet of slums.* London: New York.

De Soto, H. (2000). *The mystery of capital: Why capitalism triumphs in the west and fails everywhere else.* Basic Civitas Books.

Frieling, H. D. V. (1980). *Räumliche soziale Segregation in Göttingen. Zur Kritik der Sozialökologie, Gesamthochschule Kassel, Kassel.* (German language).

Friesen, J., Taubenböck, H., Wurm, M., & Pelz, P. F. (2018). The similar size of slums. *Habitat International, 73*, 79–88.

Gevaert, C. M., Persello, C., Sliuzas, R., & Vosselman, G. (2016). Classification of informal settlements through the integration of 2D and 3D features extracted from UAV data. *In Proceedings of the ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, Prague, Czech Republic, 12–19 July 2016. 3. In Proceedings of the ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, Prague, Czech Republic, 12–19 July 2016* (pp. 317–324).

Gevaert, C. M., Sliuzas, R., Persello, C., & Vosselman, G. (2016). Opportunities for UAV mapping to support unplanned settlement upgrading. *Rwanda Journal, 1*(1S).

Gilbert (2007). The return of the slum: Does language matter? *International Journal of Urban and Regional Research, 31*(4), 697–713.

Glaeser, E. (2011). Cities, productivity, and quality of life. *Science, 333*(6042), 592–594.

Hanslmaier, M., & Kaiser, B. (2017). Arrival City-räumliche Muster von Zuwanderung aus dem Ausland in der Landeshauptstadt München. *Stadtforschung und Statistik: Zeitschrift des Verbandes Deutscher Städtestatistiker, 30*(2), 44–53 (German language).

Hoffmeyer-Zlotnik, J. H. (1976). *Der Prozess der Sukzession: die Unterwanderung von Berlin-Kreuzberg.* (Doctoral dissertation, Deutschland). (German language).

Hofmann, P., Strobl, J., Blaschke, T., & Kux, H. (2008). Detecting informal settlements from quickbird data in Rio de Janeiro using an object based approach. In T. Blaschke, S. Lang, & J. G. Hay (Eds.). *Object-based image analysis* (pp. 531–553). Berlin u.a., S.

Hofmann, P., Taubenböck, H., & Werthmann, C. (2015). *Monitoring and modelling of informal settlements – A review on recent developments and challenges.* (Conference Pape).

Hurskainen, P., & Pellikka, P. (2004). Change detection of informal settlements using multi-temporal aerial photographs–the case of Voi, SE-Kenya. *Proceedings of the 5th African Association of Remote Sensing of the Environment conference, Nairobi, Kenya, unpaginated CD-ROM*.

İdel, C. (2018). *Hegemonic politics of homeownership and formation of neolibera subjectivieis; former gecekondu residents in Gülveren - Ankara (Master Thesis at the Graduate School of Social Sciences of the Middle East Technical University)*.

Kinkeldey, C., Schiewe, J., Gerstmann, H., Götze, C., Kit, O., Lüdeke, M., Taubenböck, H., & Wurm, M. (2015). Evaluating the use of uncertainty visualization for exploratory analysis of land cover change: A qualitative expert user study. *Computers & Geosciences, 84*, 46–53.

Kit, O., & Lüdeke, M. (September 2013). Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing, 83*, 130–137.

Kohli, D., Sliuzas, R. V., Kerle, N., & Stein, A. (2012). An ontology of slums for image-based classification. *Computers, Environment and Urban Systems, 36*(2), 154–163.

Kohli, D., Stein, A., & Sliuzas, R. (2016). Uncertainty analysis for image interpretations of urban slums. *Computers, Environment and Urban Systems, 60*, 37–49.

Kraff, N. J. (2011). *Vergleich megaurbaner Marginalviertel Mumbais durch ausgewählte Vulnerabilitätsfaktoren mittels hochaufgelöster Satellitendaten und Interviews, im Hinblick auf Beeinträchtigungen durch den Monsun.* Unpublished Diploma-Thesis. Trier (German language).

Kuffer, M., & Barros, J. (2011). Urban morphology of unplanned settlements: The use of spatial metrics in VHR remotely sensed images. *Procedia Environmental Sciences, 7*(011), 152–157.

Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from space—15 years of slum mapping using remote sensing. *Remote Sensing, 8*(6), 455.

Kuffer, M., Pfeffer, K., Sliuzas, R., & Baud, I. (2016). Extraction of slum areas from VHR imagery using GLCM variance. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9*(5), 1830–1840.

Leichtle, T., Geiß, C., Wurm, M., Lakes, T., & Taubenböck, H. (2017). Unsupervised change detection in VHR remote sensing imagery–an object-based clustering approach in a dynamic urban environment. *International Journal of Applied Earth Observation and Geoinformation, 54*, 15–27.

Liu, R., Kuffer, M., & Persello, C. (2019). The temporal dynamics of slums employing a CNN-based change detection approach. *Remote Sensing, 11*.

Lloyd, P. C. (1979). *Slums of hope?: Shanty towns of the third world.* Manchester university press.

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.

Mahabir, R., Crooks, A., Croitoru, A., & Agouris, P. (2016). The study of slums as social and physical constructs: Challenges and emerging research opportunities. *Regional Studies, Regional Science, 3*(1), 399–419.

Nuissl, H., & Heinrichs, D. (2013). Slums: Perspectives on the definition, the appraisal and the management of an urban phenomenon. *DIE ERDE–Journal of the Geographical Society of Berlin, 144*(2), 105–116.

Olthuis, K., Benni, J., Eichwede, K., & Zevenbergen, C. (2015). Slum upgrading: Assesing the importance of location – A plea for a spatial approach. *Habitat International, 50*, 270–288.

Patel, A., Crooks, A., & Koizumi, N. (2018). Spatial agent-based modeling to explore slum formation dynamics in Ahmedabad, India. *GeoComputational analysis and modeling of regional systems* (pp. 121–141). Cham: Springer.

Pratomo, J., Kuffer, M., Kohli, D., & Martinez, J. (2018). Application of the trajectory error matrix for assessing the temporal transferability of OBIA for slum detection. *European journal of remote sensing, 51*(1), 838–849.

Pratomo, J., Kuffer, M., Martinez, J., & Kohli, D. (2017). Coupling uncertainties with accuracy assessment in object-based slum detections, case study: Jakarta, Indonesia. *Remote sensing, 11*(9), 1164.

Risbud, N. (2003). Urban slums reports: The case of Mumbai. *UN-habitat: understanding slums: Case studies for the global report on human settlements* (pp. 2003). .

Roy, D., Lees, M. H., Palavalli, B., Pfeffer, K., & Sloot, M. P. (2014). The emergence of slums: A contemporary view on simulation models. *Environmental Modelling & Software, 59*, 76–90.

Rubenstein, J. M. (2011). *The cultural landscape.* NJ. Book: Upper Saddle River12.

Sandborn, A., & Engstrom, R. N. (2016). Determining the relationship between census data and spatial features derived from high resolution imagery in Accra, Ghana. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9*(5), 1970–1977.

Sassen, S. (1996). *Metropolen des Weltmarkts – Die neue Rolle der Global Cities. Neue Ungleichheiten innerhalb der Städte. (Campus Verlag GmbH). Frankfurt.* (German language).

Shevky, E., & Bell, W. (1955). *Social area analysis; theory, illustrative application and computational procedures*.

Stehle, M. (2006). Narrating the ghetto, narrating Europe: From Berlin, Kreuzberg to the Banlieues of Paris. *Westminster Papers in Communication & Culture, 3*(3).

Taubenböck, H., Dahle, F., Geiß, C., & Wurm, M. (2019). *Europe's socio-economic disparities reflected in settlement patterns derived from satellite data.* (JURSE Conference paper).

Taubenböck, H., & Kraff, N. J. (2014). The physical face of slums: A structural comparison of slums in Mumbai, India, based on remotely sensed data. *Journal of Housing and the Built Environment, 29*(1), 15–38 [Online first 2013], (print 03/2014) March 2014.

Taubenböck, H., & Kraff, N. J. (2015). Das globale Gesicht urbaner Armut? Siedlungsstrukturen in slums. *Globale Urbanisierung* (pp. 107–119). Berlin, Heidelberg: Springer Spektrum (German language).

Taubenböck, H., Kraff, N. J., & Wurm, M. (2018). The morphology of the Arrival City-a global categorization based on literature surveys and remotely sensed data. *Applied Geography, 92*, 150–167.

Taubenböck, H., Wurm, M., Setiadi, N., Gebert, N., Roth, A., Strunz, G., ... Dech, S. (2009). Integrating remote sensing and social science – The correlation of urban morphology with socioeconomic parameters. *Urban remote sensing joint event, Shanghai, China* (pp. 7). .

Temba, P., Nero, M. A., Botelho, L. M. R., & Lopes, M. E. C. (2015). *Building Vectorization inside a favela utilizing Lidar spot elevation. In proceedings of the earth observing systems, San Diego, CA, USA, 8 September 2015*.

Tewkesbury, A. P., Comber, A. J., Tate, N. J., Lamb, A., & Fisher, P. F. (2015). A critical synthesis of remotely sensed optical image change detection techniques. *Remote Sensing of Environment, 160*, 1–14.

UN-Habitat (2003). *The challenge of slums: Global report on human settlements. 2003*. London, UK; Sterling, VA, USA: Earthscan Publications Ltd.

UN-Habitat (2012). *Streets as tools for urban transformation in slums. A street-led approach to citywide slum upgrading.* Nairobi: UN Habitat.

UN-Habitat (2013). *State of the world's cities 2012/2013: Prosperity of cities. Routledge*.

UN-Habitat (2015a). *Habitat III issue paper 22—Informal settlements.* New York: UN Habitat.

UN-Habitat (2015b). *World atlas of slum evolution.* (Nairobi).

UN-Habitat (2016). *Slums Almanac 2015–16. Tracking Improvement in the Lives of Slum Dwellers. Nairobi*.

Veljanovski, T., Kanjir, U., Pehani, P., Oštir, K., & Kovačič, P. (2012). Object-based image analysis of VHR satellite imagery for population estimation in informal settlement Kibera-Nairobi, Kenya. *Remote Sensing-applications*. InTech.

Wacquant, L., & Howe, J. (2008). Urban outcasts: A comparative sociology of advanced marginality. *Polity*.

Woetzel, J., Ram, S., Mischke, J., Garemo, N., & Sankhe, S. (2014). *A blueprint for addressing the global affordable housing challenge. 2014*. McKinsey Global Institute.

Wurm, M., Goebel, J., Wagner, G. G., Weigand, M., Dech, S., & Taubenböck, H. (2019). Inferring floor area ratio thresholds for the delineation of city centers based on cognitive perception. *Environment and Planning B: Urban Analytics and City Science.*. https://doi.org/10.1177/2399808319869341.

Wurm, M., Stark, T., Zhu, X. X., Weigand, M., & Taubenböck, H. (2019). Semantic segmentation of slums in satellite images using transfer learning on fully convolutional neural networks. *ISPRS Journal of Photogrammetry and Remote Sensing, 150*, 59–69.

Wurm, M., & Taubenböck, H. (2018). Detecting social groups from space - remote sensing-based mapping of morphological slums and assessment with income data. *Remote Sensing Letters, 9*(1), 41–50.

Wurm, M., Taubenböck, H., Weigand, M., & Schmitt, A. (2017). Slum mapping in polarimetric SAR data using spatial features. *Remote Sensing of Environment, 194*, 190–204.