The Spatiotemporal Dynamics of Morphological Slums in Mumbai, India

John Friesen, Nicolas Johannes Kraff, and Hannes Taubenböck

Abstract—**Our knowledge of the spatial distribution of slums has increased enormously in recent years through research from remote sensing and other sources, although it is still incomplete and fraught with uncertainties. The physical development of slums over time and the estimation of dynamics in the slum population, however, are still little addressed in research. We analyze these dynamics in the South Asian city of Mumbai, India. We capture the spatial extent of slums at the time of three years (2005, 2010, and 2022) using manual visual image interpretation. We merge this spatial information with accepted and globally available gridded population datasets to estimate the population living in morphological slums. We see spatio-temporal dynamics of both areas and population and thereby identify clear trends: instead of showing uncontrolled urban expansion, morphological slums are areas that undergo phases of deconstruction and reconstruction. We see the dynamics are the highest in existing and not in newly emerged slums.**

Index Terms—**Morphological slums, Mumbai, population, spatio-temporal dynamics.**

I. Introduction

SINCE the year 2023, India is stated to be the most populated country on Earth [1] with a rising tendency in population growth since 1921 [2]. Thereby, urban areas, such as Mumbai, face a lack of living space due to population pressure rooting in urbanization processes. This is resulting in informal settlement and deprived areas, often referred to as "slums." The United Nations (UN) estimates that worldwide more than 1.1 billion people currently live in slums [3], making them an integral part of urban settlements.

There are manifold definitions of slums as they are a relative concept in global comparison [4], yet they have deprived shelter conditions in common as defined by the UN, fulfilling at least one of the following five aspects: 1) no access to water; 2) no access to sanitation; 3) insecure tenure; 4) undurable housing; 5) overcrowding [3]. Slums represent some of the most pressing challenges related to poverty, inequality, and urban development, which are key components of the sustainable development goals (SDG) (Goals 1, 10, and 11, respectively). In order to improve living conditions in slums, e.g., by providing access to essential services and promoting sustainable urban development, there is a demand for more systematic information on their location, physical appearance, their dimensions, and the dynamics over time. Accordingly, progress can be made towards achieving multiple SDGs and creating a more equitable and sustainable world.

The UN estimates that approximately two billion people will be residing in slums by the year 2050 [3]. However, this figure is highly uncertain, relying on the aggregation of various national statistics. Therefore, despite their significant relevance, many questions regarding these types of settlements remain unanswered. Does the extent of slums remain constant or does it expand or decrease? Is the population in these areas growing or shrinking? Consequently, there has been a surge in research efforts to dive deeper into these questions in recent years.

As a first step, considerable efforts have been made to map or categorize the numbers and areal extents of these settlements [5], [6], [7], [8]. Additionally, in recent years, there has been a growing focus on slum population estimation [11], [12], [13]. Efforts, especially considering Mumbai, have been made by Taubenböck and Kraff [10] to delineate formal and informal settlements as well as to estimate populations [11].

With respect to the dynamics of these settlements and their population, several studies were presented. Kraff et al. [14] conducted an extensive analysis of slum settlement dynamics in different cities across the globe. Their study examined building and pattern changes in selected poor urban districts. More recently, Cinnamon and Noth [15] undertook a comprehensive multitemporal analysis of informal settlements in Cape Town, South Africa, with a focus on intrasettlement changes. Kit and Lüdecke [16] analyzed the temporal changes in slums in Hyderabad, India, revealing a nearly 70% increase in slum area. Nevertheless, generally only two points in time are considered (e.g., Kit and Lüdeke [16]). Cinnamon and Noth [15] used open data to create information for more points in time but only investigated the changes inside fixed polygons instead of analyzing the dynamics of the boundaries of these settlements. Besides, none of the studies mentioned above took the population living in these areas into account.

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Furthermore, studies about Mumbai present only selected slum areas, and mostly focus on the large and famous Dharavi, e.g., [10], [17], [18], and neither cover Mumbai in its full extent with its satellite city Navi Mumbai nor its neighboring urban areas being connected to the core city. Also, there is no systematic analysis of the temporal development of slums in Mumbai, and up to now no study has captured the dynamics of slums in megacities of the Global South in the 21st century over two decades with three points in time.

Thus, how slums and their populations evolve over time in general and particularly in Mumbai is an underresearched question and widely undocumented. With this article, we therefore aim to answer the following research questions.

1) How do slum areas and the population living in these areas in Mumbai change in the 21st century, and how can the changes be classified?
2) Are there differences in temporal change between the first and second decade of the 21st century?
3) Are intraurban dynamics different with respect to proximity to infrastructure or certain topography?

The approach we follow in this study is an extension to a previous analysis on Caracas, Venezuela [19] and follows a four-step procedure. First, we identify morphological slums in Mumbai by using very high-resolution (VHR) satellite imagery. These data are commonly offered by Google Earth. For capturing data, we use image interpretation done by one professionally skilled and experienced interpreter who gained in situ knowledge in different Mumbai slum areas. In this vein, the particular different characteristics of the built environment between slums and formal settlements have been experienced, systematized and used to delineate these two structural types from each other. Yet, with respect to experience as a possible factor influencing the mapping quality, we rely on [7] and [20].

Further, we rely on [21] with respect to obstacles and replicability in geodata, and we rely on [22] with respect to local knowledge and deprivation perception.

Second, we merge the extents of the morphological slums mapped with gridded population data from various sources (e.g., WorldPop [23]). We apply methods of disaggregation as described in Breuer et al. [13]. Third, we apply newly developed metrics [24] to quantify temporal dynamics of slums. The last step is an in-depth application of these methods on specific areas within the city of Mumbai. We systematically document multitemporal dynamics of morphological slums and their populations over time. Finally, we analyze whether certain spatial patterns (such as infrastructure or proximity to water bodies) influence the dynamic change processes of morphological slums.

II. Data and Methods

A. Study Site

The South Asian City of Mumbai is the capital of the Indian state Maharashtra, an economical magnet and a crucial source of income for India. Since the land reclamation between the 17th and 18th century [25], the city has been growing spatially [26] and demographically [27] and is nowadays the largest city of India. The megacity can be subdivided into the entities Municipal Corporation of Greater Mumbai (MCGM), Mumbai Urban Agglomeration (MUA), and Mumbai Metropolitan Region (MMR). The latter comprises a vast area including satellite towns. Depending on the spatial entity, the population density varies between ca. 5000 persons/km^2 (MMR) and ca. 20 600 persons/km^2 (MCGM) with an estimated population of 23.5 mio. inhabitants (MMR) for the year 2011 [2], [28].

A major part of the population results from natural growth as well as migration. Statistics of slum populations vary between the defined areal entity, the definition of a "slum" itself and different documented sources, e.g., 1.3–2 mio. inhabitants within the smaller entity MCGM [29].

B. Identification of Slums

There is no universal truth of what constitutes a slum. Various conceptual approaches in the remote sensing domain have been approached to map this target class; however, the conceptual approaches remain inconsistent to date. Due to their local and regional singularities mirrored in local names as, e.g., favela, township, barrio populares, or in the case of Mumbai, "bustee," "shantie," or "zopadpattie," we generally refer to areas of "urban deprivation" [30], respectively, "Arrival Cities" [7]. They can be distinguished in satellite data, for instance, by their urban surroundings, higher densities, irregular patterns, small and low buildings, or smaller streets in comparison to other formal areas within the urban landscape. It was shown that this spatial configuration often correlates with a specific social group [32]. Since the data used in this study are based on the morphology of these deprived areas, we refer to them as "morphological slums," a category introduced by Taubenböck et al. [7].

As a region of interest (ROI), we chose an area similar to the MMR because it features the city as coherently built-up megaurban environment. As spatial delineation, we use the metropolitan area boundary of Mumbai, defined by Taubenböck et al. [34]. If morphological slums are located in close vicinity outside of the city boundary, we still include them into our ROI. In order to capture morphological slums and distinguish them from their surroundings, different methods have been established in recent years. The method with high accuracies in such complex deprived areas is the manual visual image interpretation (MVII), e.g., offering high exactness on the level of individual buildings, as well as high precision on district level [5], [9].

To obtain data, one image interpreter captures all existing areas of morphological slums across the entire metropolitan area of Mumbai. Each slum is digitized as one polygon that contains all rooftops within a boundary defined as follows. The boundary is shaped closely along the edges of the building rooftops; as minimum mapping unit (MMU), we define at least five buildings accumulated. Further, we define no maximum area (m^2) in size or limit in shape for a polygon, unless it is coherent. Thus, two indications cut coherent polygons: 1) a maximum distance between buildings of 30 m; or 2) streets, waterbodies, and open spaces, having a width of at least 10 or more meters. So, structurally, if there are such features of at least 10 m between identified slums, these are either counted as different polygon patches or open spaces are cut out within one polygon.

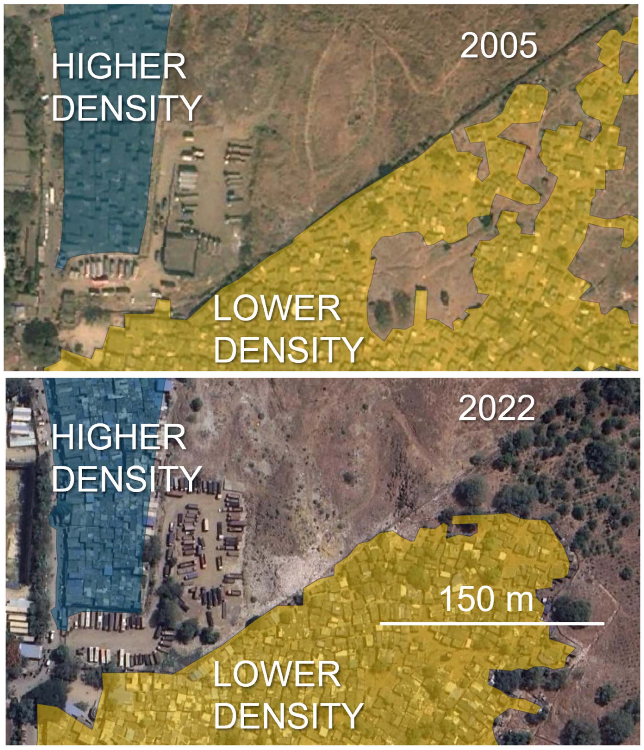

Fig. 1. Distinction between areas with a high (blue) and areas with a low density (yellow) is shown. Images are taken from Google Earth.

Furthermore, if the structural density varies significantly, a morphological boundary between these areas will be introduced. Hence, in contrast to former studies, we differentiate by image interpretation between a structurally higher density and a rather loose built-up environment, resp. lower density being respectively categorized. We define polygons containing the most nearest neighbor building distances of max. 10 m as denser, and those containing most buildings with distances up to 30 m, open spaces, and vegetation as less dense (see Fig. 1). This method contains a certain subjectivity because dozens or sometimes hundreds of building distances within one polygon cannot each be measured manually by the interpreter, as the individual building rooftops are nonexistent. Thus, when dealing with polygon patches of varying densities, the interpreter has the capability to divide them, in order to receive several homogeneously dense patches, even if a delineation between buildings closer to 10 m is necessary. In this vein, polygons of different building density can be created despite their proximity and require bypassing the aforementioned boundary delineation criteria.

All data are obtained for three points in time, for the years 2005 (t1), 2010 (t2), and 2022 (t3) with imagery from 11/16/2005 and 12/15/2005 (t1), 01/25/2010, 02/05/2010, and 02/27/2010 (t2), and several dates between 02/21/2022 and 04/07/2022 (t3). To be able to differentiate in such manner, we use very high resolution (VHR) satellite imagery from Google Earth with a geometric resolution of 0.5 m (e.g., Quickbird or WorldView) as basemap data. This approach relies on findings for slum sizes [41]. Furthermore, we rely on typical slum patterns (e.g., irregular, complex structure) documented in literature [7]. We do not obtain building heights or other physical parameters.

For further information considering the MVII approach and its advantages as well as uncertainties, we refer to [20]. However, in some cases, the delineation between slums and formal building structures remains despite clear mapping rules challenging. In these cases (e.g., if huts have been upgraded over time), we apply additional information from Google StreetView to qualify the cognitive findings.

C. Fusion of Slum Locations and Demographic Data

Spatial areas and population do not always correlate perfectly (e.g., [13]). In this study, we therefore wanted to assess both the spatial and demographic changes in slums. However, explicit knowledge about population figures in slums is very scarce, and what we do know is highly uncertain (cf., [11], [40]). Therefore, we used the most accurate population datasets to estimate the number of people living in slums. This methodology is based on previous work [12], [24], and [13].

The resulting outlines of slums are merged with gridded population data from WorldPop [23].

For the initial analyses, the WorldPop unconstrained dataset is employed, as it utilizes census information at the finest level and is available on an annual basis from 2000 to 2020. However, to assess the impact of the population dataset on the results, the UN-adjusted WorldPop dataset and the Global Human Settlement Layer [35] are also considered.

The WorldPop population grids are created using random-forest dasymetric disaggregation methods based on a number of covariates, including land cover, elevation data, night-time lights, and numerous others [23]. The population inputs are derived from census and official population estimates at the finest scale available. The UN-adjusted dataset is then readjusted so that the total population in a country aligns with the UN projections.

The Global Human Settlement Layer, where we used the GHS-Pop from [36], is created by using a binary dasymetric methodology to disaggregate the population from the GPWv4 UN-WPP-adjusted dataset onto built-up areas. Besides WorldPop, it is the only available gridded population dataset covering the time between 2000 and 2020. The pixels of all gridded population datasets have an approximate size of around 100 m $\times$ 100 m.

The method applied to disaggregate the gridded population data onto the polygons representing the morphological slums is described in detail by Breuer et al. [13]. We overlay the population grid with the polygons of the morphological slums and calculate the population located within the slums by summing up the values represented by the pixels within the slum polygons. If only parts of a pixel are covered, we assume an even distribution of the population within this pixel and calculate the proportionate population that lies within the extent of the morphological slum. The code used is freely available [24]. We discuss in detail about the uncertainties using global gridded population datasets in Section IV.

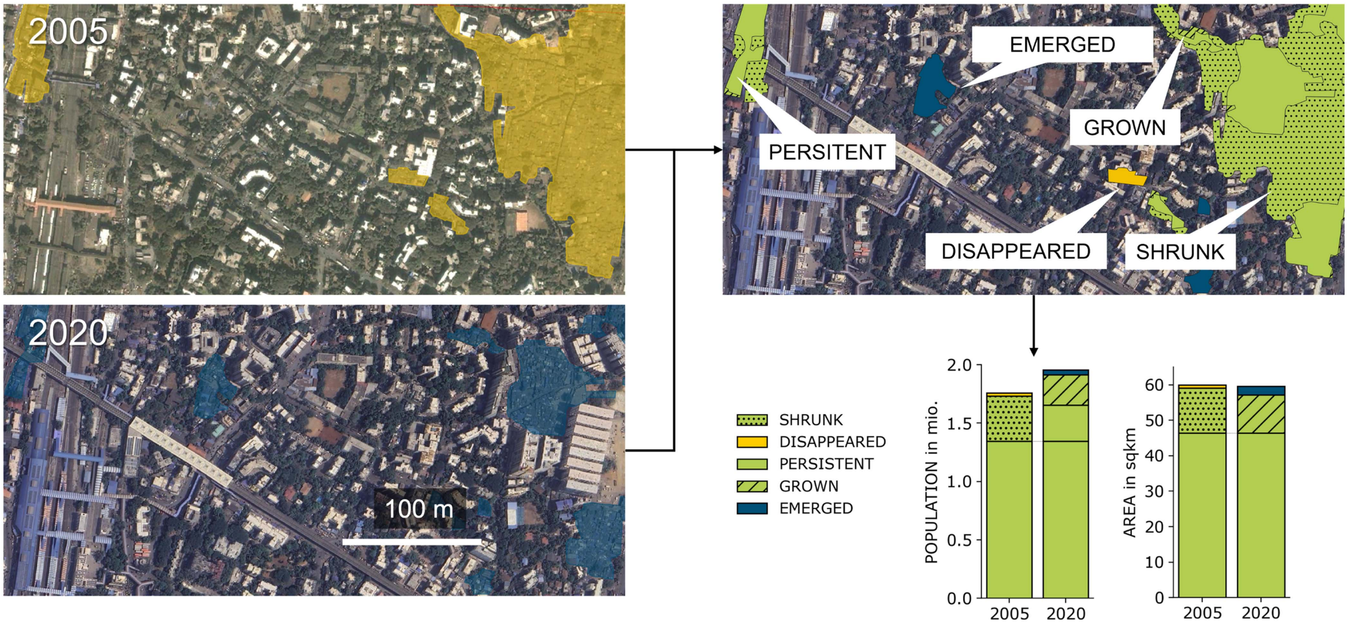

Fig. 2. Methodological framework: Using MVII, the morphological slums are captured for two steps in time (here, morphological slums are in yellow for the year 2005 and in blue for 2020). By combining both datasets, the changes in areas and populations can be identified and quantified (two graphs in the lower right). Note that the persistent population for the second year (here, 2020) is divided into two sections: The lower one representing the baseline population similar to the first year and the upper one the additional population added to persistent areas between the first and the second year. Images are taken from Google Earth.

Using the above mentioned boundary of the metropolitan area of Mumbai, we calculate the population living in Mumbai for the three points in time.

D. *Temporal Metrics for Comparing Morphologic Slums and Population*

In order to compare the dynamics of slum areas and the populations living there, Breuer and Friesen [33] presented different metrics. An overview of the framework used can be seen in Fig. 2.

The spatial delineations of the morphological slums are exemplified in this figure for two years (2005 in yellow and 2020 in blue). Combing both datasets, five different categories of changes can be distinguished. 1) Category *persistent* reveals areas apparent in the first and second year. 2) Category *shrunk* represents parts of morphological slums that shrunk between the first and the second point in time (cf., example area in Fig. 2). 3) When morphological slums extend spatially, these areas are categorized as *grown*. 4) Morphological slums that emerge from the first to the second time step are defined as *emerged*. 5) Morphological slums that disappear are defined as *disappeared*.

When the spatial datasets are merged with the respective population datasets, the following values are computed: P_1 is the total slum population in one city at the first point in time; and P_2 is the population at the second point in time. Similar to the areal changes, in the multitemporal observation, the population of morphological slums can be persistent or densified (DS), it can shrink (S), disappear (D), or grow (G) and there is also the possibility that new slums emerge (E). All of these changes can be quantified, using the slum maps merged with the respective population, as described in the previous subsection (Section II-C). The variables P_1, P_2, DS, S, D, G, E describe the number of inhabitants in morphological slums.

Based on these values, the following metrics are computed, to assess the changes in slum populations (cf., [24]).

The growth driving factor (GDF) is the ratio of population in the densified areas of persistent slums to the population added in the grown or newly emerged slums

$$\mathrm{GDF} = \frac{DS}{E+G}. \tag{1}$$

A GDF > 1 implies that the additional slum population is added to already existing slums, instead of growing or newly emerging slums. In contrast, a GDF < 1 is an indicator for additional slum population in new areas (emerged or grown) within the city.

To evaluate the difference between population added to newly emerged slums or to grown slums, we use the growth location factor (GLF). The GLF is the ratio of population in emerging slums to the populations in grown slum areas

$$\mathrm{GLF} = \frac{E}{G}. \tag{2}$$

It is a measure of the extent to which newly built parts of slums are located next to existing slums (GLF < 1) or spatially separated from them (GLF > 1).

The third metric, momentum of change (MoC), is defined as

$$\mathrm{MoC} = \frac{(G+E)/P_2}{(D+S)/P_1}. \tag{3}$$

It can be utilized to analyze whether a decline or increase in population predominates.

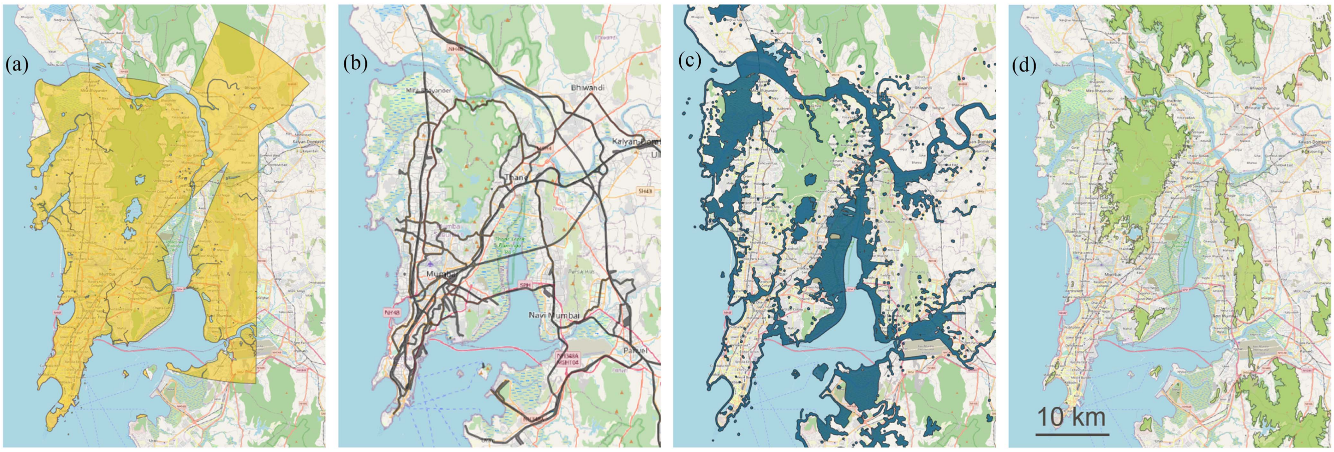

Fig. 3. (a) Metropolitan area of Mumbai, India, in yellow according to the methodology of Taubenböck et al. [34]. (b) Railways in Mumbai according to OSM data with a 100 m buffer. (c) Water bodies in Mumbai with a 100 m buffer in blue. (d) Elevation higher than 50 m in Mumbai in green.

All these metrics are used to quantify the extent to which new slums are emerging or existing slums are growing or becoming denser.

E. Geographic Applications on Multitemporal Slum Exposure

Using the metrics introduced in the previous section, slum dynamics can be quantified. Beyond this, we aim to test whether statements made in literature on location and development show empirical proof. Commonly known statements relate to the occurrence of slums in areas with higher exposure to natural or man-made hazards or suggest that slums are more likely to emerge in exposed locations like on steep slopes or alongside railways [37], [38]. To examine this assertion, we employ OpenStreetMap (OSM) railway data [see Fig. 3, (b)], include a 100 m buffer (yellow region), and compare the dynamics adjacent to the railways and outside of the buffer zone. Since 100 m is a typical magnitude, when it comes to morphological slums [39], [41], we use this distance as a threshold. Besides, we examine flood exposure in two ways—one is alongside rivers and one is in very low elevation to examine whether there is danger of floods to the rising sea-level [38], [42]. We therefore identified water bodies in and next to the entire study area [see Fig. 3, (c)]. We calculate the spatiotemporal dynamics next to water bodies using again a buffer of 100 m. To assess the second statement on elevation, we filtered ASTER satellite data to determine the elevation across the city of Mumbai. We subsequently divide the city into areas with low elevation < 50 m and areas with high elevation > 50 m [see Fig. 3(d)].

To calculate the dynamics in this different subregions, we split the spatial datasets for the years 2005 and 2022 into two separate datasets each. One with all polygons with an intersection of the bufferzones around railways, water, and elevation, and one with all polygons with no intersection to these areas. In this analysis, we only use the end points 2005 and 2020 in order to maintain clarity in the results.

TABLE I
POPULATION ESTIMATES FOR THE CITY OF MUMBAI, INDIA, USING THE BOUNDARY PROVIDED BY TAUBENBÖCK ET AL. [7]

City	Population WP	Population WP UN	Year
Mumbai	15.7 Mio.	16.4 Mio.	2005
Mumbai	16.5 Mio.	17.1 Mio.	2010
Mumbai	18.6 Mio.	18.2 Mio.	2020

III. RESULTS

A visual small scale comparison of the metropolitan area and the three points in time (see Fig. 4) demonstrates the spatial extent of morphological slums: generally, the basic spatial structure seems to stay nearly the same over time. Especially, for the western part, located on the peninsula only a few changes in the pattern can be observed. On the eastern side, i.e., the newer more recent urban expansion areas in Mumbai, more changes become apparent.

A. Analysis Based on Densification

In general, we see that morphological slums in Mumbai are predominantly of higher building density: for 2005 we detected 988 morphological slums with a high density (hd) and 294 with a low density (ld), for 2010 964 (hd) and 502 (ld) and for 2022 1359 (hd) and 266 (ld). In general, we see a trend of a rising number of slum patches (polygons) with high densities over time.

With respect to the total area we see 49.2 km^2 for 2005, 45.5 km^2 for 2010, and 52.8 km^2 for 2022 for the pockets with high density and 10.7, 15.3, and 15.7 km^2 for the low density pockets in the respective years, showing that the majority of slums have a high density.

In order to demonstrate a first overview of the population distribution, we set these findings of the total area and densities of morphological slums in relation to the areawise estimated population using the method described in Section II-C (cf., Table II).

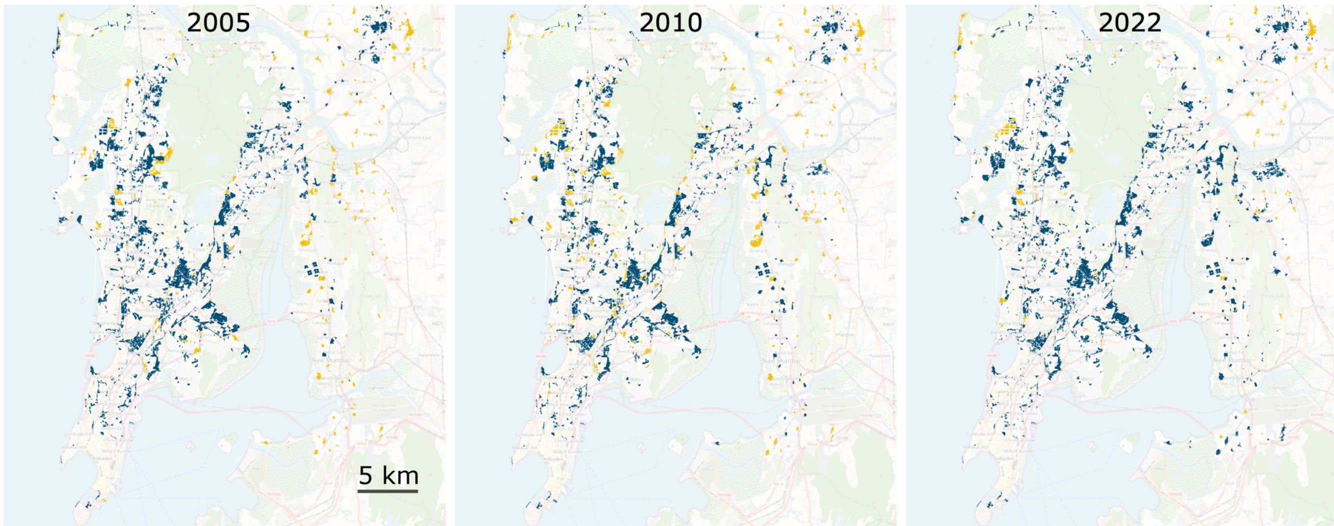

Fig. 4. Morphological slums for the metropolitan area of Mumbai for 2005, 2010, and 2022. The blue polygons represent morphological slums with a higher density, the yellow polygons represent morphological slums with a lower density.

TABLE II
MORPHOLOGICAL SLUMS, THEIR DENSITY, AREA, POPULATION ESTIMATES ACCORDING TO WORLDPOP DATA AND THE RESPECTIVE YEAR

	Density	Area	Population WorldPop	Year
MS	high	49.2 km^2	2.5 Mio.	2005
MS	low	10.7 km^2	0.3 Mio.	2005
MS	both	59.9 km^2	2.8 Mio.	2005
MS	high	45.5 km^2	2.4 Mio.	2010
MS	low	15.3 km^2	0.5 Mio.	2010
MS	both	60.8 km^2	2.9 Mio.	2010
MS	high	52.8 km^2	2.9 Mio.	2020
MS	low	15.7 km^2	0.2 Mio.	2020
MS	both	59.6 km^2	3.1 Mio.	2020

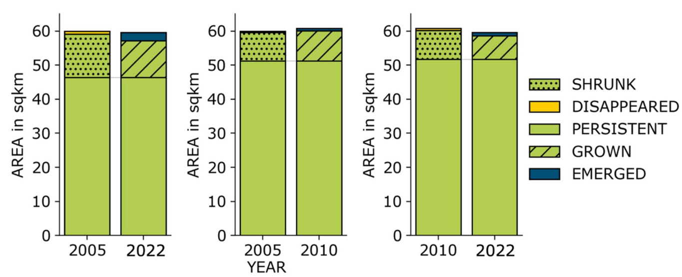

Fig. 5. Changes in slum areas from 2005 to 2022, from 2005 to 2010, and from 2010 to 2022.

Due to limited access to population data only up to the year 2020, we do list "2020" as a third point in time in all figures for the sake of simplicity. However, it should be noted that in the case of the third point in time, the areas were recorded using satellite images from 2022, as described in the method section.

We also found that the new morphological slums created between 2005 and 2010 occupy an area of 0.75 km^2, of which 46% are of low density. Between 2010 and 2020, the area of newly created morphological slums amounted to 1.03 km^2, of which 23% had a low density.

On the other hand, when focusing on the morphological slums that disappeared between 2010 and 2020, we see that 56% of the 0.58 km^2 of built-up area had a low density and 25% of the 0.28 km^2 of built-up area between 2005 and 2010 had a low density.

Therefore, we conclude that both the emergence of new morphological slums and their disappearance affect both denser and less dense areas. Due to the temporal resolution we had to choose, no direct statement can be made about the extent to which newly created slums initially have a low density and are then redensified.

B. Areal Changes Within the Metropolitan Area

While having considered both density classes up to this point, for the sake of clarity we will combine both classes of morphological slums in the following and consider their temporal development in its entirety.

With respect to the areal dynamics of the morphological slums, we observe that the total area grows only slightly from 59.9 km^2 from 2005 to 60.8 km^2 in 2010 and then declines to 59.6 km^2 until 2020. However, the detailed analysis reveals significant changes: between 2005 and 2010, 13.5 km^2 (and thereby 23%) of the initial slum area (2005) disappeared or shrunk, while 12.2 km^2 grew or emerged (see Fig. 5). Focusing on steps in time between (2005 to 2010 and 2010 to 2020), we see nearly 15 % of the initial slum area declined and got rebuilt (emerged or grown) at another place in the city.

We also find that the area grown next to existing slums has a similar area as the shrunk area. Additionally, the growing parts (hatched) of morphological slums cover larger areas than the newly emerged ones (blue). Therefore, it is much more likely that a polygon patch changes in size, than that a morphological slum completely disappears.

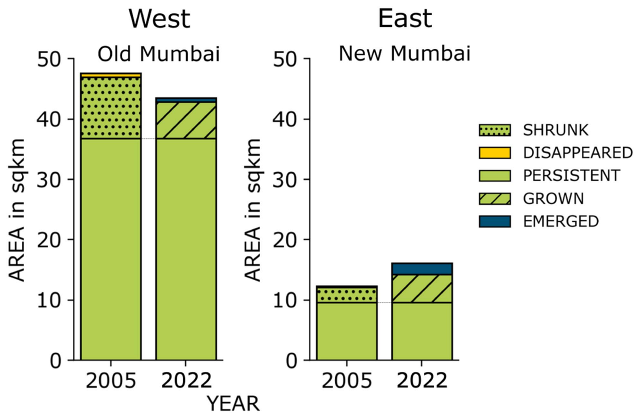

Fig. 6. Changes in areas of morphological slums for Old Mumbai and for Navi Mumbai from 2005 to 2022.

C. Substudies: Areal Changes Depending on Topography and Infrastructure

As a substudy, we divided the metropolitan area of Mumbai in two parts: West and East. The western part represents old Mumbai, situated on the peninsula, and the eastern part of Navi Mumbai is situated on the mainland. Within this substudy, we focus on the total time span between 2005 and 2020.

The results in Fig. 6 show that the dynamics of slums within the city are not uniform and depend on the intraurban location. It can be observed, that the main share of morphological slums for both years (nearly 80% in 2005 and 75%) is in the western part.

The total area of morphological slums in Old Mumbai decreased from 2005 to 2020. While 10 km^2 shrunk, 0.65 km^2 disappeared. Furthermore, the existing slums grew about 6 km^2 and new slums with an area of 0.67 km^2 emerged.

The dynamics in Navi Mumbai is different. The total slum area increased and additionally slums grew or emerged. The shrunk area is significantly smaller (2.5 km^2) than the grown area (4.7 km^2) and we find also a high amount of newly emerged slums (1.8 km^2). Thereby, 67% growth was added to the persistent area leading to an increase from 9.6 to 16.1 km^2.

In three other substudies the differences in dynamics of morphological slums next to water bodies, railways and in different elevations is investigated (see Fig. 7).

The total area of morphological slums in 2005 is lower when close to water bodies than with a higher distance (>100 m) to water bodies. This observation also fits for the year 2020. While the area of morphological slums close to water bodies decreased by 7% between 2005 and 2010, the area far from water bodies increased by 5%. This is also an indication for high intraurban dynamics.

With respect to the dynamics of distances to railways, our findings are different: while the total slum area in 2005 near railways is larger than those areas being far away from railways, we see the contrary for 2020, where areas further away from railways are larger than those being next to railways. While the slum areas near railways decrease, the areas far from these infrastructures increase. Besides that, high intraurban dynamics can be observed. 35% of the slum area of 2005 disappeared, whereas only 6.5 km^2 emerged or grew at other places.

With respect to the elevation of the slum areas, we see a significantly high share of morphological slums situated in areas with a lower elevation for 2005 and for 2020. Nevertheless, we observe that the total morphological slum area in low elevation remains the same, while the total slum area in high elevation decreases by 2%.

D. Population: Different Points in Time

In a next step, we merged the slum delineations with data from WorldPop to assess the temporal dynamics of the populations living in morphological slums (see Fig. 8). We see the total dynamics slightly different than for the areal changes. At all three points in time, there is an increase in the estimated slum population. We also find a densification in the persistent slums at all points in time. Our estimated total number of slum population states 2.75 mio. for 2005, 2.9 mio. for 2010, and 3.05 mio. for 2020, and thus, is far below other documented estimates for the city of Mumbai.

Another way of interpreting the data allows to compare the population densities for the different dynamics, categorized as demonstrated in Fig. 9. The estimated population density varies between ca. 30 000 persons per km^2 in the grown parts of existing morphological slums and more than 50 000 persons per km^2 for disappeared and emerged slums. This shows that the available space per person in slums has decreased due to the high increase in population. People's living conditions have therefore deteriorated in this parameter over the monitoring period.

Using the information on the estimated populations living in morphological slums, we calculated the mobility metrics for Mumbai for the respective time steps (see Fig. 10): the GDF is nearly 1 for the timespan 2005–2020, i.e., the population in densified areas has the same amount as the population in newly emerged and grown slums. This is different, when the temporal development is looked at in detail. While for 2005–2010 "growth" and "emergence" were the main driving factor for population growth, from 2010 to 2020 "densification" was the main driving factor.

With respect to the GLF, it becomes clear that for all time steps "growth of already existing slums" is the main driving factor for the population increase instead of the "emergence of new slums." The influence of the population increase in growing slums in comparison to emerging slums is higher for 2005–2010 than for 2010–2020.

Finally, focusing on the MoC, the disappeared population per initial slum population is higher than the grown population per morphological slum at the second time step.

E. Population: Evaluating Different Data Sources

Since there are various studies investigating the accuracy of gridded population datasets (e.g., [12]), we investigated how sensitive the results of this study are to the input datasets. Therefore, we used three different datasets accepted in literature: WorldPop, WorldPop UN-adjusted, and the GHSL to estimate the temporal dynamics of population (as mobility metrics) living

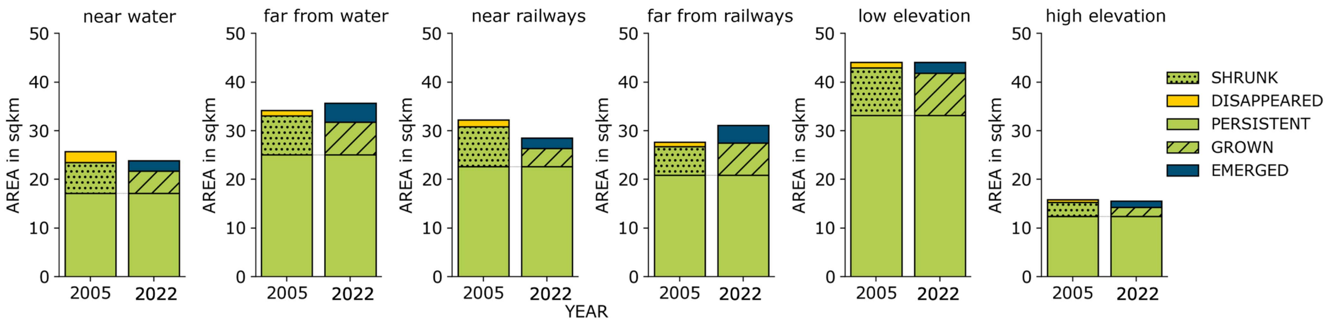

Fig. 7. Spatiotemporal development of the total slum area dependent on different topographical differences. IW: Within a 100 m buffer away from water bodies; OW: Outside of the 100 m surrounding water bodies; IR: Inside a 100 m buffer next to railways; OR: Outside a 100 m next to railways; LE: Low elevation (<50 m); HE: High elevation (>50 m). While interpreting this figure, it has to be kept in mind, that we compare all delineations of morphological slums near the bufferzones for 2005–2020. Therefore, some areas with a higher distance to water bodies could grow inside this buffer and would be classified as decreased from the algorithm, which in turn leads to higher values for grown, emerged, shrunk, and disappeared areas of morphological slums.

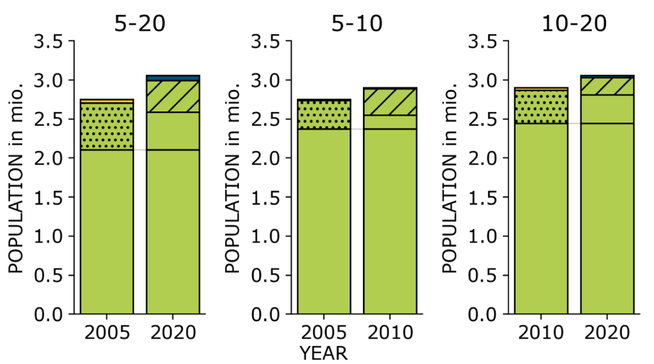

Fig. 8. Changes in slum population in Mumbai using data from WorldPop from 2005 to 2020, from 2005 to 2010, and from 2010 to 2020. Values for the disappeared and emerged populations are very low and therefore almost not visible. Note that the persistent population for the second year is divided into two sections: The lower one representing the baseline population similar to the first year and the upper one the additional population added to persistent areas between the first and the second year.

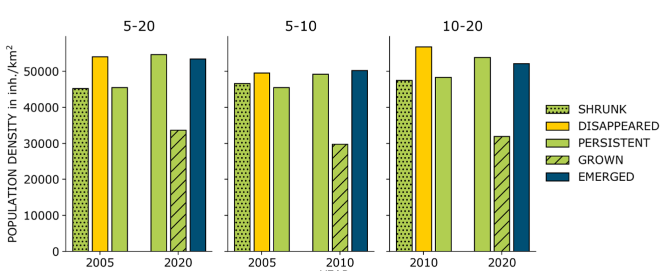

Fig. 9. Population densities for the different change classes and steps in time (inh = inhabitants).

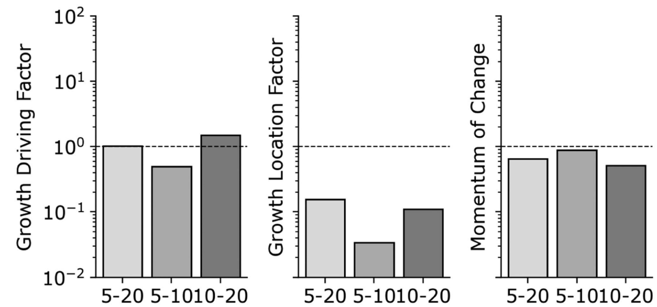

Fig. 10. Mobility metrics to assess the population dynamics for different steps in time.

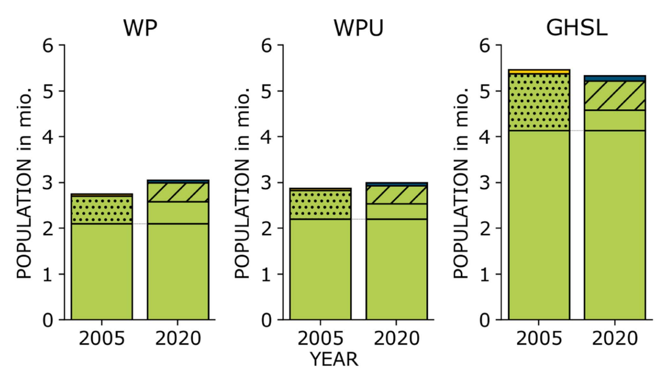

Fig. 11. Changes in estimated population in morphological slums from 2005 to 2020 depending on the data source. WP = WorldPop, WPU = WorldPop UN adjusted, GHSL = Global human settlement layer. Values for the disappeared and emerged populations are very low and therefore almost not visible. Note that the persistent population for the second year is divided into two sections: the lower one representing the baseline population similar to the first year and the upper one the additional population added to persistent areas between the first and the second year.

in morphological slums between 2005 and 2020 (see Fig. 11). While the WorldPop dataset implies a growth in population in morphological slums from 2.7 mio. in 2005 to 3.1 mio. in 2020 by 11%, the WorldPop UN adjusted dataset states, that the total number grows less than half as fast (4.1%) from 2.9 to 3 mio people. In contrast, when using the GHSL data, it is estimated that the population in morphological slums decreased from 2005 to 2020 by 2.5%.

When comparing the mobility metrics (see Fig. 12), introduced above, we see that although the absolute changes in population differ, two of the three metrics nearly stay the same for the different gridded population datasets.

While the GDF is lower for GHSL and thereby highlights that the population increase is more prominent in emerged and

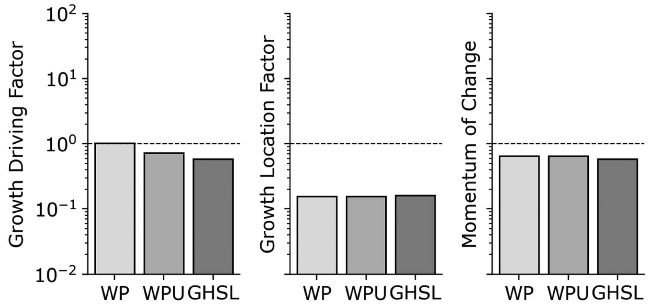

Fig. 12. Application of mobility metrics for three different gridded population datasets. WP = WorldPop, WPU = WorldPop UN adjusted, GHSL = Global Human Settlement Layer.

grown slums, both WorldPop datasets suggest that densification and emergence and growth contribute equally to the population growth.

With respect to GLF and MoC, both values are nearly the same, indicating that growth is more present than emergence and that the proportion of declined population is higher than the proportion of grown and emerged population.

These findings suggest a robustness of the mobility metrics towards different gridded population datasets.

F. Examplary Slum Developments

The temporal developments of two exemplary morphological slums are visualized in Fig. 13. For 2011, in the area shown in the upper row, no morphological slum is apparent. In 2016, just a small number of buildings are visible. Between 2018 and 2022, a big areal is covered with buildings.

In the lower row an opposite effect can be observed. While the structure remains nearly the same for the years 2011 to 2016, a great share of the buildings are demolished by 2020. Further, in 2022 the whole area is cleared.

The processes are, as these examples show, often very abrupt, i.e., morphological structures remain comparatively stable for years and are then completely changed within a short period of time. This means that 5 or 10 year intervals offer a possibility to reflect these morphological changes, but the exact temporal processes require higher temporal resolutions

IV. Discussion

This study offers a comprehensive analysis of the spatiotemporal dynamics of morphological slums in Mumbai, India. We systematically analysed how slum areas and populations change in the 21st century and classified these changes. With it, we contribute to a deeper understanding of the slums' evolution over different time periods and challenge conventional perceptions of slums as peripheral expansion. Furthermore, we expand the thematic-structural depth of the slums via the density structures. We compared our findings with previous studies (e.g., [19]), and extended our analysis to examine the temporal dynamics of morphological slums between three points in time.

A. Different Dynamics on Interurban and Intraurban Scale

Although it is stated in literature that Mumbai sees slum growth [43] and that slum growth is not slowing down [44], we suggest making more differentiated statements. Our research revealed that the metropolitan area of Mumbai did not witness significant areal growth in morphological slums in the last 20 years. In fact, the total area of slums remains relatively stable. However, beneath this apparent stability lies a complex interplay of intraurban dynamics, as evident in our analysis of the city of Mumbai. Our findings echoed a previous study performed in Caracas, Venezuela [19]. In Caracas, Venezuela, we also did not observe any change in the total slum area in the first two decades of the 21st century. Also, the values for GLF=0.09 for Caracas and GLF=0.15 were similar.

Thereby, we demonstrate that slums should not be perceived as areas of uncontrolled urban expansion but rather as integral components of the city, constantly undergoing deconstruction and reconstruction.

One of the notable observations in our study is the heterogeneity in the dynamics of morphological slums across different parts of the city. While the eastern part of Mumbai (Navi Mumbai) exhibited areal growth, it did not result in a net increase in the total slum area in the metropolitan area. Instead, the old part of the city, particularly the western region, experienced a decrease in the total area of morphological slums. This central observation underpins our analysis: morphological slums in the time frame between 2005 and 2020 should be understood as areas exhibiting significant intraurban dynamics, characterized by both growth and decline.

B. Uncertainties Related to Population and Areal Change Detection

Our investigation on the factors influencing these changes highlighted the significant role of construction projects in the decline of slum areas in the older part of the city. Fig. 14 for examples shows how morphological slums disappeared between 2005 and 2020 to make room for new skyscrapers.

This underscores the complex relationship between urban development initiatives and the persistence of slum communities. Our exemplary analyses of concrete cases of appearance and disappearance also clarify that analyses with much higher temporal results will be necessary if the temporal changes of (morphological) slums are to be understood in depth. To gain a comprehensive understanding of the spatiotemporal evolution of the city, it is essential to consider changes over multiple time steps.

For instance, a fourth point in time in 2015 would have reflected an ever more consistent time step interval. Unfortunately, this was not possible due to a lack of resources. However, a perfect reproduction of rapid changes in urban landscapes remains an utopia unless everyday satellite imagery is accessible and assessable in realtime.

So, with three points in time we are aware of not being able to cover additional changes, especially between the years 2010 and 2015 or 2015 and 2021. However, we are able to demonstrate the overall change between 2005 and 2021.

Fig. 13. Emergence and disappearance of morphological slums in East Mumbai. Images are taken from Google Earth based on Maxar Technologies input data (2023).

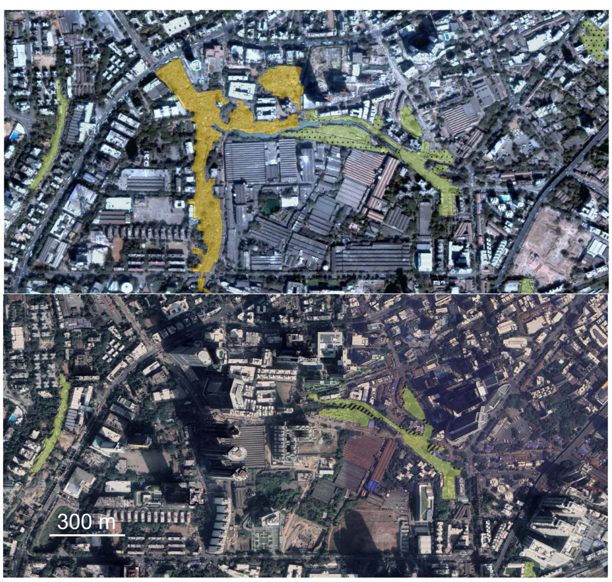

Fig. 14. Deconstruction of slums in the business district of Mumbai between 2005 and 2022. The colors correspond to the ones used in Fig. 2. Images are taken from Google Earth.

Population estimates within slums present a notable challenge, as discussed in literature [6], [11], [12], [13], [29], and [47]. These estimates often show large uncertainties when compared to data from large surveys. Breuer et al. [13] showed that the number of people living in slums in Mumbai, India, could be seven times higher than estimated using morphological slum data and ungridded Worldpop data. In addition, Thomson et al. [12] compared different gridded population datasets with self-reported data from slum dwellers in Nairobi and found a similar error. When analyzing the WorldPop unconstrained dataset, they found that the models underestimate slum populations per se, because they work well at a general level but are inadequate in extreme cases, which slums are.

Following the results of the papers introduced above, we argue, that the population counts we estimate using the mentioned gridded population datasets, could be seen as lower boundaries of the real population living in these settlements and should be interpreted with caution.

Nevertheless, we leveraged innovative methodologies, such as mobility metrics, to gain insights into this complex issue. Interpreting the low GDF for the first decade in the 21 century in comparison to the relatively high value for the second decade, we can assume, that while slums mainly grew in area in the first decade, they densified in the second decade. Assuming that these latest trends continue, these findings could be used for infrastructural planning. When a higher number of people is expected at a certain place, the capacity of infrastructure, like water distribution systems should also be increased.

Our analyses also revealed that these metrics show similar values for different gridded population datasets. This can be seen as an indicator for the robustness of the results.

Another uncertainty concerns the offsetting of population data against the spatial extent of the slums. Since, as already described in the methods, we assume that the population density within a pixel is evenly distributed, our population calculations for morphological slums can only be seen as an estimate. If it is assumed that the population density in slums is generally higher than in neighboring formal areas, our method tends towards an underestimation of the slum population. Additionally, we have to highlight that the population for the last point in time is given only for the year 2020, although the spatial delineations of slums were collected using basemaps from 2021 to 2022. Thereby, we neglect changes between these years.

Literature often states (e.g., [29]) that up to half of Mumbai's population resides in slums (e.g., [50]). Therefore, it remains an open question how many people actually live in cities like Mumbai.

C. Influence of Topography and Infrastructure

Geographical and topological factors, such as proximity to water bodies and railway tracks, were also considered in our analysis. Contrary to common assumptions that morphological slums grew near these features, our study revealed no significant relation, rather a trend that growth is topologically independent. Furthermore, we found that the total area of morphological slums at both low and high elevations remains relatively stable. However, both elevation categories exhibit significant intraurban dynamics, emphasizing the notion that slums are characterized by substantial fluctuations.

Nevertheless, the analyzed parameters are just exemplary and, in no case, to be considered complete. Future analyses could investigate the relationship between slum growth and distance to the city center (where the definition of the city center is debatable), slum growth and activity in social media [31], or many others.

D. Uncertainties Related to Data and Image Interpretation

Uncertainties in our study comprised data obtainment, input source data, and calculation methods. Capturing data relied on one subjective image interpreter. The mentioned thresholds for polygon delineation and density categorization were chosen depending on empirical experience from prior studies, e.g., [10].

Streets represent a natural border between neighborhoods and is used often in other studies [39], [41]. Empirically, in these complex urban areas, streets, pathways or gaps between accumulations of houses are hard to differentiate. In our theoretical foundation for mapping, we defined a buffer of up to 10 m, otherwise scale would be fuzzy and delineation would cut uncountable small pieces within one polygon. Mapping of spatial change effects for slums would be too fragmented. We used the 10–30 m threshold as an empirical value, that we derived by randomly measured building distances. We found that a larger distance reveals single stand-alone houses or even remote building clusters as own new polygons. We found the MMU with 5 buildings appropriate, also considering the geometrical resolution of our basemaps of approximately 0.5 m. We are fully aware that this defined mapping rules are subjective to a certain degree. However, there is no "ground truth" or universal truth to this, and thus, we opted for a logical derivation of these rules. We are aware that other definitions might influence the results. The strength of our approach lies in its consistency and thus a basis for consistent comparisons over time.

Even though, MVII remains the most accurate mapping approach, it still offers manifold uncertainties. For reasons of consistency, we approach the mapping by only one interpreter [20] which still offers highest accuracies, e.g., [46]. Other studies, e.g., [30], also recommend a deprivation framework considering in situ data to improve data quality.

Considering our exemplary substudies, e.g., on the proximity of morphological slums to infrastructures, sensitivity studies should be carried out in future work to investigate the influence of the selected values (100 m distance or 50 m elevation) on the results.

Despite these uncertainties, which can be addressed in future approaches (e.g., through the use of apps by local residents to collect population data [22], [47]), our demonstrated intersection of area data on slums and population data provides one way to quantify spatial and demographic changes in slums. It it also important to highlight the fact, that our quantitative analyses can only capture the morphological changes within the city. The changes in the socioeconomic situations of the inhabitants and the causal relationships for the changes have to be explored in detail by using additional data or by conducting qualitative studies based on our findings.

V. Conclusion

Our study provides a location-based and population-based analysis of the spatio-temporal dynamics of morphological slums in Mumbai. It challenges the perception of slums as uncontrolled structures spreading across the city and beyond and emphasises their significance for the urban landscape. The high dynamics observed in Mumbai's slums can be attributed, in part, to the insecure tenure that a significant portion of the population in the city experiences, fueling their rapid transformation and evolution.

Our research offers implications for urban planning and policy development in Mumbai and contribute to the UN SDGs. To address SDG 11 by improving living conditions, it is essential to understand the spatio-temporal dynamics of slums. The shift of slum space from the old city to newer areas, like Navi Mumbai, emphasizes the need for urban development efforts to consider the multifaceted nature of these dynamic communities. This article contributes to a more nuanced understanding of slums in Mumbai, shedding light on their significance and the complex processes that shape their dynamics in an ever-changing urban landscape. Our results can serve as a reference for spatial planners to better understand the morphologies and populations over time and it can contribute to the slum mapping community to enhance temporal change comprehension as another step toward SDG 11.1.1 data systematization.

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 article.

Data Availability

The code to merge population data and the spatial delineation of the morphological slums, as well as to calculate the mobility metrics is available through TUdatalib [24]. The data, due to its ethical topic, will be shared only upon reasonable request.

Author Contribution Statement

John Friesen, Nicolas Johannes Kraff, and Hannes Taubenböck designed the scope of the study. Nicolas Johannes Kraff was responsible for identifying the morphological slums using MVII. John Friesen merged population with the spatial delineation data and analyzed the data. John Friesen took the lead in writing the manuscript and Nicolas Johannes Kraff and Hannes Taubenböck reviewed the manuscript.

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