Misperceptions of Predominant Slum Locations? Spatial Analysis of Slum Locations in Terms of Topography Based on Earth Observation Data

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Abstract: Slums are a physical expression of poverty and inequality in cities. According to the UN definition, this inequality is, e.g., reflected in the fact that slums are much more often located in hazardous zones. However, this has not yet been empirically investigated. In this study, we derive proxies from multi-sensoral high resolution remote sensing data to investigate both the location of slums and the location of slopes. We do so for seven cities on three continents. Using a chi-squared test of homogeneity, we compare the locations of formal areas with that of slums. Contrary to the perception indirectly stated in the literature, we find that slums are in none of the sample cities predominantly located in these exposed areas. In five out of seven cities, the spatial share of slums on hills steeper than 10° is even less than 5% of all slums. However, we also find a higher likelihood of slums occurring in these exposed areas than of formal settlements. In six out of seven sample cities, the probability that a slum is located in steep areas is higher than for a formal settlement. As slums mostly feature higher population densities, these findings reveal a clear tendency that slum residents are more likely to settle in exposed areas.

Keywords: urban growth; slum; urban poverty; structure types; urban hazard; exposure; landslide; earth observation

1. Introduction

In total, 100,000 people were affected by debris flows and landslides caused by rain-induced floods in Venezuela in 1999. Most of the ten thousand disaster deaths can be traced back to residents of informal settlements being washed away during the event [1,2].

As the example above drastically shows, low-income groups are often pushed into these hazardous locations, as this land, actually unsuitable for settlement, is often not occupied and the only one affordable [3,4]. This is due to the fact that the value of land and therefore its affordability for various social groups is determined not only by, e.g., the accessibility to work, connection to public infrastructure and services but also by the physical nature of the land [5,6]. Consequently, areas of low economical value tend to be less suitable for human settlements and are therefore often the only spaces available and affordable for low income groups [7]. This effect becomes severe and is threatening the life of the poor when it comes to the exposure to hazards such as landslides, as they are one of the most destructive dangers in terms of death toll [8]. The poor, as the most vulnerable group in society, are as a consequence more likely to live in the most hazard-prone areas [3], which is also called "land unwanted by others" [9].

In the face of global changes such as population growth, rural–urban migration, urbanization and climate change, the proportion of people and assets potentially exposed to natural hazards is increasing simply because of larger and denser populations [10,11]. Additionally, the urban poor and therefore the most vulnerable group of the growing society—one indicator of this is that the slum population increased by 28 percent within 24 years [4]. Regarding landslides in particular, the pressure of urban development and population growth on available land intensifies anthropogenic drivers of landslide risk, which are activities such as altering slope geometry with earthworks, loading slopes with buildings and infrastructure, changing the vegetation, and consequential changes in slope surface water and groundwater regimes [12–14]. In addition, climate change is likely to increase the frequency of landslide-triggering events such as heavy rainfall [3].

Based on these considerations there seems to be no doubt that the urban poor often settle in predominantly unsuitable hazard-prone areas. In 2016, the United Nations estimated that "four out of every ten non-permanent houses in the developing world are (…) located in areas threatened by floods, landslides and other natural disasters" [4]. Considering about 881 million slum residents worldwide [4], this is indeed a high risk for a in general very vulnerable group.

However, estimations of the United Nations have not been empirically verified yet as data on slum locations and dimensions [15] or slum populations have high uncertainties [16], are outdated or are not globally available in a consistent manner. Furthermore, in urban geographic studies, most theories about slum exposure to natural hazards are based on qualitative observations [17–19] rather than on spatial evidence [20]. This is mostly due to manifold challenges for comprehensive and consistent data as well as for measurement techniques of the urban poor. In consequence, there has, to the best knowledge of the authors, not been any study that quantified the number of slums being located in steep terrain (as proxy for possible landslides) in a consistent and comparable manner. This study aims to provide empirical evidence on the prevailing location of slums in relation to steep areas.

To ensure a consistent and thus comparable dataset, the following proxies are used: (a) Characteristic morphologic features of the built-up landscape to locate living environments of the urban poor called "slums"; (b) The terrain situations as proxies to evaluate the susceptibility of certain areas to landslides. These proxies are used to address the following questions: (1) how large is the proportion of slums in exposed locations? (2) Is it more likely for slums to be located in steep areas than for formal settlements? (3) Are there differences in the distribution of land shares across the slope classes depending on the morphological settlement type?

The definition of these proxies is the subject of the following Section 2. In Section 3, the workflow of the study as well as data and methods used are introduced, followed by the presentation of the results (Section 4), their discussion (Section 5) and a conclusion of the study (Section 6).

2. Conceptual Foundation

2.1. The Concept of Morphological Slums

As described above, global, comprehensive, consistent and comparable datasets for evaluating such complex issues such as the "location of a certain social group" or "landslide risk" are non-existent. Against this background, we apply proxies that allow an approximation of these issues.

Poverty is often conceptualized as a multidimensional phenomenon consisting of indicators such as household income, access to public services, environmental exposure, among many others [21]. Measurements of the social group of the "urban poor", however, are predominantly based around income levels, either in absolute or relative terms. In absolute terms, the income level is a fixed dollar income, such as one dollar per day, or an income below a certain threshold [22]. Relative poverty describes the situation in comparison to the rest of the society [23]. These statistics require data on the income of the population, in most cases obtained through household surveys or tax data [24].

With regards to slum dwellers, however, they are often underrepresented in both datasets. Unemployed people or people working in the informal sector are not recorded in tax data.

In household surveys, deprived areas are not visited by the enumerators because they appear hostile, unsafe or hard-to-reach. Additionally, political incentives render populations in slums invisible in the data. In addition to practical and political reasons, unrepresentative sampling frames cause an underrepresentation of slum dwellers in household surveys. For example, census data are mostly collected only every 10 years. In times of rapid urbanization, these data can very quickly become out of date [16,25]. Furthermore, these data collection methods lack information on the spatial distribution of slum-dwellers [26].

Since the availability of very high-resolution (VHR) satellite data in 1999, it has become a new important data source for the mapping of the urban poor [27]. The advantage of remote sensing lies in its consistent data sources, its comprehensive large area to global coverage and its timeliness. As a result, different methods have been developed to extract slums from remote sensing data by their morphologic differences to formal settlements [15,28–31]. In several studies, e.g., the structure of layouts, built-up densities and building sizes were calculated to extract different residential types [29,32]. Significant morphological differences between slums and formal settlements were also found by using grey level co-occurrence matrices (GLCM) [33–35], the Normalized Difference Vegetation Index [27], the vegetation-impervious surface-soil (V-I-S) model [36], or by using polarimetric SAR-data as descriptors of local textures [37], among others.

These studies show that slum locations can be mapped using remote sensing data as a physical expression of urban poverty that is reflected in the morphology of the built-up area [26]. Studies show a clear link between income and physical building structure [38,39]. However, as Taubenböck et al., 2018 [40] set out, the morphologic characteristics of slums allow mapping only for a part of urban poverty as physical forms of housing are highly diverse across the globe. In addition, urban poverty can also be found in formal areas, such as resettlement colonies in India [41]. However, these studies proved that in the absence of other datasets, the physical approach is a legitimate proxy for mapping a part of urban poverty. Therefore, in the following analysis, settlement types are classified as either morphological slums or formal settlements. A more detailed description of the methodology is given in Section 3.4.

2.2. The Concept of Landslide Suspectibility

According to Cruden et al., 1996 [42], the term "landslide" denotes "the movement of a mass of rock, debris or earth down a slope". Thus, landslides can be classified by determining the material and the type of movement. To determine the likelihood for the occurrence of landslides, two different concepts are used in literature [43,44]: landslide "susceptibility" is considered as the likelihood of a landslide occurring in an area on the basis of the local terrain [45], and landslide "hazard" is considered as the probability that a landslide of a given magnitude will occur in a given period and in a given area [46]. The occurrence of a landslide hazard is thus determined by the stability of a slope, as well as preparatory factors, triggering mechanisms and aggravating factors that interact and change over time [3].

Because a uniform database must be available for all cities for our study, this analysis does not quantify the probability of the occurrence of landslide hazards, but the susceptibility of an area to landslides. The assessment of landslide susceptibility requires the following factors, among others: slope inclination, soil type and stability. However, these data are not available in such high resolution for most cities. Therefore, we quantify the susceptibility of an area to landslides as a function of slope inclination. We consider an approximation to the susceptibility to landslides by calculating the slope inclination of the terrain as legitimate, since slopes have a natural predisposition to landslides due to their geological and topographical characteristics, among other things [47]. Of course, this is a simplification of the complex situation and the probability of landslide hazards occurring cannot be quantified. However, with this proxy we provide a uniform database for our test cities.

Therefore, we approach the susceptibility to landslides with the proxy of the topographical situation that represents the slope of the terrain. A more detailed description of the calculation and classification of slope inclination can be found in Section 3.5.

With the spatial combination of both, the proxy of settlement morphologies for detecting slums (or poor urban areas) and the proxy for areas of potential landslides, i.e., the steepness of slopes, we aim to quantify the susceptibility of a certain social group towards a specific natural hazard.

3. Workflow, Materials, and Methods

3.1. Study Workflow

Our analysis consists of three methodological steps (Figure 1): the classification of morphological settlement types (Figure 1a), the evaluation of the topographic situation (Figure 1b) and an analysis combining both datasets to derive spatial statistics on susceptibility to landslides for morphological slums and formal settlements (Figure 1c). The spatial extents of the cities are according to the boundaries as of the database of global administrative areas [48].
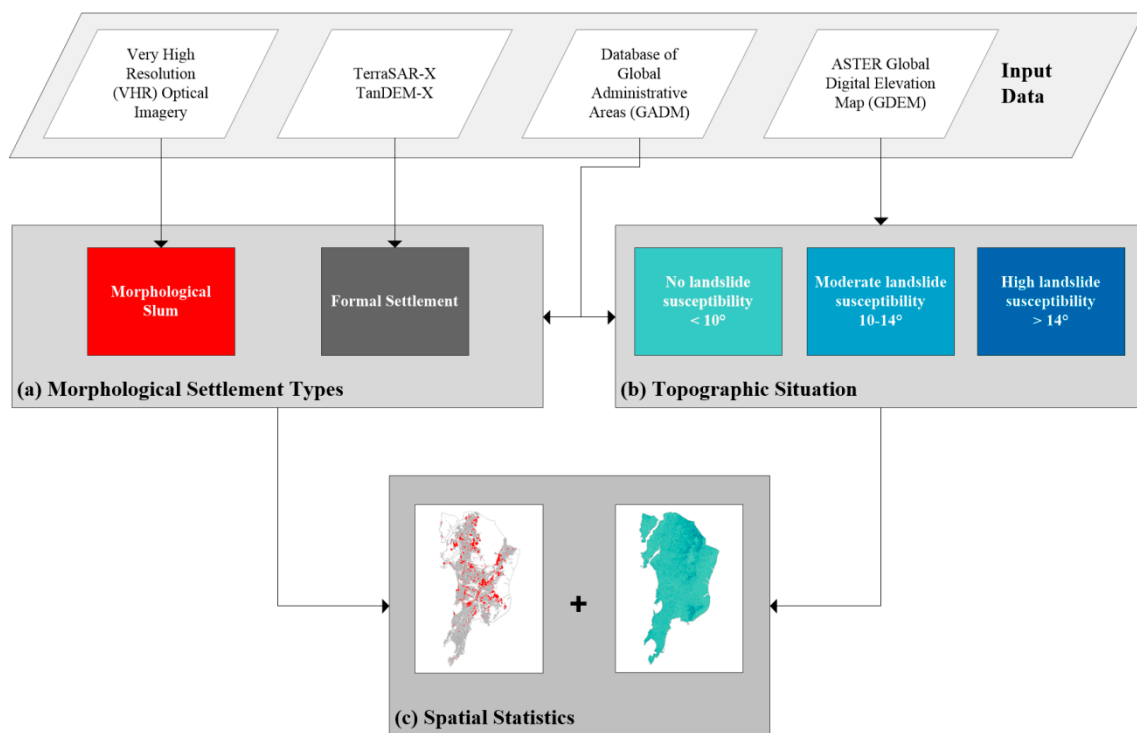

Figure 1. General workflow and data sources for the classification of morphological settlement types (**a**), the evaluation of the topographic situation (**b**) and the derived spatial statistics (**c**).

We classify the settlement structures of each city into two morphological settlement types (Section 3.3): either into morphological slums, which we derive by visual image interpretation from very high-resolution optical images (morphological slum); or, into formal settlements, which we record from TerraSAR-X and TanDEM-X data (Table 1). The topographic situation (Section 3.4), which is a proxy to evaluate the susceptibility of slums and formal settlements to landslides, is calculated based on a Global Digital Elevation Model of the Advanced Spaceborne Thermal Emission and Reflection Radiometer [49]. In the end, both classification results are spatially combined and analyzed using the chi-squared test of homogeneity (Section 3.5).

Table 1. Remote Sensing Data Details.

Earth Observation Data	Product	Spatial Resolution	Derived Information
VHR Optical Imagery	-	0.25–1 m	Morphological Slums
TerraSAR-X, TanDEM-X	Global Urban Footprint (GUF)	30 m (GUF)	Formal Settlements
ASTER	ASTER GDEM	30 m (ASTER GDEM)	Slope Classes

3.2. Study Area

We base our sample selection on the following criteria: first, we select cities that feature a clear distinction of morphological building characteristics between formal and slum settlements. Secondly, we select cities that have a documented prevalence of urban poverty. Third, we select cities where classifications of both structural morphologic types are available based on a consistent conceptual approach. Fourth, we select cities that have different relief energy. Last but not least, we select study areas from different continents and thus cultural areas. The resulting cities are Rio de Janeiro, Sao Paulo (Brazil), Caracas (Venezuela) in America; Cairo (Egypt) and Cape Town (South Africa) in Africa; Mumbai (India) and Manila (Philippines) in Asia (Figure 2).
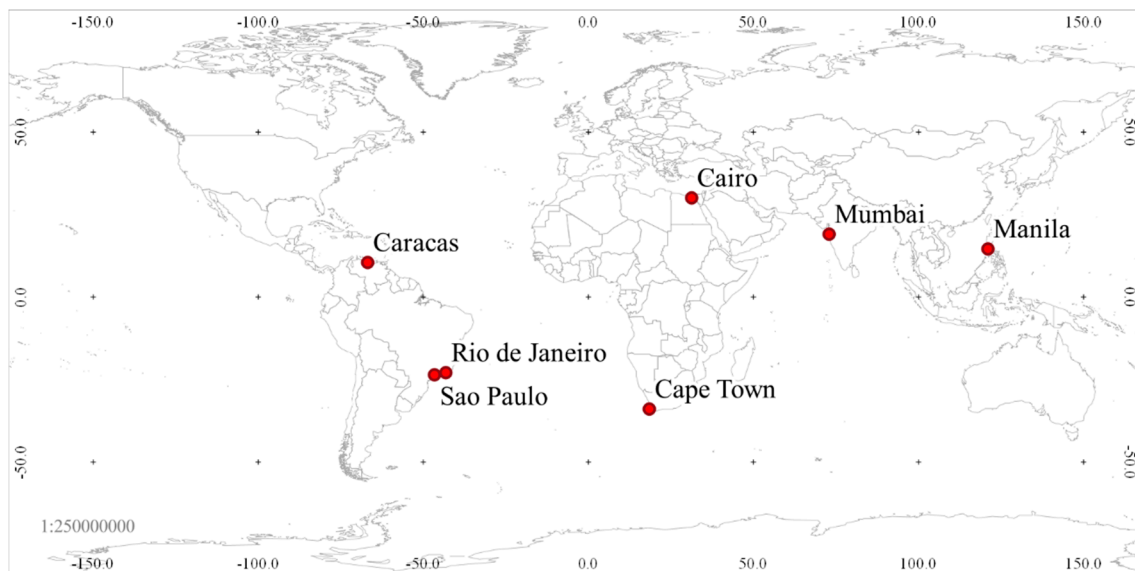
Figure 2. Study Area.

3.3. Morphological Settlement Types

As introduced in Section 2.1, we classify the settlement landscape of the entire cities as either formal settlement or morphological slum, based on different data sources.

Formal settlements are derived from the Global Urban Footprint (GUF) product [50,51], which was derived from radar data from the TerraSAR-X and TanDEM-X mission. Urban landscapes are characterized by the spatial complexity of different objects in a small space. In radar data, this results in highly textured image regions. The Urban Footprint Processor uses this information along with the intensity information of the backscatter to delineate "settlements" from "non-settlements" by an unsupervised image analysis technique [52,53]. The accuracies of the settlement classification in dense urban areas of central Europe have been measured beyond 90% [54]. We chose the GUF mapping product because of its global availability and the general consistency of the data, which is important for the comparative analysis of different cities.

Morphological slums are derived from very high resolution (VHR) optical satellite sensor systems, such as QuickBird and WorldView that provide geometric resolution of 1 m and better. All data were acquired between 2010 and 2013 (Table 2).

Table 2. Satellite data used for classification of morphological settlement types.

Study Area	Date of Acquisition	Sensor	Spatial Resolution
Cairo	19.06.2012	WorldView-2	0.5 m
	24.06.2012	WorldView-2	0.5 m
Cape Town	28.09.2011	GeoEye-1	0.5 m
	07.10.2012	WordlView-2	0.5 m
Caracas	02.10.2012	GeoEye-1	0.5 m
Manila	25.10.2010	WorldView-2	0.5 m
Mumbai	27.03.2013	Pléiades	0.5 m
	03.04.2013	Pléiades	0.5 m
Rio de Janeiro	06.10.2011	Ikonos-2	1 m
	09.03.2012	WorldView-2	0.5 m
	02.04.2012	Ikonos-2	1 m
	13.04.2012	WorldView-2	0.5 m
	05.05.2012	Ikonos-2	1 m
	01.07.2012	WorldView-2	0.5 m
Sao Paulo	13.04.2012	QuickBird-2	0.8 m
	06.07.2012	WorldView-2	0.5 m
	17.07.2012	GeoEye-1	0.5 m

The classification is based on the ontology suggested by Kohli et al., 2012 [26] and the empirical study completed by Taubenböck et al., 2018 [40]: they conceptualize spatial features such as "highest building density", "non-regular, complex alignment of buildings", "homogeneity of the pattern", "small building sizes", and "low building heights" for delineating areas terminologically named "morphologic slums" as exemplified in Figure 3.

The classification is executed by visual image interpretation on a scale of 1:5000 based on a mapping protocol, as this offers the best capabilities to derive these complex structures [55]. The details of mapping protocol have been introduced by Taubenböck and Kraff, 2014 [28].

The spatial overlay of the morphologic slum classification and the formal settlement classification results in our final delineation of morphologic settlements types. In Figure 3 the morphologic differences of complex slums morphologies and patterns are contrasted to the regular, geometric arrangement of building morphologies in formal settlements, exemplified in the cities of Caracas, Mumbai and Cape Town. The resulting binary classification introduces the two morphological settlement types—formal settlements and morphological slums as exemplified in the city of Caracas in Figure 4.

Figure 3. Slum demarcation based on morphological classification of very high-resolution (VHR) images in (**a**) Caracas, (**b**) Mumbai and (**c**) Cape Town.

3.4. Topographic Situation

To obtain the topographic situation, the Global Digital Elevation Model (GDEM) of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), which is onboard the earth observation satellite Terra, is used. ASTER GDEM is a product of the United States National Aeronautics and Space Administration (NASA) and the Japanese Ministry of Economy, Trade, and Industry (METI). The product provided by the United States Geological Survey has a spatial resolution of 30 m [56].

As tall buildings can affect the uncertainty of digital elevation models in urban areas, we empirically tested focal statistics to minimize land cover induced errors. By comparing filtered and unfiltered slope rasters, a median filter with a window size of 13 × 13 pixels proofs to minimize these errors best. Since high vertical building structures define the surface very locally and high relief energy is usually more extensive, it was found that this filter size in the highly built-up area best smoothed these artificial structures without smoothing the terrain structures. We have also tested minimum or maximum filters.

However, the median was chosen because it is robust to extreme values (tall buildings) and thus eliminates them best. Filtering the digital elevation model affects the vertical accuracy of the model according to the Root Mean Squared Error (RMSE) in Table 3. The calculated slope raster contains the maximum rate of change for each cell to its neighbors in degree and has a spatial resolution of 30 m.
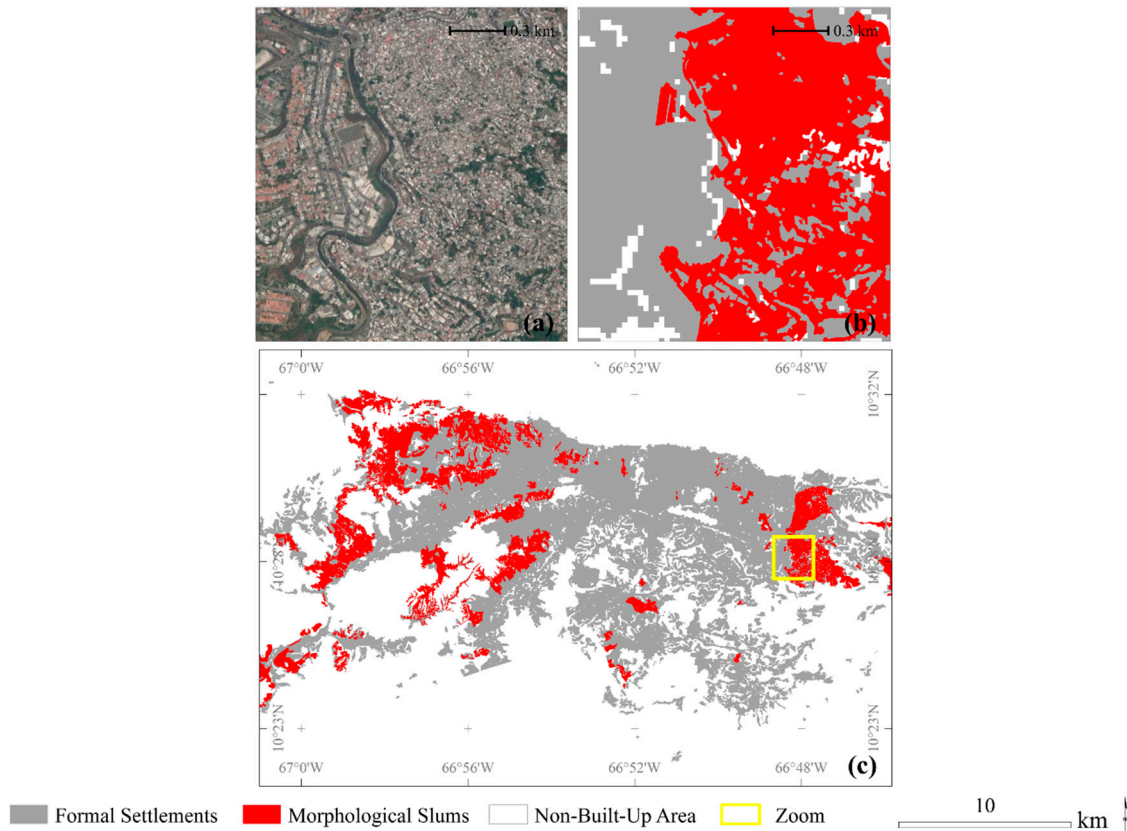

Figure 4. (**a**) Classification of morphological settlement types in Caracas based on VHR images (WorldView-3) resulting in (**b**,**c**) either formal settlements or morphological slums.

Table 3. Root Mean Squared Error (RMSE) of filtered ASTER GDEM.

Study Area	Span Width ASTER GDEM	RMSE
Cairo	495 m	5.65 m
Cape Town	1561 m	6.91 m
Caracas	2701 m	16.53 m
Manila	270 m	3.83 m
Mumbai	484 m	4.85 m
Rio de Janeiro	983 m	7.99 m
Sao Paulo	1216 m	8.97 m

According to Schuster and Highland, 2007 [57], no house should be built on slopes that exceed 14 degrees as the risk of landslides increases enormously there. In order to add further information to this general indication, we create a more detailed picture by deriving three classes of landslide susceptibility which are defined as follows: no landslide susceptibility ($<10°$), moderate landslide susceptibility ($10–14°$) and high landslide susceptibility ($>14°$). In Figure 5 the original ASTER DEM data, the derivation of the three classes with respect to "steepness of slopes" and the distribution of the variable steepness of the slopes across the built-up area of Caracas are illustrated.
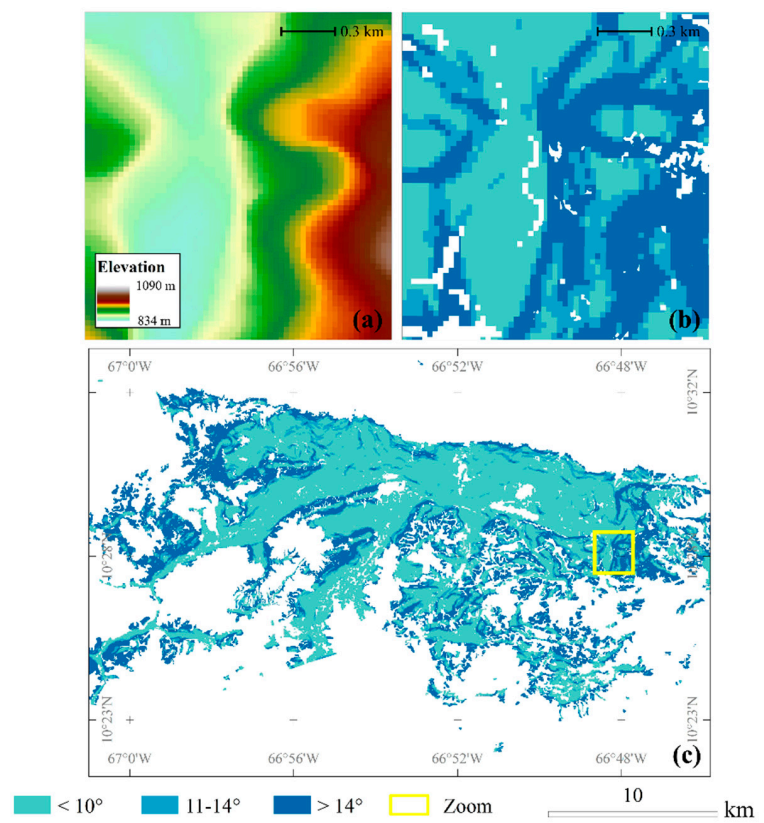
Figure 5. (**a**) Classification of the topographic situation in Caracas based on the ASTER Digital Elevation Model resulting in (**b**,**c**) three classes (<10°, 10–14°, >14°) of slope inclination (only built-up area is displayed).

3.5. Spatial Analysis for Assessing Landslide Susceptibility

For the assessment of landslide susceptibility, we combine the classifications of the morphological settlement types and the topographic situation in a spatial analysis: we compare the landslide susceptibility of morphological slums vs. formal settlements in a quantitative manner. For each city the following questions are addressed: (1) how large is the proportion of slums in exposed locations? (2) Is it more likely for slums to be located in steep areas than for formal settlements? (3) Are there differences in the distribution of land shares across the slope classes depending on the morphological settlement type? The first two questions are examined empirically and the third is investigated by a chi-square test of homogeneity that was performed for each study area to compare the morphological slum (ms) locations with the formal settlements (fs) locations in terms of topography (x). It is assumed that in steep terrain the proportion of slums is identical to the proportion of formal settlements. We check this also for the other slope classes (H_0). A significant level of 0.05 was considered statistically significant.

$$H_o = F_{ms}(x) = F_{fs}(x) \tag{1}$$

$$H_1 = F_{ms}(x) \neq F_{fs}(x) \tag{2}$$

Since the sizes of the morphological settlements vary greatly, a uniform spatial unit is required, that enables to assign the terrain information to the morphological slums and formal settlements. We chose a fishnet with a net size of 30×30 m that matches the slope raster. Thus, each cell receives a slope value, which is assigned to the respective areas of the slums as well as to the formal settlements that are located within the cell. The areas of the morphological slums and formal settlements are then aggregated according to the assigned slope class to compare the shares of morphological slums and

formal settlements. In our quantitative analysis we compare shares of morphological slums and formal settlements depending on their location with respect to the topographic situation.

4. Results

To investigate the prevailing location of morphological slums regarding their landslide susceptibility, we used two datasets: the extent and distribution of morphological slums on the one hand and the topography of the cities on the other hand. The main characteristics of these two datasets and the results of their combination are presented in this section.

4.1. Morphological Slums

The visualization of the classification of morphological slums and formal settlements within the study areas shows that the proportion and size of slums varies greatly across cities (Figure 6).
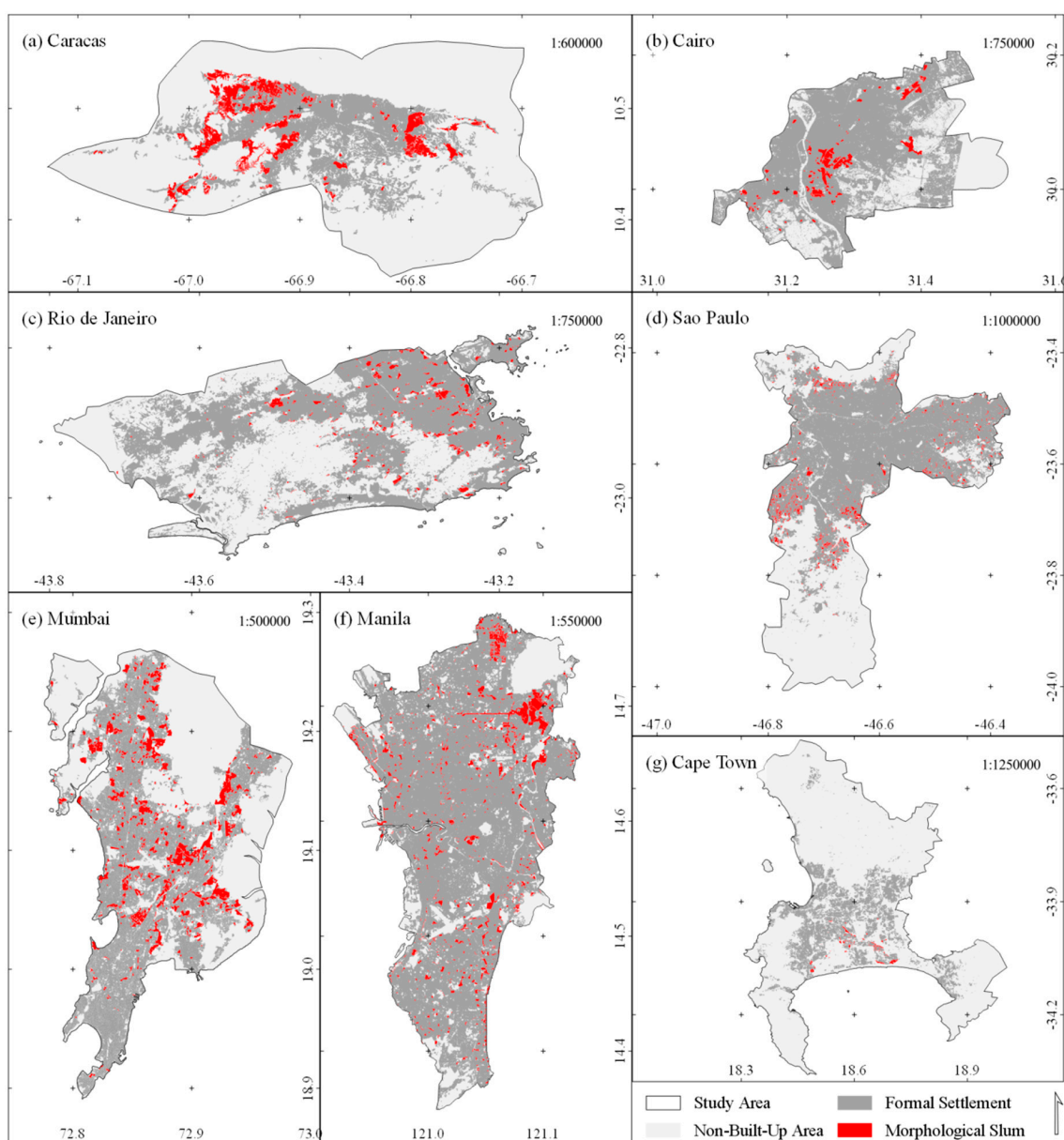

Figure 6. Classification of morphological settlements types (formal and morphological slums) within the particular administrative boundaries of the seven sample cities: (**a**) Caracas, (**b**) Cairo, (**c**) Rio de Janeiro, (**d**) Sao Paulo, (**e**) Mumbai, (**f**) Manila, (**g**) Cape Town.

In general, we found that the cumulative share of morphological slums is relatively low at 6.94% of the built-up area of all cities (322,017 ha). However, a comparison of the percentages in the individual cities shows that the share of morphological slums varies from 1.8% in Cape Town to 20.9% in Caracas (Figure 7). Both in percentage (20.9%) and absolute terms (3705 ha), most slums are located in Caracas, although it is the smallest of all investigated cities in terms of built-up area.
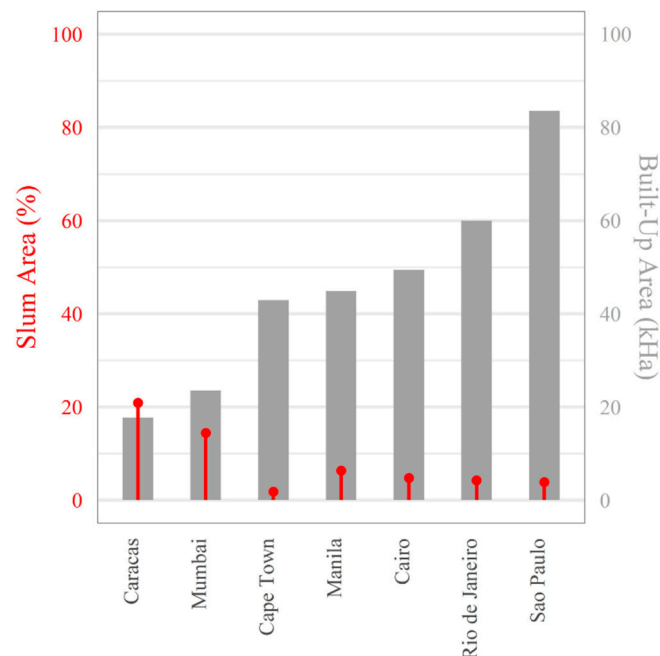

Figure 7. Grey: Built-up area in thousand hectare (kHa); Red: Share of slums in percentage per city surveyed.

Despite the different sizes of the cities—in absolute numbers—a similar area of morphological slums was detected in all cities (2352 ha in Cairo up to 3705 ha in Caracas), except for Cape Town, where townships are not included due to their differing morphology (755 ha). Nevertheless, no correlation was found between the slum area and the size of cities (Figure 7).

4.2. Topographic Situation

Naturally, the reliefs of the investigated cities are very different. Manila and Cairo lie in generally flat terrain, while the relief energy of Caracas and Rio de Janeiro is very high. This is also reflected in the proportion of settlements located in steep areas. Across all investigated cities, most settlements built in areas steeper than 10° are in Rio de Janeiro (4188 ha) and Caracas (4125 ha). These steep areas are about four times as large as in Sao Paulo, 16 times as large as in Cairo, and 125 times as large as in Manila. An area of 4125 hectares is especially remarkable for the city of Caracas as it is the smallest of all the cities investigated. Therefore, in Caracas, 4125 ha accounts for 23.3% of the built-up area, whereas in Rio de Janeiro 4188 ha accounts for only 6.9% of the built-up area.

4.3. Spatial Analysis for Assessing Landslide Susceptibility

To verify the assumption, often made in the literature that slums are usually located in highly exposed areas [58,59], we combined the prepared datasets of morphological settlement types and topographical conditions. With it, we firstly quantified the shares of morphological slums and formal settlements in the slope classes for all cities examined (Figure 8).

In general, we found that only a small proportion of the morphological slums are located in the areas of steep slopes. In five of our seven sample cities less than 5% of all morphological slums

are located in areas steeper than 10° (see table Figure 8). In absolute figures, however, the shares of morphological slums in steep areas vary greatly across these five cities: in Sao Paulo, 41 times as many morphological slums (156 ha) as in Manila (3.8 ha) are located in steep areas. In contrast, in the two cities with the highest relief energy, the proportion of slums in steep terrain is well over 5%: in Rio de Janeiro 23.6% (604 ha) and in Caracas 43.29% (1.604 ha) of the morphological slums are located in areas steeper than 10°. This is remarkable, since even in the cities with high relief energy the majority of informal settlements were not to be found in these exposed locations.
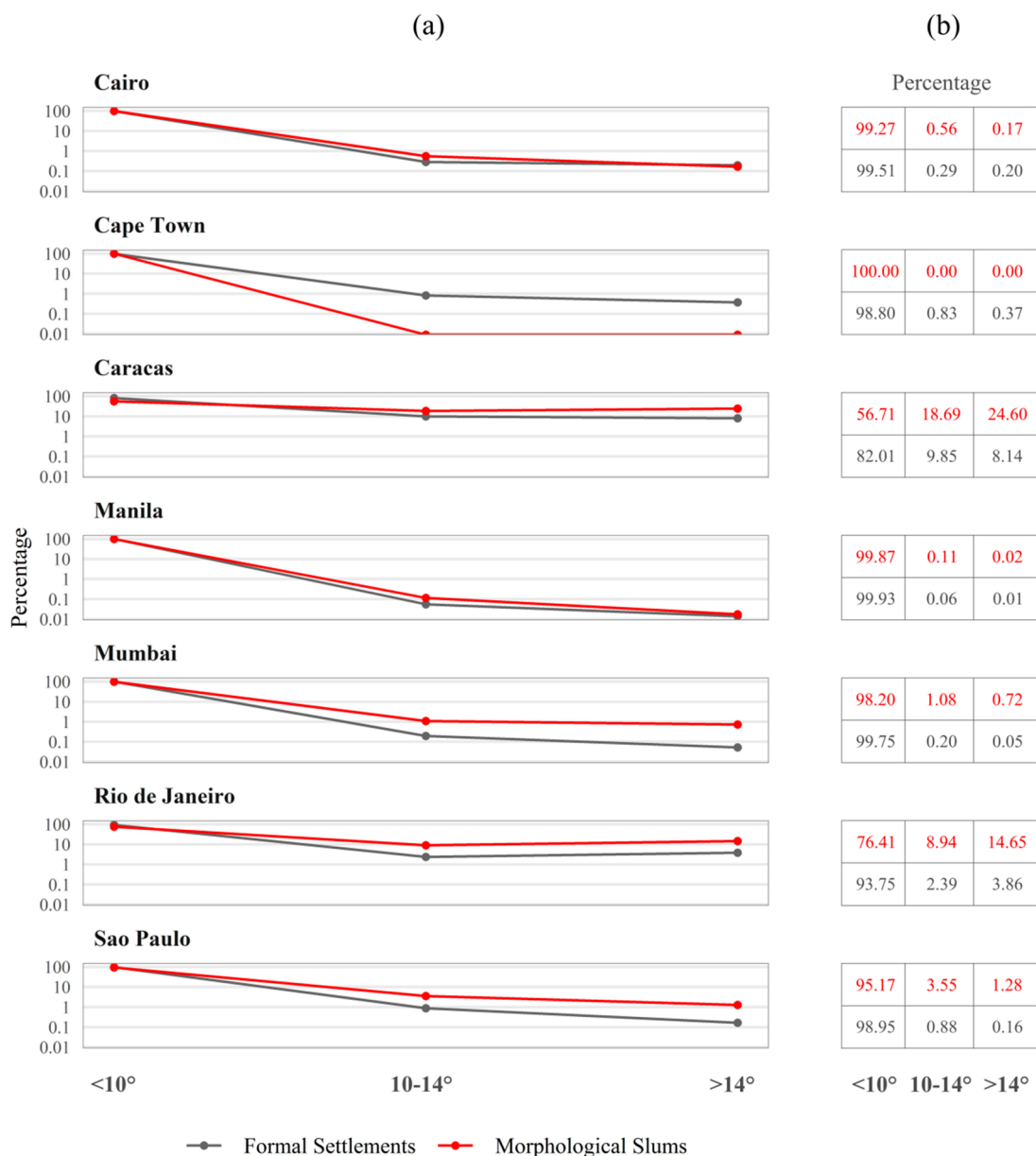

Figure 8. Graphical (**a**) and tabular (**b**) representation of the areal shares (in percentage) per settlement type in slope classes.

Despite the mostly small proportion of formal settlements and morphological slums in steep areas (>10°) compared with the total urban area, the results show, that in all cities except Cape Town—where no morphological slum is located in steep areas—morphological slums are proportionately much more frequent located in steep areas than formal settlements. For this, we have compared the probabilities

that slums are located in steep areas with the probabilities that formal settlements are located in steep areas.

In a comparison of all cities, the largest proportion of morphological slums in steep terrain was found in those two with the highest relief energy. However, in those cities (Caracas and Rio de Janeiro) this also applies to the formal areas. Therefore, in Rio de Janeiro, it is only 3.8 times more likely and in Caracas, it is only three times more likely that morphological slums are located on slopes above 10° compared to formal settlements. In contrast, this probability is 6.4 times higher in Sao Paulo and seven times higher in Mumbai.

Comparing only the likelihoods of the location of morphological slums and formal settlements in very steep areas (>14°), these inequalities increased even further. In Sao Paulo, it is 7.8 times more likely and in Mumbai, it is 13.8 times more likely that morphological slums are located on slopes above 14° compared to formal settlements. Figure 9 illustrates the findings for Caracas exemplarily. In addition, the absolute and relative changes of the shares of formal settlements and morphological slums are presented in dependence of the assigned slope class.
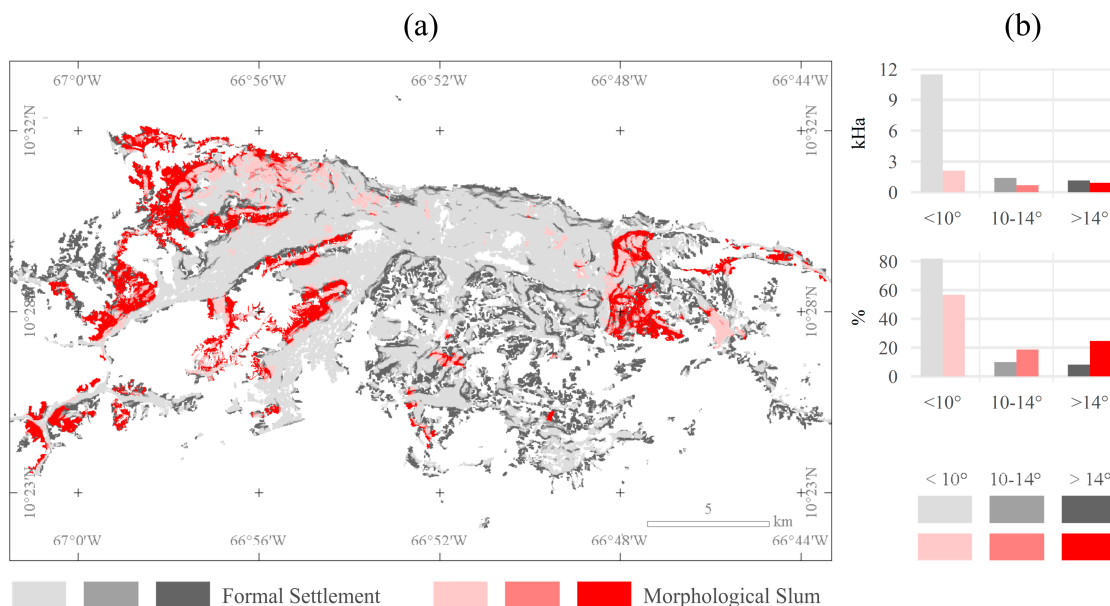

Figure 9. Location of the settlement types and their calculated slope inclination (**a**) and absolute and percentage shares of settlement types in areas with different slope inclinations in Caracas (**b**).

The results of the chi-squared test of homogeneity showed that there is a significant difference between the ratios of areas in the slope classes of morphological slums versus formal settlements. We found this for all cities except for Cairo and Manila (Table 4). In Caracas, Mumbai, Rio de Janeiro and Sao Paulo the observed shares of morphological slums in steep areas were higher than the expected ones, whereas the observed shares of formal settlements were lower than the expected ones. Additionally, Cramér's V (φc) indicates a stronger association between the settlement types and the slope classes in Caracas and Rio de Janeiro than in the other cities. Thus, the test shows, for five of seven cities, that there are significant differences in the distribution of the shares of slums and formal settlements over the slope classes.

Although it is significant that slums lie disproportionately more often on steep slopes, we also found that these are not the dominating locations for slums. Even for cities with high relief energy we found that most slums are located not on steep slopes. In all cities, however—except Cape Town—the likelihood that a slum is located in steep areas is higher than for a formal settlement. This difference was verified as statistically significant for all cities except Cairo and Manila.

Table 4. Results of chi-squared test of homogeneity.

Study Area	N	X^2	df	α	φc
Cairo	49,415	5.49	2	0.05	0.01
Cape Town	42,929	9.43	2	0.05	0.01
Caracas	17,719	1,125.32	2	0.05	0.25
Manila	44,884	1.58	2	0.05	0.01
Mumbai	23,553	158.58	2	0.05	0.08
Rio de Janeiro	59,966	1,133.17	2	0.05	0.14
Sao Paulo	83,550	416.65	2	0.05	0.07

5. Discussion

The aim of this study was to provide empirical evidence on the prevailing locations of slums in relation to their topographic situation. This is operationalized as a proxy for their exposure to landslides, i.e., a hazardous zone.

We mapped and analyzed the distribution of morphological slums and formal settlements across terrains of different slope for seven sample cities across the globe. Our analysis revealed that in none of the investigated cities are the morphological slums mostly located in steep terrain. In fact, in five out of seven cities, less than 5% of the morphological slums are located in these hazardous, steep terrains. Nevertheless, in cities of high relief energy, the shares of morphological slums in areas steeper than 10° are considerably higher: in Rio de Janeiro, 23.6% (604 ha) and in Caracas, even 43.29% (1.604 ha).

However, these results did not show whether a comparable proportion of formal settlements in cities is also located in steep areas. Thus, the probability of morphological slums being located in steep areas was compared with the probability of formal settlements being located in steep areas. The results showed that in all cities except Cape Town it is more likely for slums to be located in steep areas than for formal settlements. In Rio de Janeiro, it is 3.8 times more likely and in Caracas, it is three times more likely that morphological slums are located on slopes above 10° compared to formal settlements. In contrast, this probability is 6.4 times higher in Sao Paulo and seven times higher in Mumbai. The chi-squared of homogeneity statistically verified that morphological slums are more likely to be located in steep areas in Caracas, Mumbai, Rio de Janeiro and Sao Paulo whereas the association between the settlement types and the slope classes is strongest in Caracas and Rio de Janeiro. Evaluating these results, several limitations regarding the selected data and methods must be taken into account: urban poverty has many faces. The spatial mapping requires consistent data (e.g., economic, social, demographic or physical) as well as the clear conceptual definition what poverty refers to. However, since these data are not comprehensibly available in many places and their collection is very labor- and time-intensive [27,60], many studies are based on different slum definitions depending on the methods used, which, in turn, lead to different results. Therefore, as no dataset comparable to that produced in this study is known so far, no comparison to other datasets can be carried out. Most image classification studies on slums use visual image interpretation results for accuracy assessment (as reference data). As our study used the result of visual image interpretation to map morphological slums, no quantitative assessment on the accuracy of the classification results is provided, as both data would share the same uncertainties. For example, when defining slums in terms of their morphology, it must be taken into account that only a part of urban poverty is represented [40]. In addition, misidentification can occur, for example by identifying similar morphological characteristics such as a local market as a slum. However, as socio-economic data are scarce for these environments, and the measurement of poverty complex, the spatial approach using remotely sensed data provides, as it has been argued by Taubenböck et al., 2018 [40] and Engstrom et al., 2017 [38], a legitimate and consistent proxy across cities.

The morphological approach offers consistent and thus comparable and high-resolution data. Beyond this, in literature, the manual classification of slum areas, as applied in our study, has always been attributed as the most accurate method [55]. Since there are mostly no slum classifications at

all for our test cities, and if they exist, they are incomplete, inconsistent or based on other conceptual approaches, they cannot be used for comparison. Nevertheless, based on our clear mapping concept, we believe our spatial data represent the slum morphology well. However, one should keep the following in mind: urban areas are not equally suitable for the classification of morphological types by visual image interpretation as the quality of the delineation depends on the ontology chosen to detect morphological slums [61,62]. The delineation is influenced by the spectrum of morphological building types occurring in the cities. For example, in Mumbai and Caracas, few morphological types differing significantly from formal settlements are present, whereas in Cape Town morphological types occur that show only slight morphologic differences to none slum areas (Figure 3). Therefore, the delineation of morphological slums depends on the spectrum of morphological settlement structures of the respective city. Besides the spectrum of morphological types, homogeneity is decisive in terms of how certain morphological slums can be captured. The more compact and homogeneous individual morphological types occur; the easier it is to assign them to either the morphological slums or the formal settlements. According to Mahabir et al., 2018 [60], different complexities of the landscapes result in high variability of delineations.

In addition, the classification results are not strictly objective because the images are interpreted visually. Therefore, the results are influenced, for example, by the experience of the interpreters [63]. To reduce the subjectivity, individual physical indicators can be translated into either pixel or object-based image analysis tools [29]. However, the most suitable combination of methods and corresponding thresholds to extract different residential types must be evaluated and adapted for each city individually [26]. Additionally, in both manual and semi-automatic approach decisions have to be made to distinguish morphological types; in the former, this is performed by visual interpretation, in the latter, by the determination of thresholds. Which method achieves the best results has to be decided on a case-by-case basis. However, as Sliuzas and Kuffer 2008 [55] remark, the visual interpretation still offers the best capability for deriving these complex structures. However, we are also aware of the fact that different interpreters remain prone to produce inconsistencies in the mapping, even if the concept is clear.

Besides the limitation regarding urban poverty mapping based on remotely sensed data, there are also limitations concerning the terrain analysis. In this study, the topographical situation is derived from the slope inclination, which is calculated on the basis of ASTER GDEM v2. Although ASTER GDEM v2 has an overall accuracy of around 17 m at the 95% confidence level [64], there are also limitations regarding the data's accuracy. In this study, a high gradient is observed where building heights vary greatly. Despite the suspicion of higher deviations of the elevation model in urban areas, the accuracy of the data is due to missing reliable reference data not further investigated in this analysis. Instead, a median filter that is applied to the elevation models of all cities reduces the impact of these outliers on slope calculation. Therefore, the accuracy of the slope calculation is not quantified in this study.

We also need to be aware that the selection of seven cities is not representative for a global study. Nevertheless, the results show a trend that is worthy of further investigation: particularly in view of the United Nations' sustainable development goal of making "cities and human settlements inclusive, safe, resilient and sutainable", with particular attention to the urban poor [65] (p. 26). Since the population density in slums can be considerably higher than in formal settlements [66–68], a study comparing not the areas but the population shares are suspected to even reveal larger inequalities. However, the availability of data on the number of slum dwellers at intra-urban level is very limited. As an example, however, using the 2011 Indian census of 5,206,473 slum dwellers in Mumbai would lead to a population of more than 93,700 people living on slopes with a gradient of more than 10°. It must be considered that these estimates are subject to great uncertainty. Although data availability in some cities (e.g., Mumbai) is high, Taubenböck and Wurm, 2015 [67] have shown that estimates vary strongly. Beyond this, the areas of morphological slums and the census data are based on different slum definitions as well as on different study areas. Nevertheless, if further data on slum dwellers at

city level become available, these estimates will reveal the exposure of these particularly vulnerable people towards different natural hazard.

Last but not least, we need to be aware that the evaluation of exposure to landslides only based on slope inclination is a very strong simplification of a complex hazard. Nevertheless, considering the number of cities and the lack of comparable datasets on, e.g., soil stability, focusing on the most important precondition was in the context of this study evaluated as the best option available. Finally, investigating only landslides as one of many potential risks slum residents are facing is too short-sighted with regard to other risks such as other natural hazards (e.g., floods), environmental or social risks among others. However, this study still reveals a trend that slums and slum dwellers are, with a higher likelihood, exposed to landslides. This paves the path towards a more holistic analysis towards the multi-faceted risks certain social groups are exposed to.

Beyond measuring one aspect of inequality, understanding why they exist is of course of central importance. Inequality in cities, e.g., visible by the proportions of the formal and slum populations, is a result of complex interactions of different developments: general conditions such as migration and birth rates, economic developments and poverty levels, or local conditions such as land prices, little available land for construction in flat areas, political programs, among many others. In order to understand why the percentages of slums in steep areas are high in Caracas and Rio de Janeiro, whereas, e.g., in Sao Paulo they are low, extensive multidimensional studies are necessary where these influencing global drivers as well local particularities are integrated.

6. Conclusions

This study clearly shows that low-income earners are much more likely to settle in potentially exposed urban areas, i.e., in our particular investigation in landslide prone terrain. As landslide prone we defined—as a proxy—areas of steep slopes as the main precondition. Although the study shows, contrary to the perception in descriptive geography, that only a comparatively small proportion lives in areas of steep slopes, it is another piece of the mosaic to prove the disadvantage of a social group. Future studies are suggested to investigate the actual risk by using further data on, for example, the soil or the likelihood of the occurrence of triggers such as high rainfall events. Additionally, larger sample of cities and extending the analysis with other hazards and risks to the society are suggested; however, it must be ensured that the classification of areas of urban poverty needs to rely on one consistent approach; this is a still limiting aspect for larger-area or even global comparisons. Beyond this paper, we suggest studies analyzing the sensitivity of measurements with respect to input data (e.g., economic poverty vs. areas of morphologic slums).

In general, we conclude that recent trends of massive urbanization will continue to pull more and more people into cities across the globe [69]. With the increasing pressure of urban growth, highly exposed areas such as steep terrains will remain spots for living, especially for the urban poor. As we have proven in this paper that the relative share of slums is significantly higher in landslide susceptible areas than of formal settlements, it can be seen as one indicator increasing discrepancies within societies.

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