Multitemporal Landslide Exposure And Vulnerability Assessment In Medellín, Colombia

Marlene Kühnl (marlene.kuehnl@slu-web.de)
Sachverständigenbüro für Luftbildauswertung und Umweltfragen (SLU) https://orcid.org/0000-0003-1078-4825

Marta Sapena
German Aerospace Centre DLR German Remote Sensing Data Center: Deutsches Zentrum fur Luft- und Raumfahrt DLR Deutsches Fernerkundungsdatenzentrum

Michael Wurm
German Aerospace Centre DLR German Remote Sensing Data Center: Deutsches Zentrum fur Luft- und Raumfahrt DLR Deutsches Fernerkundungsdatenzentrum

Christian Geiß
German Aerospace Centre DLR German Remote Sensing Data Center: Deutsches Zentrum fur Luft- und Raumfahrt DLR Deutsches Fernerkundungsdatenzentrum

Hannes Taubenböck
German Aerospace Centre DLR German Remote Sensing Data Center: Deutsches Zentrum fur Luft- und Raumfahrt DLR Deutsches Fernerkundungsdatenzentrum

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Abstract

Landslides are often deadly natural events. Steep slopes and certain loose soil types are predestined areas for them. Moreover, in the context of climate change, extreme weather events such as heavy rainfall, which often trigger landslides, are becoming even more likely. All this is well known. It therefore stands to reason that this knowledge will lead to the avoidance of these risks. On the other hand, however, there are highly dynamic urbanization processes which often overtake formal urban planning processes by rising population figures and areal expansion. In the course of these processes, economically-deprived population groups often have no other option than to informally build on high-risk areas. Against these backgrounds, we systematically examine in this study how these risks develop over a 24 years' time period with respect to the city-wide exposure and in particular with respect to different social groups. For this purpose, we use heterogeneous input data from remote sensing, hazard maps and census data. Our case study is the city of Medellín in Colombia. We develop and apply a set of methods integrating the heterogenous data sets to map, quantify and monitor exposure and social vulnerability at a finer spatial resolution than administrative units. Our results document first of all the highly dynamic growth in total population and urban areas. However, our results reveal that the city's expansion is socially unevenly distributed. People of higher vulnerability proxied by informal settlements are found to settle in significantly more areas exposed to landslides. This study proposes a methodological set-up that allows to monitor exposure and social vulnerability over long time spans, allows to bring inequality into the spotlight and provide decision makers with better information to develop socially responsible policies.

1 Introduction

Landslides are one of the most frequent geological hazards in the world (Skrzypczak et al. 2021). Disasters related to landslides are directly associated with loss of lives as well as property, infrastructure and environmental damages. Moreover, urbanization and raising population numbers with, sometimes, a simultaneous lack of urban planning practices have led to informal developments in hazardous hillslopes of urban agglomerations (Mendes et al. 2018; Kurniawan & Krol 2014). Especially, low-income population is forced to settle in those hazard-prone areas (Müller et al. 2020; UN Habitat 2016; UN 2015), increasing the landslide risk through man-made changes like vegetation removal or sewage disposal systems (Mendes et al. 2018; Reichenbach et al. 2014; Glade 2003). According to UN Habitat, in 2016 four out of ten non-permanent houses in development countries were built on areas threatened by natural disasters like landslides; besides, climate change is increasing the occurrence and risk to experience a hazardous landslide event (UN Habitat 2016). Therefore, considering the 1 billion slum residents worldwide (UN 2020), this risk must not be underestimated.

As a consequence, the exposure of physical, social, economic, and environmental assets, known as the elements at risk, is increasing (Kurniawan & Krol 2014; Pellicani et al. 2013; Taubenböck et al. 2008). In this context, risk reduction measures play a very important role in diminishing the impact in case of a landslide, especially since the magnitude of a disaster has been directly related to the vulnerability and exposure of the assets at risk (Carvalho de Assis Dias et al. 2018; Birkmann & Welle 2015). Similarly, the Sendai Framework 2015-2030 for Disaster Risk Reduction by the UN recommends that disaster risk assessment, prevention, mitigation and implementation of response measures are established by analyzing the hazard in all its dimensions (i.e., vulnerability, capacity, exposure, hazard characteristics and environment) (UNISDR 2015).

Landslide risk assessment depends on the complex interplay of the hazard, the exposed elements at risk and their vulnerability (e.g., Birkmann, 2006). The hazard is defined as the probability of a disastrous event happening in a certain period of time, with a particular intensity at a particular location (Unesco, 1973). Indicators such as probability of occurrence, intensity or duration specify the hazard event (Geiß & Taubenböck, 2013). Exposure refers to the elements present in the potentially affected area, such as people, infrastructure or values. Vulnerability refers to the resilience of these elements. This can be, for example, the stability of building structures (Geiß et al., 2015), or the potential to recover from the effects of the natural hazard through economic reserves. With respect to the social component of vulnerability, the vulnerability of economically-deprived communities is generally understood higher due to more precarious conditions of

their assets and livelihoods. Therefore, informal settlements are more impacted by natural disasters like landslides (Hallegatte et al. 2017; Wiesner et al. 2003). In order to look at the big picture and based on their mutual influence, it is suggested to analyze exposure and vulnerability together. To this end, it is also crucial to pay special attention to the social aspect. The same loss is more severe with increasing social vulnerability, which influences the ability of a community to cope, resist and recover from a disaster (Carvalho de Assis Dias et al. 2018; World Bank Group 2017; Vranken et al. 2015). Nevertheless, studies related to risk in urban systems often analyze exposure independently as an individual part of risk assessment. An example is the identification of exposed people and housing through the spatial overlay with hazard susceptibility zones (Geiß et al. 2017). The combination with the social aspect, although only few studies exist here, allows to specify our understanding of risk.

However, the number of studies dealing with landslide exposure and vulnerability simultaneously is limited (Puissant 2014; Hollenstein 2005). The analysis of vulnerability has been predominantly approached from an economic, physical or environmental perspective, focusing on the monetary loss or severity of damage to buildings, infrastructure or environment (e.g., Guillard-Gonçalves et al. 2016; Vega & Hidalgo 2016; Vranken et al. 2015; Galli & Guzzetti 2007). The social aspect in regards to the socio-economic status is almost never investigated, and when considered, social vulnerability is expressed as the number of affected people regardless of their socio-economic status (e.g., Kurniawan & Krol 2014; Puissant et al. 2014; Pellicani et al. 2013; Papathoma-Köhle et al. 2007). To the authors knowledge, only two studies approached vulnerability from the aforementioned social perspective: Carvalho de Assis Dias et al. (2018) calculated the amount of exposed people for three municipalities in the Río de Janeiro State in Brazil, including the population structure as well as the state of sanitary sewage and water supply. Holcombe et al. (2012) investigated the exposure and vulnerability of property in an unplanned community with a high social vulnerability consisting of 20 households in Castries, Saint Lucia.

This shows, not only the definition of vulnerability varies, but also the geographic scale. Most of the studies investigate landslide risk on a macro-scale level, where the study area covers a whole region, generally with the focus to identify and rank the elements at risk to produce risk maps (e.g., Promper et al. 2015; Vranken et al. 2015; Pellicani et al. 2013; Jaiswal et al. 2011). The mesoscale level is mostly used for local planning purposes in cities or municipalities (e.g., Guillard-Gonçalves et al. 2016; Carvalho de Assis Dias et al. 2014). At this level, potential losses and consequences (i.e., physical or economic vulnerability) can already be partially quantified, for example, by clustering assets with similar characteristics (Puissant et al. 2014). Micro-scale level analyses are performed for local areas, quantifying physical, social, environmental and economic vulnerabilities and aiming to implement technical and protective measures (e.g., Singh et al. 2019; Holcombe et al. 2012). Therefore, the amount of data required to conduct such studies is proportional to the detail of the analysis scale (Puissant et al. 2014).

Likewise, time plays an important role in risk assessment (UNISDR 2015) and should not be neglected. On the one hand, the temporal probability of landslide occurrences is based on historical records, and on the other hand, exposed elements and their vulnerability are subject to temporal changes (Van Westen et al. 2006). Few studies analyzed landslide exposure including the development of elements at risk (Promper et al. 2015, Kurniawan & Krol 2014), however, none of these studies considered the temporal change of vulnerability. In this sense, multitemporal risk assessment requires consistent data over time.

Accordingly, Earth Observation (EO) has become more popular in the last decades in the landslide analysis domain as source of data. The advances in the space borne sector make EO techniques increasingly effective for landslide detection, mapping, monitoring and hazard assessment (Casagli et al. 2017). For instance, the detection and mapping of landslides has been conducted by analyzing land cover changes through vegetation indices (e.g. Behling et al. 2014) or machine learning techniques (e.g., Ghorbanzadeh et al. 2019). Besides, remotely sensed data is also used to identify the exposed elements at risks over time (e.g., Promper et al. 2015; Kurniawan & Krol 2014). Particularly, land use and land cover (LULC) information is commonly applied to classify the physical assets like built-up areas (Rahman & Di 2017). Whereas population distribution data, the social assets, can be estimated from official population counts supported by information

derived from remotely sensed data (e.g., Taubenböck & Wurm 2015; Taubenböck et al. 2011). Likewise, the social component of the assets can be retrieved from space, for example, Stark et al. (2020) and Kühnl et al. (2021) identified economically-deprived settlements based on their morphological characteristics with high resolution satellite data.

The population in Medellín, Colombia, is growing fast and often informal, thus more and more people with a high social vulnerability live in the risk-prone hills of the city due to scarce land availability. This fact along with climate change-induced higher occurrences of heavy rainfalls leads to the increase of landslides events (IDEAM-UNAL 2018). Against this background, we conduct in this study a long-term multitemporal, intra-urban and meso-scale landslide exposure and social vulnerability assessment in the city of Medellín. This is accomplished by utilizing multitemporal satellite and census data for three time-steps (1994, 2006, 2018), as well as machine learning algorithms and population disaggregation methods. We quantify the physical assets as the urban structures composed of buildings and infrastructure, and the social assets as the amount of population in those areas, separating between formal and informal settlements to approximate social groups and relate this to vulnerability. This analysis enables us to highlight different aspects of landslide risk assessment. We want to illustrate the evolution of city and population growth throughout time and on this basis investigate whether exposure and the social vulnerability, in absolute and relative terms, has increased over time.

2 Material And Methods

This section introduces the general workflow of the study, the study area, the employed datasets and their processing steps as well as the methodology of the exposure and social vulnerability analysis. Moreover, a conceptual note explains the assumptions taken in the context of this paper.

We developed the workflow shown in Figure 1 for the long-term multitemporal, intra-urban and meso-scale landslide exposure and social vulnerability assessment. First, for the generation of urban masks for three time-steps (1994, 2006 and 2018), we perform land cover (LC) classifications based on Landsat mosaics (a); second, we divide the built-up area of the city into two thematic groups: using the informal settlement layer from Kühnl et al. (2021), we classify informal and formal settlement areas to approximate social groups (b); third, population is estimated at the pixel level using disaggregation methods (c) and specified into population of informal settlements (d). These results (i.e., multitemporal urban masks, informal settlements and population) are combined with the landslide hazard map for the exposure and social vulnerability analysis (e).

Fig. 1 Workflow of the study composed of land cover classifications based on Landsat data in order to conduct multitemporal urban masks (a), multitemporal informal mask calculations based on an informal settlement layer from Kühnl et al. (2021) (b), population disaggregation methods based on census data separating between formal (c) and informal areas (d) as well as the exposure and as social vulnerability analysis using all pre-processed data and a landslide hazard map (e)

2.1 Study area

Our study area, the city of Medellín, is the second largest city in Colombia. It is the capital of the Department of Antioquia as well as of the Metropolitan region of the Aburrá Valley, a political and administrative unit of ten municipalities with a population of 3.5 million (Figure 1b; Garcia Ferrari et al. 2018; Hernandez Palacio 2012).

The municipality of Medellín (Figure 2, white boundary) is composed of urban (Medellín and San Antonio) and rural parts (Figure 2a and c). The area of interest (AOI) in this study refers to the urban, expansion and urbanized areas of Medellín (Figure 2a). Expansion areas are in the process of getting added to the administrative urban areas, but do not yet fully belong to this planning level (Alcaldía des Medellín, 2014 a, b). Urbanized areas are officially rural zones, but we include

them into our AOI since they are characterized by mostly informal urban structures growing in the city's outskirts. This allows the analysis to reflect the built-up conditions beyond administrative boundaries.

Geographically, Medellín is situated in a 14 km north-south expansion in the Aburrá Valley between two mountain ranges of the Andes in the west and in the east, crossed by the Medellín river running from north to south along the valley. The valley itsself has a 10 km maximum width and the height difference between the highest and lowest point is about 1 km (Garcia Ferrari et al., 2018; Hernandez Palacio, 2012). These characteristics lead to a very steep topography of the valley slopes in the east and west with a significant landslide risk (Claghorn & Werthmann 2015).

Socio-economically, the living conditions get worse with distance to the Medellín river and higher up in the mountains. Especially, the landslide and flash-flood prone slopes in the west and east of the city are mainly occupied by informal settlers. Also, a north-south seggregation can be identified. The neighborhoods with low unemployment rates are located in the south-east of the city whereas the contrary is dominant in the north-east and -west (Garcia Ferrari et al., 2018).

Fig. 2 Location of the study area. Urban, expansion and urbanized areas of the Municipality of Medellín within the Aburrá Valley in Colombia. In the background the hillshade of a digital elevation model shows the topography (DEM AMVA: Open data Medellín)

2.2 Data

In this study we relied on long-term multitemporal data; therefore, we used Landsat satellites imagery at a 30-meter resolution to derive land cover (LC) maps, with a special focus on the urban layout. To do so, we created cloud-free Landsat mosaics for three time-steps: 1994, 2006 and 2018. We used the Google Earth Engine platform (Gorelick et al. 2017) for building the cloud-free mosaics and downloading the resulting images. Since the time span is fairly wide, we used the atmospherically corrected surface reflectance datasets from Landsat 5 ETM (L5), Landsat 7 ETM+ (L7), and Landsat 8 OLI/TIRS (L8) sensors. We filtered cloudy pixels by masking low-quality pixels using the *pixel_qa* band. Due to the tropical climate in Medellin, the chances to get cloud free pixels are quite low, and thus, we set long-term periods for the mosaicking to obtain good enough results for each date. Hence, we used imagery from the year 1989 to 1994 to create the 1994 mosaic, images from 2003 to 2006 to create the 2006 mosaic, and from 2013 to 2018 to create the 2018 mosaic. For the LC classification, we selected a subset of spectral bands and calculated additional indices. On top of the visible red, green and blue (RGB), near infrared (NIR) and short-wave infrared (SWIR) bands (bands 1,2,3,4,5,7 in L5 and L7, and bands 2,3,4,5,6,7 in L8), we calculated the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI) and the Normalized Difference Buildings Index (NDBI) as well as their 10th, 25th, 50th, 75th and 90th percentiles. The NDVI gives information about the greenness of vegetation (Rouse et al. 1973), the NDWI indicates water features (positive values) or soil and terrestrial vegetation (negative values; McFeeters 1996) and the NDBI acts as indicator for built-up areas (Zha et al. 2003). As a result, each image mosaic (see Figure 1a) has 24 bands (composed of spectral bands, indices and percentiles). These indices and their percentiles provide additional information for training the LC classification algorithm.

Secondly, to retrieve information on the social vulnerability, we proxied the socio-economic status based on the morphologic characteristics of the living environment and built-up structures. We used an informal settlement mask based on a scene-based Local Climate Zone (LCZ) classification of Medellín, performed with the use of a very high-resolution satellite image from the year 2019 and urban blocks (Kühnl et al. 2021). The *lightweight low-rise* class is an urban structural type within the LCZ schema (Stewart & Oke 2012), which shows typical morphological features of informal settlements like high density, small and low-rise buildings, lightweight construction materials and sparse vegetation. We extracted the *lightweight low-rise* polygons with their centroid in our AOI (Figure 3a and 1b). Figure 3b and c show two examples of the neighborhoods and building types identified as informal. The accuracy of the informal settlement layer has been measured at 86% (Kühnl et al. 2021). For this study, we manually checked and corrected over- and under classifications to improve the informal settlement mask.

Fig. 3 (a) Location of formal and informal settlements in Medellín based on the improved lightweight low-rise built-up. (b) Google Street View image (© Google Street View 2021) of an exemplary housing structure in an informal settlement, and (c) of one of their characteristic slopes. (d) Landslide hazard map from the POT 2014 (*Plan de Ordenamiento Territorial de Medellín).* The map categorizes landslide hazard into very low, low, medium and high. (e) and (f) are visual examples of the high hazardous slopes (own source)

Thirdly, to estimate the amount of population at risk over time we used population data from the official population projections (*Proyecciones de Población 1993-2005 a 2015 de Medellín;* Alcaldía de Medellín 2015) for the years 1994 and 2006 and the Colombian census (*Censo Nacional de Población y Vivienda;* DANE 2018) for the year 2018 (Figure 4). We used these dates since the projections coincide with former census surveys from 1993 and 2005 and the uncertainty in the projection is expected to be lower. Depending on the year, the population data is available in different spatial units (i.e., commune, neighborhood, sector and section levels; Figure 4). Data from 2018 is existing at different spatial levels, therefore we use the sector level to disaggregate the population to the pixel level and the section level, with higher detail, to validate the result.

Fig. 4 Population density for the years 1994, 2006 and 2018 as well as the different spatial levels of availability. In 2018 the sector level is used to disaggregate the population to the pixel level and the section level to validate the result

Finally, we use an open source landslide hazard map for the whole municipality in vector format provided by the land use plan from Medellín (*Plan de Ordenamiento Territorial de Medellín*; POT 2014). The hazard map was created by combining all risk-related information available (Figure 3d). It relies on hazard maps from the POT 2006 and from the National University of Colombia from 2009, as well as mass movement inventories by the Administrative Department of Disaster Management (DAGRD), morphodynamic process maps and all geotechnical and slope stability studies carried out for the municipality of Medellín since 2006. It categorizes landslide hazard into very low, low, medium and high susceptibility zones (Alcaldía de Medellín 2014c). Hence, it is the best hazard map that is available at the city level, since it includes multi-source data and it was created by local experts.

2.3 Conceptual note

Landslide estimation, exposure, and population vulnerability is a multifaceted and highly complex problem. This requires highly accurate, diverse and, in our approach, multi-temporal data sets. Since these are not available in the necessary spatial and thematic depth, nor are they consistent, complete, and given over time, we must make some conceptual assumptions based on the available data.

First, we analyze landslide risk using a hazard map from 2014 assuming that the hazard areas keep constant over time. In this study, we consider two risk levels, risk areas when the hazard of a landslide in the POT is medium or high, and non-risk areas when the hazard is low or very low.

Secondly, with respect to exposure and the capabilities of remotely sensed data available since the 1990s, we make the following assumptions: pixels classified as urban that are categorized as ‘formal’ in 2018, are per definition also ‘formal’ in previous time steps if they were identified as urban in 1994 and 2006, otherwise they are non-urban pixels. Similarly, urban pixels categorized as ‘informal’ in 2018 are also informal in previous time steps, when the pixels are urban. Therefore, formal development does not change to informal over the time, since this transition is very unlikely. At the same time, we disregard informal settlement upgrade, since we do not have data on informality over time as our informal settlement mask is from 2019.

Thirdly, socio-economic indicators allowing to approach the social sphere in a multi-temporal manner are inexistent, especially on such a high spatial granularity. Thus, we tackle social vulnerability using morphological parameters as proxy.

We assume that people living in informal settlements are more vulnerable. We assume their economic capabilities reduce the chances of recovering after a disaster. Besides, the definition of morphologic informality differs slightly to informal settlements from a socioeconomic perspective; however, as Kühnl et al. (2021) show, it is a fairly accurate proxy of precariousness and informality.

2.4 Land cover classification

Our focus for the analysis of exposure towards landslide hazard are settlement areas. In this regard, we use Landsat mosaics for the three time steps to classify Medellín into basic land covers (urban, open vegetation, forest, bare soil). We apply a supervised pixel-based classification method using the Random Forest (RF) machine learning algorithm (Breiman 2001). In preparation, we manually create ground truth sample data. This is done independently for the three time steps by visual interpretation with the help of historical and very high resolution images from Google Earth©. The sample data are polygons covering areas of homogeneous land cover, which are equally split into spatially independent training and testing polygons (50/50). The image pixels for the training and testing datasets are subsequently randomly selected from the respective polygons. We use the training dataset to build a RF model for each year that is validated against the testing dataset of the respective year. Using spatially independent pixels in the validation, we thus avoid spatial correlation between classification and evaluation. Table 1 shows the accuracy of the RF classifications for the different thematic classes and the overall accuracy for each time step.

Table 1 Land cover classification accuracy metrics per year

	1994		**2006**		**2018**	
Land Cover	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**	**Producer's Accuracy**	**User's Accuracy**	**Producer's Accuracy**
Urban	**96.40**	**99.60**	**92.39**	**99.43**	**89.97**	**99.79**
Open vegetation	86.82	99.56	98.28	97.22	99.75	99.86
Forest	95.28	83.66	96.75	98.63	83.59	93.32
Bare soil	89.17	48.43	97.13	70.33	75.94	32.30
Overall Accuracy (OA)	**90.85**		**96.45**		**93.61**	

We use the urban land covers to build the urban masks for 1994, 2006 and 2018. In order to diminish temporal fluctuation in the data, we apply a change trajectory analysis similar to the ones applied by Taubenböck et al. 2012. This approach solves errors from the classifier when it is unable to correctly detect urban areas over time. The assumption is that urban pixels cannot change to non-urban pixels. Therefore, several rules where established following the majority rule. For example, if a pixel is urban in 1994 and 2018, but it is non-urban in 2006, we change the status to urban pixel in 2006 to keep consistency. Similarly, if a pixel is urban in 1994 and 2006, it should be also urban in 2018. However, if a pixel is urban in 1994, but it is non-urban in 2006 and 2018, the state of 1994 is changed to non-urban.

2.5 Identification of informal settlements

In order to produce the multitemporal informal settlement masks, we rely on the urban block level vector dataset with informal settlements in 2019 (see section 2.2).We applied morphological filters to fill the gaps between urban blocks, such as roads, to obtain a continuous surface, and then it is transformed to raster format using the majority rule with a spatial resolution of 30 m. Finally, the informal settlement mask 2019 is spatially overlapped with the multitemporal urban masks,

and matching pixels are considered informal settlements. As a result, we have three consistent informal settlement masks for the years 1994, 2006 and 2018.

2.6 Disaggregation of population to the pixel level

We estimate population at the pixel level using a top-down binary dasymetric disaggregation method originally developed by Wright (1936). This method consists of redistributing population counts from larger spatial units into smaller spatial units (Reed et al. 2018; Stevenson et al. 2015; Wu et al. 2005).

In this study, we use administrative boundaries as source zones where population counts are known (i.e., communes, neighborhoods and sectors for 1993, 2006 and 2018 respectively) and urban pixels, from the urban masks 1994, 2006 and 2018, as target zones. In a first step, we calculate for each source zone the population density by dividing the population count by the urban area. Then, the population at target zones (pixels) is estimated by multiplying the area of the pixel by the previously calculated population density from the source zone where the pixel is located. For those remaining target zones outside of the boundary of a source zone (a few urban pixels in the west and east of Medellín are not covered by the administrative units), we use the population density of the closest urban pixel. Once we have the population at the pixel level for 2018, we extract the pixels covered by the informal settlement mask from the same year to obtain the informal settlement population at pixel level. Lastly, we validate the disaggregation method with official population counts at a higher spatial detail. We use the population counts at section level from the year 2018 as validation zones to evaluate the performance of the disaggregation method (Grippa et al. 2019). Therefore, the population at pixel level is summarized using the boundaries of the validation zones, and subsequently this sum is compared to the population counts from the validation zones to measure the root mean square error (RMSE) and the RMSE divided by the mean validation zone population count (%RMSE).

The same process is then applied to the remaining time-steps 1994 and 2006 using the respective commune and neighborhood levels.

2.7 Quantifying exposure and social vulnerability to landslides

To quantify the development of exposure and social vulnerability in Medellín over time, we spatially overlapped the multitemporal assets and people (urban and informal settlement masks and pixel population, Figure 1 a, b, c and d) with the landslide hazard map (Figure 1e).

In order to estimate how much urban area and population are at risk, we first intersected the multitemporal urban masks with the hazard map to summarize the total urban area for each hazard level and year. For those pixels crossed by the boundary of a hazard level, only the proportional area of the pixel covered is summarized. Secondly, and similarly, the multitemporal population at pixel level is intersected with the hazard map and the total population is summarized. Likewise, when a pixel is crossed by the boundary only the proportional population of the pixel is summarized for each hazard level and year, and this is calculated using the population density of the pixel and the proportional area of the pixel covered. Finally, this process is replicated with the multitemporal informal settlement masks as well as the informal population at pixel level.

The results of these spatial analyses enabled the calculation of the amount of exposed and socially vulnerable areas and their population based on their spatial localization for the years 1994, 2006 and 2018 by separating into no-risk and risk areas. Since the landslide hazard map consists of four levels (very low, low, medium and high; see section 2.2), we calculate the results based on this division, but focus on risk (medium and high landslide hazard) and no-risk (very low and low landslide hazard) areas in the interpretation. We also calculated the ratio between formal and informal settlements

over time, using both, the area and population. In addition, we monitored the development of urban areas and population with respect to their risk to answer the question whether exposure and social vulnerability have relatively increased over time in Medellín.

3 Results: Spatial And Statistical Development Of Landslide Risk Over Time

In 1994 we find 4% (2 km²) of the settlement area**s** (51 km²) in Medellín in landslide prone areas (Table 2: Urban settlements). In the 12 years up to 2006, the settlement areas expanded to 61 km². In this context, settlement areas have been increasingly built into landslide prone areas in the east and west of the city (see Figure 5a): they grew to a spatial share of 7% (4 km²). And until 2018, the city expanded to 77 km², with the share in landslide prone areas steadily growing to 9% (7 km²). Thus, considering the spatial location of the city growth from 1994 to 2018 (see Figure 5a and b), it is clear that urbanization in Medellín occurs disproportionately on these exposed slopes, predominantly in the east and west of the city. Landslide risk is increasing.

Table 2 Development of the urban layout within the study area from 1994 to 2018. Urban settlements include both formal and informal settlements. Percentage values are rounded up

Area (km2)		1994				2006				2018			
Risk category	Hazard class	Urban settlements		Informal settlements		Urban settlements		Informal settlements		Urban settlements		Informal settlements	
no risk	very low	15.58	30%	0.24	2%	17.06	28%	0.24	2%	19.06	25%	0.25	1%
	low	33.51	65%	10.10	82%	39.56	65%	12.17	75%	50.97	67%	14.39	72%
	total	**49.09**	**96%**	**10.33**	**84%**	**56.62**	**93%**	**12.41**	**77%**	**70.03**	**91%**	**14.64**	**74%**
at risk	medium	1.52	3%	1.33	11%	2.61	4%	2.26	14%	3.96	5%	3.03	15%
	high	0.70	1%	0.65	5%	1.58	3%	1.45	9%	2.59	3%	2.20	11%
	total	**2.23**	**4%**	**1.98**	**16%**	**4.19**	**7%**	**3.71**	**23%**	**6.54**	**9%**	**5.23**	**26%**
Total		**51.32**	**100%**	**12.31**	**100%**	**60.81**	**100%**	**16.12**	**100%**	**76.58**	**100%**	**19.86**	**100%**

Fig. 5 (a) Urban settlement masks 1994 – 2018 extracted from the Land Cover (LC) classifications implemented with Landsat data. The urban settlements include formal and informal areas of the city. (b) Informal urban settlement masks 1994 – 2018 calculated based on the informal settlement mask 2019 (Kühnl et al. 2021) and the urban settlement masks 1994-2018 based on the LC classifications. (c) Population estimation 2018 per pixel in the extent of the urban settlement mask 2018 through disaggregation and extrapolation based on the census 2018. Since the estimates are based on official data, their administrative boundaries are still visible to a certain extent. (d) Spatial localization of at risk areas in Medellín for the time-step 2018. The areas at risk are separated according to their social vulnerability status proxied by formality and informality

Focusing on the informal settlements, proxying the social group of higher vulnerability, we find for the year 1994 that 24% (12km²) of the whole urban layout was classified as informal (Table 2: Informal Settlements). Of these informal areas, 16% (2km²) were located in risk areas at that time. It is interesting to see, how by 2006, the share of informal areas grows to 26% (16km²) and that the share at locations of risk is also increasing to 23% (4km²). Until 2018 the expansion of informal areas continues, however at slower rates to around 20km² (~26% of the urban layout). The informal areas at risk remain at around a quarter (26%; 5km²).

In this sense, a large amount of settlements areas at risk in 1994 was simultaneously classified as informal (1.98 out of 2.23 km²). This means that 89% of the landslide prone elements were more socially vulnerable areas. Similar results were calculated for the years 2006 (3.71 out of 4.19 km², 89%) and 2018 (5.23 out of 6.54 km², 80%). However, even though the total settlement areas at risk grew from 1994 until 2018 (from 2.23 km² to 6.54 km²) and also the informal settlements at risk increased (from 1.98 km² to 5.23 km²), the relative share of informal settlements at risk has become smaller (from 89%

to 80%). This indicates that formal settlements with lower social vulnerability were also built in landslide prone areas over the last 24 years. Figure 5d separates risk areas into formal and informal settlements for 2018, illustrating this finding.

Regarding the population the RMSE was measured in 695 people with a %RMSE of 30%. Figure 5c shows the result of the pixel-level population disaggregation for the year 2018. Results for the years 1994 and 2006 can be found in the appendix. It can be seen that especially in the north-eastern and the western slopes, where informal settlements are predominantly located, the population density is high. In contrast, lower densities are found in the heart of the city and along the Medellín river. In 1994 Medellín was inhabited by around 1.7 million people. Out of them, 6% (109,000 people) were exposed to landslides (Table 3: Urban settlements). Until 2006 the population grew to 2.2 million, with 10% (around 217,000 people) now located in areas prone to landslides. This means that the total number of people living in areas at risk doubled in 12 years. Afterwards, population growth slowed down reaching 2.3 million people by 2018. Similarly, the share of people in risk areas decreased compared to the period from 1994 to 2006. In 2018, 13% of the population were living in landslide prone sites (around 290,000 people).

Table 3 Development of the population structure within the study area from 1994 to 2018. The percentages in the table are rounded. Percentage values are rounded up

Population		1994				2006				2018			
Risk category	**Hazard class**	**Urban settlements**		**Informal settlements**		**Urban settlements**		**Informal settlements**		**Urban settlements**		**Informal settlements**	
no risk	very low	300,574	17%	8,711	1%	287,650	13%	23,553	3%	234,337	10%	12,383	1%
	low	1,331,178	76%	501,827	82%	1,663,515	77%	656,839	75%	1,742,139	77%	671,131	73%
	total	**1,631,752**	**94%**	**510,538**	**84%**	**1,951,165**	**90%**	**680,392**	**78%**	**1,976,476**	**87%**	**683,514**	**74%**
at risk	medium	74,750	4%	66,421	11%	133,735	6%	117,243	13%	173,980	8%	137,113	15%
	high	34,366	2%	32,168	5%	82,988	4%	76,269	9%	115,684	5%	98,860	11%
	total	**109,116**	**6%**	**98,589**	**16%**	**216,723**	**10%**	**193,512**	**22%**	**289,664**	**13%**	**235,973**	**26%**
Total		**1,740,868**	**100%**	**609,127**	**100%**	**2,167,888**	**100%**	**873,904**	**100%**	**2,266,140**	**100%**	**919,488**	**100%**

When we consider the vulnerability of the population by our proxy, we find that in 1994, 35% of the total population was living in informal settlements, with a share of 16% (around 99,000 people) located simultaneously in landslide prone areas (5.6% of the total population). In the years up to 2006, the share of people living in informal settlements grew to 40% of the total population. Regarding the total number of people exposed to landslide risk and living in informal settlements, the value doubled (around 194,000 people, 22%), which represents 9% of the total population in 2006. Similar to the total settlement and population growth rates between 2006 and 2018, population growth in informal settlements also slowed down until 2018. In this case, around 41% of the total population were located in informal areas in 2018, and 26% of them (around 236,000 people) were located in risk areas at the same time (10.4% of the total population). Therefore, the increase in the share of people at risk is coupled with an increase in the number of socially vulnerable people. However, over the 24 years period, there has been a decrease in the relative share of exposed people living in informal settlements at the same time (1994: 90%, 2006: 89%, 2018: 82%), despite the increase in absolute figures. This indicates that formal settlements are also being developed in landslide prone slopes.

4 Discussion

Increasingly frequent landslides due to climate change and uncontrolled urbanization are the cause of huge human and economic losses worldwide. Multi-source data from Earth Observation in combination with hazards maps or census data has the capability to provide key information for supporting risk management. Objective, accurate, up-to-date and frequent data can be produced on several scales. However, multitemporal risk assessment studies that tackle exposure and vulnerability of people and assets at the same time, especially from a social perspective, are still limited or even nonexistent. With this study, we show an approach that can close this gap: we performed a long-term multitemporal

analysis on the evolution of landslide exposure and social vulnerability for a large, complex and fast-growing urban area, the city of Medellín, Colombia.

First, because remote sensing data with resolutions in the 1-meter range did not emerge until the early 2000s, a long-term study since the 1990s requires lower resolution data. The use of medium resolution Landsat images and machine learning algorithms allowed us to produce this long-term LC information with fairly good quality (overall accuracies above 90%) and resolution for a city-wide analysis. And still, Landsat data is not suitable for detailed intra-urban studies. Alternative open satellite imagery solutions such as Sentinel-2 or PlanetScope can overcome this problem. However, only in exchange of a shorter temporal resolutions. The LC classifications are still very reliable providing a good basis for the urban mask extraction for three time steps, proxying the elements that may be exposed to landslide hazards. The results were consistent over time and minor gaps were solved using the temporal series. With this approach it becomes possible to determine the urban development over time, spatially and quantitatively: We quantified that in the last 24 years Medellín grew by 50% of its total area. The spatial analysis with the hazard zoning map showed that urban areas exposed to medium and high landslide risks have tripled in this period. Medellín had 4% of the urban areas in exposed slopes in 1994 and this value has increased to 9% in 2018. The average growth rate of exposed areas in the city is 0.2 km^2/year, indicating that indeed the city is growing towards hazardous areas.

Secondly, regarding the social component of risk assessment, it is widely understood that a disaster affects differently depending on who experiences it. The same loss is more severe for low-income people since they have less resources to recover. However, such data sets on socio-economic status or the like are often outdated or even inexistent, especially at the high spatial resolution applied in this study. Here, we assumed that people living in informal settlements have a lower socio-economic status than their pairs living in formal settlements, and thus they are more vulnerable. This allowed us to proxy vulnerability of social groups based on the morphology of the built-up structures. We are aware that this approach can only spatially proxy a social group and it does not do justice to the complexity of social complexity in reality. But, as Wurm and Taubenböck (2018) have shown, building structures of this type are certainly a legitimate proxy when other data are not available. Using this conceptualization, we produced informal settlement masks for the three time steps. In our setting, it was due to data limitation impossible to consider informal settlement upgrade over time and we also assumed that formal settlements do not change to informal over time. We quantified that the ratio between formal and informal settlements is quite constant in the last 24 years, one quarter of the urban settlements are in precarious conditions in Medellín. This means that informal settlements are growing at a similar trend as the overall growth of the city. However, when we measured the share of informal settlements that are exposed to landslide hazards, we found an increase from 16% to 26% over the monitoring period compared to an increase from 1% to 2% for formal areas. This confirms that informal settlements are in comparison to formal settlements more exposed to landslide hazards. What is particularly interesting is that more than 89% of the exposed areas in the city were informal settlements in 1994, and this was measured in 80% in 2018, indicating that formal settlements are being established on exposed slopes more often than before.

Thirdly, for the assessment of population density, we produced multitemporal pixel-level population maps by means of urban masks and official population counts. We validated the disaggregation approach using population data on two spatial levels in 2018: we measured an error of 30% in the mean population at section level, which is lower than in other studies (e.g., Grippa et al., 2019; Stevens et al. 2015). This shows that this approach is very well able to estimate the population at a very high resolution with high accuracies. This is crucial because landslides are often small-scale, local events and therefore estimates on an administrative level are spatially unsuitable. The population maps were estimated both, for the entire city and particularly for the informal settlements. We found that in general population has grown immensely since 1994, in total a 30% percent, which is more than half a million inhabitants. In the first place, we measured a sharp increase in the exposed population between 1994 and 2018 from 6% to 13%. Figures of people exposed have doubled with more than 180 thousand new people living in risk areas in 2018. This result indicates that population growth is taking place in hazardous areas. This is probably due to uncontrolled, informal urbanization and lack of available land

forcing people into unsuitable, exposed areas. In the second place, we were able to estimate the share of people living in informal settlements. In 1994, 35% of the population was living in informal settlements, and this amount raised to 41% in 2018, which is around 300 thousand more people living in precarious settlements. It shows that informal urban growth exceeds formal urban growth in Medellin. This 41% is higher compared to the share of informal settlement areas (26%) because these tend to be more densely populated. What is more, 6% of the total population in Medellín was exposed to landslides and at the same time had a high social vulnerability in 1994, which increased to 10% in 2018. In absolute terms this is an increase of 137 thousand people in 24 years. Focusing on the exposed population, this study documents how unequal and different risks are for different people, and people living on informal settlements are more exposed to risks. One out of ten people in Medellin lived in informal settlements and at the same time were exposed to landslide risks in 2018. However, the share of informality in exposed populations decreased from 90% in 1994 to 82% in 2018. This result is in line with the areal analysis, showing that less vulnerable population are also settling in exposed areas of the city.

In this sense, we have seen that the combination of EO data with other data sets has a huge capacity to improve knowledge on natural hazard risks of many urban dwellers. Our results are a reliable city-wide estimation of exposed locations, urban structures, people and social groups. We are aware that these assessments are influenced by the spatial resolution of the urban masks, or misclassifications and errors in the population estimation. While due to the dynamics of the urbanization process and data and methodological issues, one might take the absolute numbers cautiously. However, we expect our relative results to be a realistic picture that is consistent in itself. With it, we provide an approach for a comprehensive picture of environmental, economic and social risks as basis for informed decision-making leaving no one behind. An extension of interdisciplinary approaches, e.g., with demographers, landslide modelers, structural engineers, among others promises great potential for further development. In the domain of open EO data and techniques our approach was developed to increase the potential transferability to other geographical regions in the world. This is especially interesting as we showed that the results from the exposure and vulnerability analyses based on the area and population are quite similar and show similar trends. This means that the methods based on urban areas over time could be replicated in areas where no population data is available to obtain good estimations of populations at risk.

5 Conclusion

In this study, we demonstrated how a long-term analysis of a city's landslide risk can be mapped and quantified with high accuracy from the combination of remote sensing data, hazard maps, and census data. We documented how the total population as well as the total urban area increased significantly from 1994 until 2018 in Medellín, Colombia. Formal as well as informal areas were partly built in areas of landslide risk. It was found striking that growth, however, of informal settlements proxying the social group of higher vulnerability, had a significantly higher share in landslide prone areas. It was observed that the total amount of people at risk and living in more vulnerable conditions at the same time more than doubled from 1994 until 2018. This shows how inequality can be mapped and measured with these heterogeneous data. It is a way to bring this inequality into the spotlight and provide decision makers with better information to develop socially responsible policies.

Declarations

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Figures

Figure 1

Workflow of the study composed of land cover classifications based on Landsat data in order to conduct multitemporal urban masks (a), multitemporal informal mask calculations based on an informal settlement layer from Kühnl et al. (2021) (b), population disaggregation methods based on census data separating between formal (c) and informal areas (d) as well as the exposure and as social vulnerability analysis using all pre-processed data and a landslide hazard map (e)

Figure 2

Location of the study area. Urban, expansion and urbanized areas of the Municipality of Medellín within the Aburrá Valley in Colombia. In the background the hillshade of a digital elevation model shows the topography (DEM AMVA: Open data Medellín)

Figure 3

(a) Location of formal and informal settlements in Medellín based on the improved lightweight low-rise built-up. (b) Google Street View image (© Google Street View 2021) of an exemplary housing structure in an informal settlement, and (c) of one of their characteristic slopes. (d) Landslide hazard map from the POT 2014 (*Plan de Ordenamiento Territorial de Medellín).* The map categorizes landslide hazard into very low, low, medium and high. (e) and (f) are visual examples of the high hazardous slopes (own source)

Figure 4

Population density for the years 1994, 2006 and 2018 as well as the different spatial levels of availability. In 2018 the sector level is used to disaggregate the population to the pixel level and the section level to validate the result

Figure 5

(a) Urban settlement masks 1994 – 2018 extracted from the Land Cover (LC) classifications implemented with Landsat data. The urban settlements include formal and informal areas of the city. (b) Informal urban settlement masks 1994 – 2018 calculated based on the informal settlement mask 2019 (Kühnl et al. 2021) and the urban settlement masks 1994-2018 based on the LC classifications. (c) Population estimation 2018 per pixel in the extent of the urban settlement mask 2018 through disaggregation and extrapolation based on the census 2018. Since the estimates are based on official data, their administrative boundaries are still visible to a certain extent. (d) Spatial localization of at risk areas in Medellín for the time-step 2018. The areas at risk are separated according to their social vulnerability status proxied by formality and informality

Supplementary Files

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- Fig.6.png