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Shallow landslide prediction and analysis with risk assessment using a spatial model in the coastal region in the state of São Paulo, Brazil

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regation, accumulation of capital in dangerous areas, and global changes (Winchester and Szalachman, 2009). Such factors have assumed (1) that developing countries and the poorest are those who will experience the highest number of fatal casualties and disasters, (2) the dangerous areas (hazard zones) focus on cities in port areas and river plains (areas that facilitate trade and the sale of products), (3) the technological advancement of communications, where the registry, storage and transmission of disaster data can lead to a higher count of events in relation to previous periods, (4) and global changes, including the change of climate dynamics and the increase in number of storms in the last decades (Anbalagan, 1992; Kobiyama et al., 2006; Marcelino et al., 2006).

Several studies have focused on evaluating the causes and mechanisms of inducing mass movements on the slopes and where they can occur based on a set of environmental characteristics, as well as their intensification in the last decades due to two main factors: the growing awareness of the economic importance of such disasters and increasing pressure from development and urbanization on the environment (Varnes et al., 1984; Aleotti and Chowdhury, 1999; Carrara et al., 1995; Guzzetti et al., 2005; Chung and Fabbri, 2005).

However, mapping and prediction of landslides probability are not simple tasks, because they depend on a very complex knowledge of mass movements on the slopes as well as the factors that control them. The reliability of landslide susceptibility maps depends mainly on the quantity and quality of available data, the scale of work and the selection of the appropriate methodology of analysis and modeling (Ayalew and Yamagishi, 2005). A map of slope instability should provide information about the spatial distribution, type, volume, speed and distance achieved by mass movements in a given area in a given period of time (Hartlen and Viberg, 1988; Cascini et al., 2013).

The mapping of the susceptible landslide areas in urban areas then becomes a work of the utmost importance, because, in particular, of the relationship of the landslides to losses (human or materials), resulting in a more complex analysis. Some sites are densely populated areas and the assessed landslide damages are highly significant.

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The input data for this analysis include environmental factors, triggering factors, historic landslide occurrences and elements at risk. Historical information about occurrences of landslides is the most important, since it is related with the frequency of the phenomena, types, volumes and the damage that was caused, but it is not always available (Sassa et al., 2004; van Westen et al., 2006).

The purposes of the studies involving landslides prediction and assessments are to support and promote public policies that use such information on disaster mitigation, essentially exposing the main causal factors in relation to possible anthropogenic interference also for the development of the phenomenon. Particularly in Brazil, in 2011 the Brazilian Centre for Monitoring and Warnings of Natural Disasters (CEMADEN) was created, whose goals are to develop, test and implement a system for predicting the occurrence of natural disasters in susceptible areas of the whole country; to identify vulnerabilities in the use and occupation of land; and to do acts raising awareness and consequently raise readiness of the population at risk, leading to early and effective actions of prevention and harm reduction (<http://www.cemaden.gov.br/>).

One of the regions of Brazil that requires disaster risk assessments involving landslides is the coastal plain in the state of São Paulo, near the Serra do Mar, which is a mountain chain of more than 1000 m above sea level. Such location accompanied by population growth, lack of urban planning and property speculation are some triggers of natural disasters. This region is an important tourist center and has one of the important ports of the country, in addition to experience with frequent natural disasters during the summer rains. So, the objective of this study was to evaluate the landslide susceptibility (specifically for shallow translational landslides, induced and natural) in four coastal municipalities in the state of São Paulo, based on a methodology using a free geographic information system and a free database, aiming at landslide susceptibility mapping, which can provide a useful and reliable tool for natural disaster management. Additionally, information on human occupation was integrated with landslide susceptible areas to indicate possible risk areas, which was validated by comparing the results with risk sectors previously mapped by the Brazilian Geological Survey.

2 Study area

Located on the coast of São Paulo State, the Serra do Mar region presents a set of rugged mountains, becoming a region of strategic importance for the development of the country and the state and national economy, including ports, roads, pipelines, and important tourist centers. The historical recurrence of phenomena associated with landsliding on the slopes of the Serra do Mar has often resulted in the loss of human lives and significant damage to the economy, society and environment (Almeida and Carneiro, 1998). Four municipalities in this region were chosen for a preliminary analysis since they have a natural disaster history involving landslides and, also, have great economic importance, mainly due to their port facilities, industrial centers and local tourism. They are Santos, Ubatuba, Cubatão and Caraguatatuba (Fig. 1).

Table 1 characterizes the four municipalities evaluated in this study. They occupy an area of approximately 1600 km². Santos and Caraguatatuba stand out for HDI-M (Municipal Human Development Index) values considered too high; Cubatão and Ubatuba were classified as HDI-M high, reaffirming the importance of these municipalities in Brazil.

Practically in every rainy season (November–April) there are isolated occurrences of landslides in the region. Although Fig. 2 represents the monthly distribution of rainfall, the extreme meteorological events that trigger landslides usually occur between January and mid-March, and that does not appear necessarily in climatological normals.

According to IPMet (2013), these municipalities have 21 registered landslide events in the last 20 yr (1993–2013), with 2182 victims (homeless and displaced persons) and 12 deaths, as shown in Table 2. However, there are also records of great landslide disasters before this period and those must be highlighted. For example, in the municipality of Santos, on 10 March 1928, there were landslides in large part on the slopes of Mont Serrate that buried many homes and several outbuildings of the Holy House of Mercy and resulted in 80 deaths (Instituto Geológico, 2009); in 1946 there was a landslide with 56 deaths; and on 24 March 1990 there was a landslide with 2 fatal ca-

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sualties and 174 homeless. In the city of Cubatão, on 6 February 1994 the Presidente Bernardes Oil Refinery was partially buried by debris flow without victims, but with damage of USD 44 million (Cruz et al., 1998; Massad et al., 2004). In the municipality of Caraguatatuba, on 18 March 1967 the city was the target of an extreme rainfall event (576 mm in 48 h) which triggered hundreds of landslides, resulting in 120 people killed and 400 houses destroyed (Kanji et al., 2003).

During the second half of the last century, the regular areas that relied on the local infrastructure were practically exhausted due to the great population growth and property speculation. These cities have some legal restrictions about the verticalization process, which has led the urban sprawl to migrate toward areas close to the slopes and hills (Fig. 3). This feature, linked to property speculation, favors the illegal occupation in conservation areas and/or in risk areas.

3 Methodology

Figure 4 summarizes schematically the data and the methodology used in the present study. The software SPRING, a free GIS (geographic information system) with image processing functions, spatial analysis, numerical modeling of land and spatial databases query, was used. The download is available at <http://www.dpi.inpe.br/spring/portugues/download.php>. The used satellite images (Resourcesat and others) are also distributed for free by the National Institute for Space Research – INPE (<http://www.dgi.inpe.br/CDSR/>).

The land use and land cover map was obtained based on images of the LISS (Linear Imaging Self-Scanner) III sensor, on board in Resourcesat satellite, for the 2012 year, which are also provided by INPE. The supervised classification and graphic edition for the correction of the commission and omission errors was utilized. The final map, including agriculture, urban area, *Eucalyptus*, forest, mangrove, pasture, “restinga” and bare soil classes was generated, in which the weights assigned to each land use class depend on the type of vegetation coverage. As highlighted by Atkinson and Massari

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(1998), several factors may influence the landslide susceptibility (enhancing or mitigating) – such as presence and type of vegetation, vertical and horizontal curvature, slope, soil and geology – and must be evaluated.

The topography was considered by using the database for slope and horizontal and vertical curvatures, provided by TOPODATA project (Valeriano, 2005) and available at <http://www.dsr.inpe.br/topodata>, with 30 m spatial resolution, which is a product of SRTM (Shuttle Radar Topography Mission). The vertical curvature corresponds to the terrain's concave/convex character. The horizontal curvature refers to the divergent/convergent character of water/matter flows on the ground when analyzed on a horizontal projection. Several geomorphological studies have called attention to the role played by the concave portions of the relief (hollows) on the convergence of water streams, both surface and sub-surface, favoring the development of soil saturation conditions and ultimately the generation of landslides on the slopes (Tsukamoto et al., 1982; Reneau et al., 1984; Crozier and Vaughan, 1990; Dietrich and Dunne, 1993; Fernandes et al., 1994, 2004). Thus, convergent (horizontal curvature) and concave (vertical curvature) relief forms received the highest weights in susceptibility analysis (Neuhauser and Terhorst, 2007; Brenning, 2005; Talebi et al., 2008). For the slope map, the steeper slopes are more disposed to landslides, and this is one of the key factors in inducing slope instability. As the slope angle increases, shear stress on soil or other unconsolidated material generally increases as well. Gentle slopes are expected to have a low frequency of landslides because of generally lower shear stress associated with low gradients (Anbalagan, 1992). The slope classes were given weights in descending order. Each class, in each map, was attributed a weight in relation to susceptibility, as shown in the Table 3.

The geological data (1 : 750 000) were obtained from the Brazilian Geological Survey, available on the website of the CPRM (Research and Mineral Resources Company, <http://www.cprm.gov.br/>). The relationships of different types of rock with landslides were considered as the basis for the weighting. Igneous rocks had the lowest land-

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slide probabilities, while intermediate metamorphic and sedimentary rocks had a lower resistance to weathering, i.e., a greater landslide probability (Dai et al., 2001).

A soil map at a 1:500 000 scale was acquired from the IAC (Agronomic Institute of Campinas), produced by Oliveira et al. (1999). For the different soil classes, the weights were based on the principle that soils with a higher amount of sand and/or that are shallow and non-cohesive tend to be more susceptible than soils with more clay and/or that are deep, generally with high cohesion. The susceptibility values for all classes present in the different themes addressed are presented in Table 3.

Figure 5 presents some features of the study area. The main geological units in the study area are the migmatite/gneiss and biotite, the first with a low degree of susceptibility to landslides (see Table 3). The Haplic Cambisols are the most common, coming to occupy 80% of the study area, with high degree of susceptibility. Analyzing the horizontal curvature of the terrain, the classes are distributed evenly, unlike vertical curvature for which extreme classes are those that occur more (very convex and concave). The class very concave occupies approximately 50% of the study area and is the one that has the greatest degree of susceptibility. The slope of the terrain appears in about 70% of the area to fall into strongly wavy and hilly classes, also the most susceptible to landslides. The predominant land cover and use is “forest”, occupying 75% of the total area, this mostly on the slopes and tops of the hills. After the forested area in presence on the coastal plain was the urban area (8% of the total area), getting close to the mountainous region of the Serra do Mar.

The six themes were combined to generate a final susceptibility map using the fuzzy gamma operator. The fuzzy operator was introduced by Zadeh (1965) and allows a more realistic treatment of the imprecise and subjective data that are part of analyses of physical environments. The fuzzy theory employs the idea of member functions and expresses the degree of membership with respect to some attribute, in this case

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landslide susceptibility. The fuzzy gamma operator is presented in Eq. (1).

$$\mu_{\text{combination}} = \left(1 - \prod_{i=1}^n \mu_i (1 - \mu_i) \right)^\gamma \cdot \left(\prod_{i=1}^n \mu_i \right)^{1-\gamma}, \quad (1)$$

where γ (gamma) is a parameter within the range (0,1). Susceptibility maps were generated with values of gamma equal to 0.8, which was divided into five susceptibility classes equidistant, with gaps equal to 0.20, from 0 to 1.0. Finally, aiming at a better visualization of the results, a “mask” was created to filter the mapping areas with slopes less than 10 %. This step is based on the regional historical data and consulted literature that indicate there is no occurrences of landslides for these cases.

3.1 Validation of results

The application of techniques for mapping susceptibility to landslides requires the validation step in order to evaluate the results, which is generally done by comparing it with some prior real data, such as images, hazard reports and, mainly, location of scars (Begueria, 2006; Huabin et al., 2005). As the methodological proposal of this study includes techniques and data obtained from the public domain, the validation of the results of the fuzzy gamma technique was not made through landslide-scar maps, as is commonly done in many works of literature (Vieira et al., 2010; Dymond et al., 2006; Ercanoglu and Gokceoglu, 2004; Vahidnia et al., 2010), because there is no available data for this purpose.

In this context, a base of spatial data of risk sector mapping was used in the validation step, which was done by CPRM and provided by CEMADEN. CEMADEN uses these risk sectors as the basis for decision-making in the possible warnings of landslide disasters, through monitoring meteorological extreme events for some selected municipalities. The risk sectors correspond to spatial polygons delimited by experts (geologists, civil engineers, geotechnical, and others), which include urban areas where landslides present a risk to the population. The CPRM survey considered the following proce-

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dures: in situ recognition; identification of soil subsidence and scars; estimation of the reach of the mass movement, the sketch of the situation, and the risk level for the residences threatened; and, finally, design of the risk area sectors in the GIS environment and input of their metadata.

5 It is important to note that CPRM risk sectors correspond to places that show evidence of possible mass movements (cracks/signs of soil subsidence, scars, inclined trees and/or lampposts, etc.) and that threaten urban occupations. Areas of natural preservation as well as urban areas in conditions that still do not present any evidence of mass movements were not included in the CPRM survey.

10 Analyzing the CPRM database, it was possible to identify different designs and types of the risk sectors. Thus, in order to use correctly the risk sectors mapped by CPRM for the validation step, they were classified in three different typologies. Typology 1: steep slopes, predominantly with urban constructions, which present a risk of landslide slip with residences; Typology 2: areas with smooth/undulated relief, that have activities and/or urban occupations (roads and buildings) at risk of landslides that may occur on the slopes above or below where they are; Typology 3: steep slopes, predominantly uninhabited and/or preserved, generally forested, which present risks of landslides and, consequently, could reach buildings nearby (Fig. 6).

20 The classification into typologies is important because not all risk sectors represent locations where fuzzy gamma weighting (Table 1) will predict with high susceptibility. In the case of Typology 2, for example, the risk sectors represent locations where landslides do not occur, but can be reached for it. Therefore, for the method validation it is necessary to filter these typologies by using only representative risk sectors which must indicate high susceptibility.

25 After the generation of the map of susceptibility by the fuzzy gamma technique, the matrix file is transformed into a polygon shapefile. Using GIS the area (in m^2) of each susceptibility classes was quantified, histograms were obtained and they were related with the polygons of risk sectors. Through simple GIS functions (such as the “Clip”),

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it was possible to identify and quantify the susceptibility classes that are inside of the polygons that form the risk sectors.

For the results it is expected that the risk sectors must be composed mostly by the higher susceptibility classes. Thus, the proportional areas occupied by each class of susceptibility inserted in the risk sectors were quantified and are represented through the index “Risk Concentration” (RC), i.e., RC is the frequency (percentage) of each susceptibility class within the risk sector boundaries. Another index also was used: “Risk Potential” (RP). The RP index is the ratio between the area occupied by each susceptibility class inside of the risk sectors, and the total area of each susceptibility class inside all urban boundaries of study area. In some studies in literature, similar indexes are used, generally named “Landslide Concentration” (LC) and “Landslide Potential”, but referring to the same ratio. The different nomenclature is due to the ordinary use of the landslide-scar maps instead of risk sectors (or risk areas) and can be used for comparison between different studies.

Besides these analyses, another approach was adopted based on the terminology “risk levels” used by CPRM and considered by some recent studies (Listo and Vieira, 2012; Pascarelli et al., 2011). The risks are classified based on natural and anthropogenic factors and represent four probability levels of landslide occurrence and their probable impacts, defined through in situ analysis done by experts from the Brazilian Geological Survey. The description of the risk levels is presented below (Table 4). In this analysis, the aim is to find correlations between risk levels and the landslide susceptibility classes (the higher the risk level, the higher the susceptibility classes are).

4 Results and discussions

4.1 General discussions for landslide susceptibility maps

In general, the final results (shown in Fig. 7) indicate that the spatial patterns of susceptibility to landslides are in accordance with the expected, that is, (i) hilltop regions,

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tively (column “Total” at Fig. 9). These values are much higher than the average of the study area (30.8 % and 0.5 %, respectively), which indicates a positive correlation between risk sectors and high susceptibility classes. This fact indicates the accuracy of the technique used, and also it becomes more representative when only Typology 1 is analyzed, that is, inhabited steep slopes that are at risk of slipping. For Typology 1, the two classes “high” and “very high” account together for a RC of 72.5 % (60.5 % and 12 %, respectively).

Concerning the classes “low” and “medium” susceptibility, it is expected to find a negative correlation with risk sectors, which should be less composed by these classes. For the whole study area analyzed, 23.3 % of the area belongs to the class “low” and 44.7 % to “medium” (Fig. 8). On the other hand, the RC index for all risk sectors (considering three typologies) is 1.7 % for the “low” class and 33.7 % for the “medium” class. So, these values are less than the ones found for the average of the study area, especially for “low” class, which really establishes a negative correlation for these classes.

This result indicates that only an insignificant portion of the risk sector is located in the “low” susceptibility class and probably this residual value of 1.7 % is due to the different designs/drawing of the sectors. Also, this result is better observed when the Typology 3 is analyzed, which is the one with largest portion in the “lower” class, with RC equal to 6.8 %. Among the three typologies, this is the sector where the risk has not been defined from the location of the urban area; so, the risk refers to the slopes (usually forested) that can slip and reach nearby residences. For Typology 3, the land use class is mostly “forest”, whose weight is the lowest (0.4 – Table 3). Therefore, we are likely to find lower values of susceptibility for this type of sector, which justifies the highest RC for the “low” class. Although the value of 6.8 % is the highest among the typologies, it should be noted that it is still well below the regional average (23.3 %).

Analysis of the chart shown on the far right in Fig. 9 also corroborates the importance of risk sector classification in different typologies, which allows its use for the validation of the results, since they consider different characteristics and make possible separate evaluation. While risk sector of Type 1 stands out in having the highest RC for the

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20% of the scars, while the following class (SF between 0.8 and 1.0) held values around 30%. For the present study (considering Typology 1 and the fuzzy gamma technique), about 72% of the area of risk sectors belongs to the classes that are more susceptible (12% in areas of “very high” and 60% for “high” susceptibility). This result is consistent with the studies carried out considering the concentration of scars for validation, that is, around 75% in the most critical classes (for example, Crosta and Frattini, 2003; Salciarini et al., 2006).

One of the studies considering a similar analysis for heavily urbanized areas in the city of Juiz de Fora, Minas Gerais State, Brazil, was performed by Zaidan and Fernandes (2009). They also used a high-resolution DEM and the SHALSTAB mathematical model and found about 19% of the total area in the classes was considered unstable, with a high scar concentration (SC index) in these classes, approximately 70%. In our study, it was found that 0.5% of total study area is in the most susceptible class (“very high”), while 30.8% is in the class “high”, and the RC index (comparative to SC index) is 72.5%.

Another approach was used by using the Risk Potential index for all typologies and the results are presented in Table 5.

For comparative purposes of results presented in Table 5, some important studies that used related indexes were listed out. The Landslide Potential index (LP – similar to RP) found in the study presented by Vieira (2010) was approximately 5.7% for the most unstable class (FS between 0.4 and 0.8) and decreasing to 1% for stable classes (FS between 1.5 and 7.0). Thus, the LP indicates that 5.7% of all locations identified by the model as unstable are inserted into the mapped landslide-scars, and this value (higher than 5%) is recognized in literature as good quality.

In another study, Listo and Vieira (2010) used SHALSTAB model to map the landslide susceptibility in a small catchment area (9 km²), with a high-resolution digital terrain model (4 m²) and geotechnical parameters for evaluating only 13 risk sectors. Listo and Vieira (2010) found a RC index close to 70% for the two classes most unstable (41% for the most critical) and a RP index equal to 12% for the most critical class

and reaching values below 1 % for the less critical class. As previously shown, for the present study the RP index for Typology 1 (RP_1) was about 6.00 % and the RC index for the two more susceptible classes shown in Fig. 7 was 72.5 % (12 % for “very high” and 60 % for “high”). Thus, the indexes used for validation indicate a satisfactory quality of the methodology results, approaching the values found in recent literature, even without high-resolution data being used.

4.3 Risk levels analysis

In Fig. 10, the comparative analysis between risk levels defined by CPRM (R1, R2, R3 and R4) and susceptibility classes are shown. This analysis was performed considering only the risk sector of Typology 1, which among the three types of classification presents the risk within the sector boundaries, thus allowing this type of analysis.

In Fig. 10 it can be seen that the higher the risk rating, the lower the proportion of predicted areas with low susceptibility is (low and medium). On the other hand, the classes most susceptible occupy a larger portion of these sectors (when adding classes “high” to “very high”) as shown in following:

- 52 % for R1: 21 sectors (12.62 ha), RC = 52 % for high, RC = 0 % for very high;
- 75 % for R2: 51 sectors (42.31 ha), RC = 70 % for high, RC = 5 % for very high;
- 76 % for R3: 56 sectors (64.07 ha), RC = 57 % for high, RC = 19 % for very high and;
- 82 % for R4: 24 sectors (22.63 ha), RC = 78 % for high, RC = 4 % for very high.

Interestingly, the R3 risk category showed the highest RC for the “very high” susceptibility class (19 %). Analyzing the database, it was noted that this fact occurred due to the largest risk sector found in the study area (approximately 14.2 ha – 142 000 m² – in Cubatão), almost entirely in an area with “very high” susceptibility. Assuming that this classification for risk sectors is defined by criteria which may be considered differently

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The index of Risk Potential, found to be close to the value of 6 %, is within the average found in the literature for high-resolution studies and it means that 1 out of every 16 ha categorized from the methodology as “very high” susceptibility class indicates one area of real risk already mapped. Taking into consideration that there is the possibility of some cases that have not been mapped yet, this is indicative for a satisfactory quality of the results and points out that the methodology can support the management of landslide risk, as well as providing a basis for decisions as to warnings of natural disasters.

The Risk Concentration index for Typology 1 achieved the value of 72 % by joining the two most susceptible classes. Although this value of 72 % is also satisfactory in the cited literature, it means that the remaining 28 % of the total area indicated from the model has lower susceptibility areas that belong to the sectors of risk. In this case, it was observed that this “error” comes mainly due to the subjectivity of the drawings/design-stage of sectors at risk, done by the responsible agencies (CPRM). On the other hand, when analyzing the same RC index for the different risk categories (R1, R2, R3 and R4), it was found that the model provides enhanced adherence for the most critical sectors: R3 (RC = 76 %) and R4 (RC = 84 %). Therefore, this fact reflects a trend that the methodology is best suited to indicate areas of risk in the most critical situations.

Thus, in view of the emergency demands of Brazil regarding the mitigation of impacts caused by landslides every year, this methodology proved robust and had high usability not only to analyze the risk inherent in the present day, but provided the ability to analyze future risk areas that may result from population growth toward the slopes.

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Table 1. Demographic and geographic characteristics of the four municipalities evaluated.

Municipality	Area (km ²)	Population (census 2009)					Demographic density (pop. km ⁻²)	HDI -M
		Total	Urban zone (pop.)	%	Rural Zone (pop.)	%		
Santos	280.30	419 400	419 086	99.93	314	0.07	1496.26	0.840
Cubatão	142.28	108 309	107 661	99.40	648	0.60	761.23	0.772
Caraguatatuba	483.95	100 899	97 449	96.58	3450	3.42	208.49	0.802
Ubatuba	723.82	78 870	76 958	95.58	1912	2.42	108.96	0.751

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Table 3. Evaluated data and their weights associated with landslide susceptibility.

Theme		Weight	Theme	Weight
Geology	<i>Type of rocks</i>		Vertical/Horizontal Curvature	
	<i>Igneous</i>		Very convex/Very divergent	0.2
Granite		0.37	Convex/Divergent	0.3
Migmatite, gneiss		0.43	Retilineous/Flat	0.5
	<i>Metamorphics</i>		Concave/Convergent	0.8
Biotite		0.57	Very concave/Very Convergent	1.0
Schist		0.67		
Metagabro		0.70	Slope Class	
Monzogranite		0.60	> 45° Mountainous	1.0
Mylonite		0.77	20 to 45° Heavy undulation	0.8
Leucogranite		0.50	8 to 20° Undulation	0.5
Orthogneiss		0.47	3 to 8° Smooth undulation	0.3
	<i>Sedimentary</i>		0 to 3° Plane	0.2
Sediments unconsolidated: alluvium, colluvium		1.00	Land use	
			Agriculture	0.8
Soil Class	<i>Acronym</i>		Urban area	1.0
Haplic Cambisols	CX	0.80	<i>Eucalyptus</i>	0.7
Spodosol Ferrocarbic	ES	0.75	Roads	0.9
Salic Gleisol	GZ	1.00	Pasture	0.7
Red-yellow Latosol	LVA	0.40	Restinga	0.5
Urban	URB	1.00	Mangrove	0.4
			Bare soil	0.9

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Table 4. Criteria for defining the probability of occurrence of the destructive processes of landslide in occupied slopes (version used in the southeast of Brazil by CPRM).

Risk level	Description
R1 (low to null risk):	The geological and geotechnical predisposing factors (slope, terrain types, etc.) and the level of intervention in the sector show low potential for development of landslide processes. There is no evidence of destructive process development on the slopes. This is the least critical condition. Maintaining existing conditions, the occurrence of landslide events in the rainy period is not expected.
R2 (medium):	The geological and geotechnical predisposing factors and the level of intervention in the sector show low potential for development of landslide processes. Notes the presence of some evidence of instability on slopes, however incipient. Maintaining existing conditions, the possibility of landslide events during heavy rains and prolonged episodes during a rainy period is reduced.
R3 (high):	The geological and geotechnical predisposing factors and the level of intervention in the sector show high potential for the development of processes of landslide. Significant evidence of instability is present (cracks in the soil, etc.). Maintaining existing conditions, it is quite possible to have the occurrence of landslide events during heavy rains and prolonged episodes during a rainy period.
R4 (very high):	The geological and geotechnical predisposing factors and the level of intervention in the sector show high potential for the development of processes of landslide. The evidence of instability (cracks in the soil, fissures in houses or containment walls, trees inclined, landslide scars, erosive features, etc.) is significant and is present in large numbers and/or at magnitude. This is the most critical condition. Maintaining existing conditions, the occurrence of landslide events is very possible during heavy rains and prolonged episodes during a rainy period.

Source: Ministério das Cidades/ Cities Alliance (2006).

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Table 5. Risk Potential index calculation for Typology 1 (RP₁), Typology 2 (RP₂) and Typology 3 (RP₃).

Classes	1	2	3	4	5	6	7	8	9
	Total Study Area (ha)	Urban Area (ha)	% (2 + 1)	Typ1 Area (ha)	Typ2 Area (ha)	Typ3 Area (ha)	RP ₁ (4 + 2)	RP ₂ (5 + 2)	RP ₃ (6 + 2)
Very Low	191	0.7	0.4 %	0.0	0.0	0.0	0.0%	0.0%	0.0%
Low	38 571	174	0.5 %	1.3	0.2	3.2	0.7%	0.1%	1.8%
Medium	72 073	4837	6.7 %	48.8	16.9	29.3	1.0%	0.4%	0.6%
High	49 649	7449	15.0 %	110.1	33.5	14.8	1.5%	0.4%	0.2%
Very High	770	364	47.3 %	21.8	2.3	0.3	6.0%	0.6%	0.1%
Total	161 254	12 825	8.0 %	181.9	52.9	47.6			

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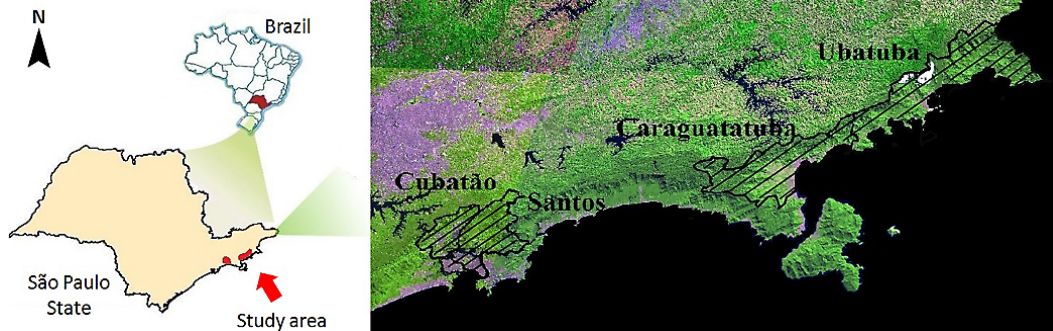


Fig. 1. Study area in São Paulo State, Brazil. On the right, the image is a color composition (RGB 453) of Resourcesat/LISS III.

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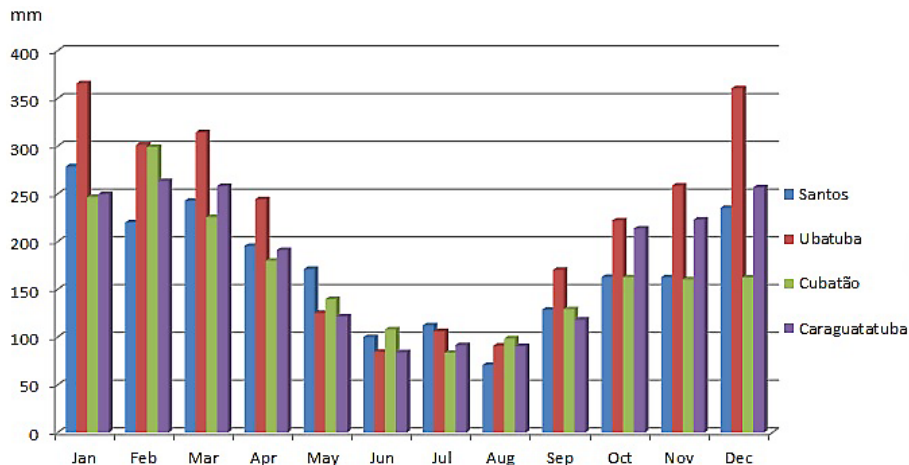


Fig. 2. Climate-normal precipitation in the period 1961–1990 for the study area. Source: INMet (<http://www.inmet.gov.br/portal/index.php?r=clima/normaisClimatologicas>).

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Fig. 3. Picture illustrating an irregular occupation of the slopes in Santos, SP, Brazil. Photo by: J. C. de Carvalho.

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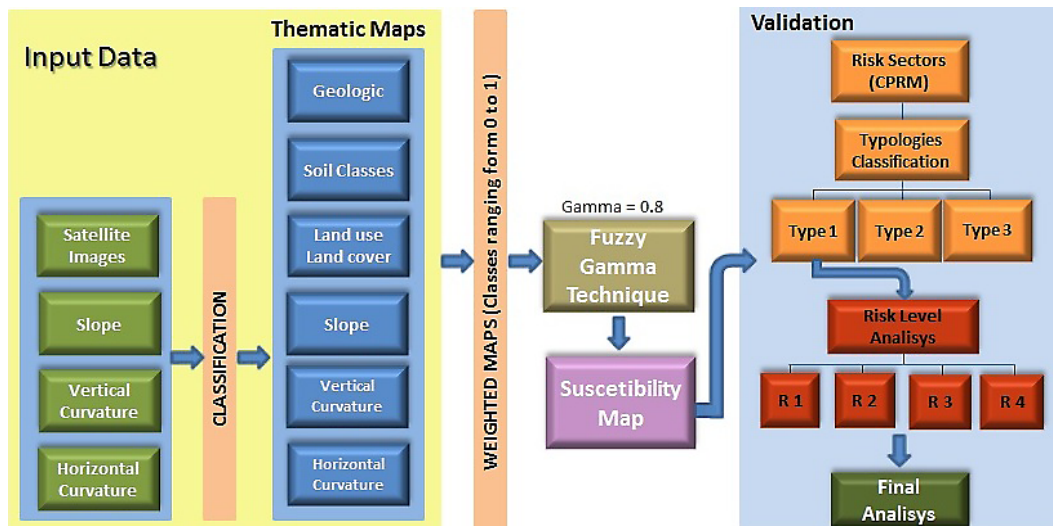


Fig. 4. Data and methodology flowchart.

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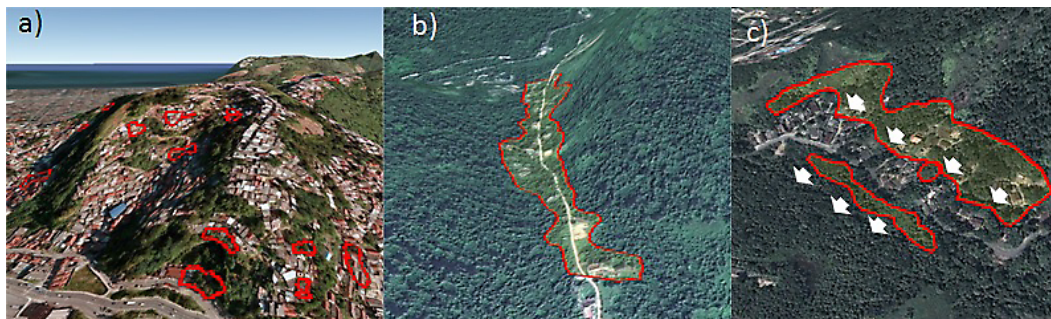


Fig. 5. Three main types of risk sectors (red lines) found on CPRM mapping. Examples for: **(a)** Typology 1, **(b)** Typology 2, and **(c)** Typology 3. The images are from Google Earth® 2013.

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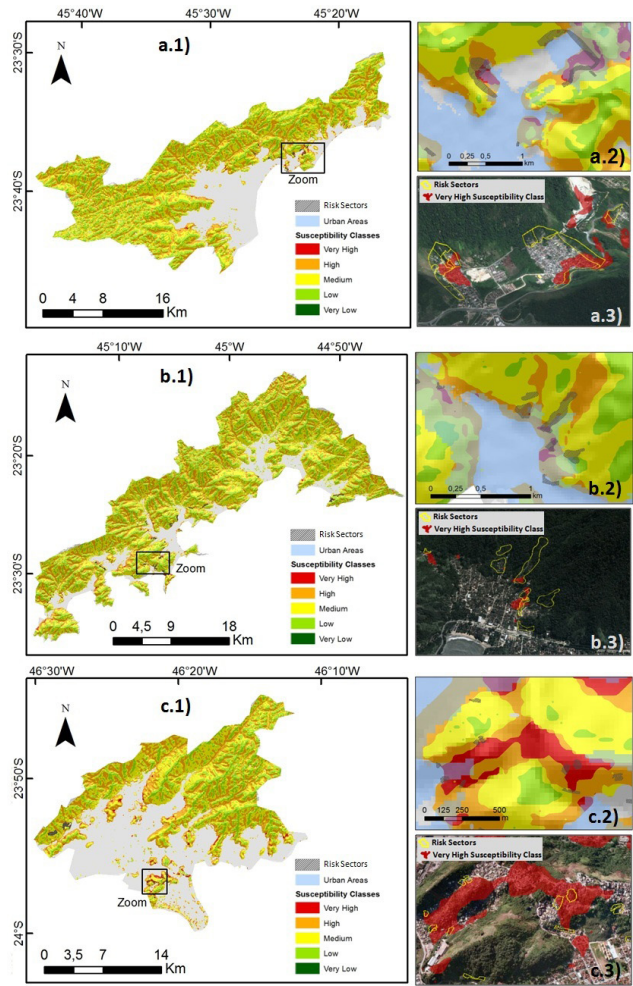


Fig. 7. Caption on next page.

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Study Area Profile		
Classes	Area (ha)	
Very Low	191	0,1%
Low	38571	23,9%
Medium	72073	44,7%
High	49649	30,8%
Very High	770	0,5%
Total	161254	100%

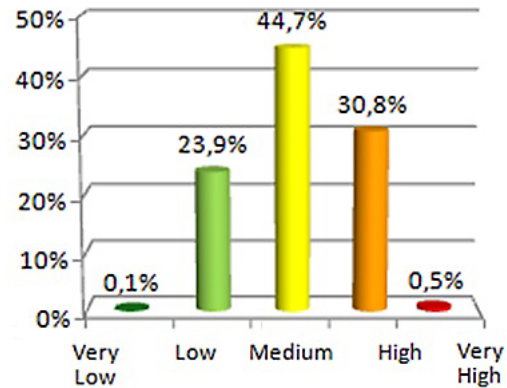


Fig. 8. Frequency of occurrence for each susceptibility class for the whole study area.

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	Typology 1		Typology 2		Typology 3		Total	
Quantity	150	(64.38%)	37	(15.88%)	46	(19.74%)	233	(100.0%)
Area in ha	181.93	(64.42%)	52.94	(18.74%)	47.57	(16.84%)	282.44	(100.0%)
Classes	Area (ha)	RC index	Area (ha)	RC index	Area (ha)	RC index	Area (ha)	RC index
<i>Very Low</i>	0.00	0.0%	0.00	0.0%	0.00	0.0%	0.00	0.00%
<i>Low</i>	1.27	0.7%	0.21	0.4%	3.22	6.8%	4.70	1.67%
<i>Medium</i>	48.84	26.8%	16.94	32.0%	29.31	61.6%	95.09	33.67%
<i>High</i>	110.06	60.5%	33.48	63.3%	14.77	31.0%	158.31	56.05%
<i>Very High</i>	21.77	12.0%	2.30	4.3%	0.27	0.6%	24.33	8.62%

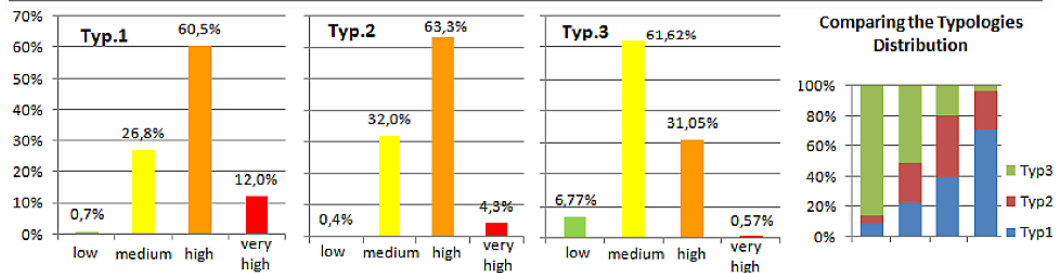


Fig. 9. Frequency of susceptibility classes related with the three different typologies of risk sector (Risk Concentration index – RC). The far right chart shows the percentage areas occupied by each susceptibility class, grouping the three typologies.

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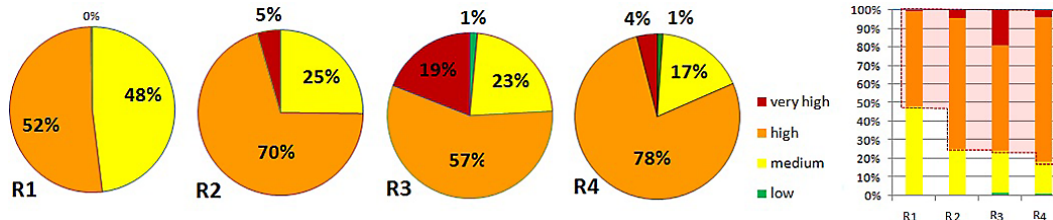


Fig. 10. Susceptibility classes' distribution for the four risk levels used by CPRM (R1, R2, R3 and R4). Analysis for all 150 risk sectors of Typology 1. Higher risk levels are associated with larger areas occupied by the most susceptible classes (high and very high).

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