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Research Paper

Scales of inequality: The role of spatial extent in environmental justice analysis

Camila Carvalho [a,b,*], Ainhoa González Del Campo [b], Diogo de Carvalho Cabral [c]

[a] School of Architecture and Urbanism, Universidade Federal Fluminense, Brazil
[b] School of Geography, University College Dublin, Ireland
[c] Department of History, School of Histories and Humanities, Trinity College Dublin, Ireland

HIGHLIGHTS

- Spatial extent alters the assement of environmental justice.
- In metropolitan areas and municipalities the most vulnerable to hazards are minority groups.
- At the borough scale there are well-to-do white people exposed to hazards (especially flooding)
- Elite self-exposure to risk is supported by spatially unjust distribution of infrastructures.

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ABSTRACT

Although environmental justice scholars have been addressing spatial scale for at least thirty years, one of its components remains largely overlooked, namely extent. In this paper, we investigate the effects of extent variation in environmental (in)justice patterns by analyzing the statistical associations between socio-economic marginality and environmental vulnerability at three different spatial scopes: metropolitan areas, municipalities, and boroughs. Using census and geospatial data, our case study focuses on the relations between income and color/race, on the one hand, and susceptibility to flooding and landslides, on the other, in Brazil's two largest cities (São Paulo and Rio de Janeiro). We constructe an integrated, census tract-level database using areal weighting interpolation combining census with susceptibility data to perform k-means multivariate clustering analysis. Although our results show that the most vulnerable to landslides and flooding are non-white, low-income people – confirming common environmental justice claims – they also suggest that spatial extent impinges on statistical patterns. While the clusters are very similar in the metropolitan and municipal scales, pointing to a fractal-like structure, they differ significantly at the borough scale. This smaller scale reveals a different picture, one in which well-to-do white people are just as exposed to hazards (especially flooding) as non-white, middle- to lower-middle-class people. We argue this is a result of elite self-exposure to risk, which is supported by socio-spatially unjust distribution of risk-mitigation infrastructures. Policymakers should pay attention to such scale-dependent complexities in devising ways to cope with the increasing inequities brought about by climate change.

1. Introduction

There is consolidated literature on how social variables such as income, ethnicity, gender, and education differentially predispose people to environmental hazards (e.g., Ajibade et al., 2013; Cutter, 2017; Forrest et al., 2020; Hamann et al., 2018; Romero et al., 2012; Walker & Burningham, 2011). Under the label of environmental justice, this line of research has been paying attention to spatial scale for almost thirty years now. "The potential variation in results at different geographic levels suggests a need to at least explore a number of scales simultaneously," wrote Zimmerman (1993, p. 652) in one of the earliest calls for scale-dependency research in environmental justice scholarship, urging scholars to "conduct sensitivity analyses to ensure that the implications for equity at different scales are not wildly different." Since then, the

* Corresponding author at: R. Passo da Pátria, 152-470 - São Domingos, Niterói - RJ, 24210-240, Brazil
E-mail addresses: carvalhocamila@id.uff.br (C. Carvalho), ainhoa.gonzalez@ucd.ie (A.G. Del Campo), decarvad@tcd.ie (D. de Carvalho Cabral).

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vast majority of studies – most often equating spatial scale with data resolution or "grain" – confirmed Zimmerman's insight, showing that scale strongly affects statistical associations (Anderton et al., 1994; Bowen et al., 1995; Cutter et al., 1996; Debbage, 2019; Fisher et al., 2006; Kurtz, 2003; McMaster et al., 1997; Tan & Samsudin, 2017; Zou et al., 2014). However, relatively few environmental justice studies have followed landscape ecologists' methodological tenet according to which scale is determined by both resolution and extent (Turner et al., 1989; Wu et al., 2002), thus neglecting the latter's role. Lately, landscape ecologists have focused on what they call "scale of effect," or "the spatial extent at which landscape structure best predicts the response" of targeted biological species (Jackson & Fahrig, 2015, p. 53). Analogously, environmental justice scholars should be putting more effort in elucidating what specific geographical scopes of analysis elicit the statistical associations backing their claims, as failure to do this undermines the policy relevance of their findings (Baden et al., 2007).

Although scholars of urban socio-economic dynamics have shown that spatial frames are consequential for statistical analysis (Barros & Feitosa, 2018; Carvalho et al., 2019; Cottineau et al., 2017), relatively few studies have addressed the effects of spatial extent on environmental equity patterns. McMaster et al. (1997) discussed the importance of extent and resolution, showing that neighborhood-wide analyses are more appropriate than municipal- and regional-wide ones to ascertain the relations between racial characteristics and environmental risks. Baden et al. (2007) argued that inconsistencies in the environmental justice literature could be explained by the different resolutions and extents (or scopes) adopted. In general, smaller extents tend to yield weaker evidence of environmental justice than larger ones. For example, Fisher et al. (2006) used scale as a variable to determine the spatial scopes in which patterns of disaster events are more pronounced. Likewise, Kedron (2016) used three spatial techniques to identify clusters of statistically significant groups of minority people, showing a considerable spatial overlap between the clusters and places of risk. However, one should note that this method makes it difficult to find areas inhabited by non-minority groups exposed to hazards.

As this literature makes clear, assessing the role of spatial extent or scope implies running statistical analysis in different geographical frames. Single-scope approaches overlook that scale might be argued to be an inherent geographical property of objects (Montello, 2001). Inversely, from an epistemological perspective, different scales "produce" different objects for human observation. Therefore, variation in extent (the total area analyzed) and resolution (level of data detail or aggregation) lead to the confirmation, intensification, or contestation of environmental justice claims (Anderton et al., 1994; Cutter et al., 1996; Debbage, 2019; McMaster et al., 1997; Tan & Samsudin, 2017). This also impinges directly on policy-making, for the assessment and tackling of environmental unjust real-world situations involve various scales ranging from the local to the global. For example, on the planetary scale, climate change will impact most severely on Global South countries and regions (Carmin et al., 2012). Füssel (2010) refers to this issue as "double inequity" in reference to the fact that developing nations not only contribute less to climate change but also are less socio-economically resilient to its consequences. Replicating this process at local scales, minority groups are also more affected by environmental hazards (Hamann et al., 2018; Romero et al., 2012) and have more difficulty coping with its effects (Maantay & Maroko, 2009).

In Brazil, one of the world's most unequal countries (World Bank, 2018), social inequality decisively shapes urban landscapes, forcing ethnic minorities and economically disadvantaged people to live in peripheries with precarious infrastructure and services (Carvalho & de Carvalho Cabral, 2021). These groups are also exposed to higher environmental risks (Morato et al., 2018; Morato & Kawakubo, 2007; Young, 2013). An analysis by the Brazilian Institute of Geography and Statistics demonstrated that in 2010 more than eight million people lived in areas at risk of flooding and landslides, with 18% of the affected population being children and elderly groups (IBGE, 2018). Other studies have shown that 26% of households do not have access to sewage (Alvalá et al., 2019; Assis Dias et al., 2018; IBGE, 2018). This infrastructure problem is also a byproduct of urban sprawl towards natural areas (Herzog, 2014). While several studies consistently document that Brazil's non-white, poverty-stricken population is disproportionally exposed to environmental risk, to this date no study has investigated how the spatial frames of analysis (extents) impinge on such environmental inequities.

In this article we tackle this problem by analyzing the relations between socio-economic and racial variables and susceptibility to flooding and landslide in Brazil's two largest cities (São Paulo and Rio de Janeiro) using three different spatial frames: metropolitan areas, municipalities, and boroughs. Defined by administrative boundaries, these scales may allow us to inform public policies designed to minimize the effects of environmental injustice. The broader scale, the metropolitan area, is an ensemble of municipalities whose built-up areas form a single continuous urban fabric. Its delimitation considers the relations of production, work, consumption, and mobility. There is an ongoing debate in Brazil regarding what ought to be the institutional responsibilities of metropolitan areas. Currently, they are legally required to devise Integrated Urban Development Plans (PDUI) to organize urban sprawl and address critical issues such as housing deficits, social vulnerability, the availability of sanitation and water infrastructure as well as environmental amenities, in addition to mobility, transport, and logistics (Brazil, 2015). Our second scale is the municipality, one of the three political-administrative levels making up the structure of Brazil's federation (the other two being States and the Union). This means that municipalities have the autonomy to manage local affairs, including environmental inequality issues. The third scale is the borough, a sub-municipal region that is in some cases endowed with administrative status and deals with local urban projects and community organization. Each one of these spatial levels has specificities regarding the assessment and management of environmental issues.

2. Materials and methods

2.1. Study areas

For this study, we selected the two largest Brazilian cities: Rio de Janeiro and São Paulo. In 2010 these cities had 12 and 20 million residents in their respective metropolitan areas (IBGE, 2010). They are also the two most important urban economies in the country. In 2018, the combined GDP of these two metropolitan areas made up one-fourth of the national GDP (IBGE, 2020). Rio was the capital of Brazil from 1763, still under Portuguese colonial rule, until 1960, when a new capital (Brasilia) was constructed from scratch in the central plateau. During these two hundred years, the city transitioned from a small South Atlantic entrepot to one of the largest metropolises in South America, profiting from economic, cultural, and, most importantly, institutional-bureaucratic concentration (Lessa, 2000). However, from the early twentieth century on, Rio began to lose its place as the country's economic powerhouse. Bolstered by the flourishing coffee economy, the expanding railway network, and intense European immigration, São Paulo witnessed an industrial boom in the first half of the twentieth century (Dean, 2012). This economic leadership was consolidated toward the end of the century, reaching a symbolic climax in 2002, when the São Paulo Stock Exchange absorbed its counterpart in Rio.

The two cities have very different biophysical settings. While Rio developed in a challenging coastal site where rocky massifs as high as 1,025 m protrude from plains barely above sea level, São Paulo developed in a plateau environment which, though not deprived of topographic gradients, lack such extreme geomorphological contrasts (see Fig. 1B). Using the Köppen-Geiger classification, Rio has a tropical savanna climate (Aw) characterized by dry winters and rainy summers. As both the regional atmospheric systems and the sea breeze flow northward from the Atlantic, the highest precipitation levels occur on

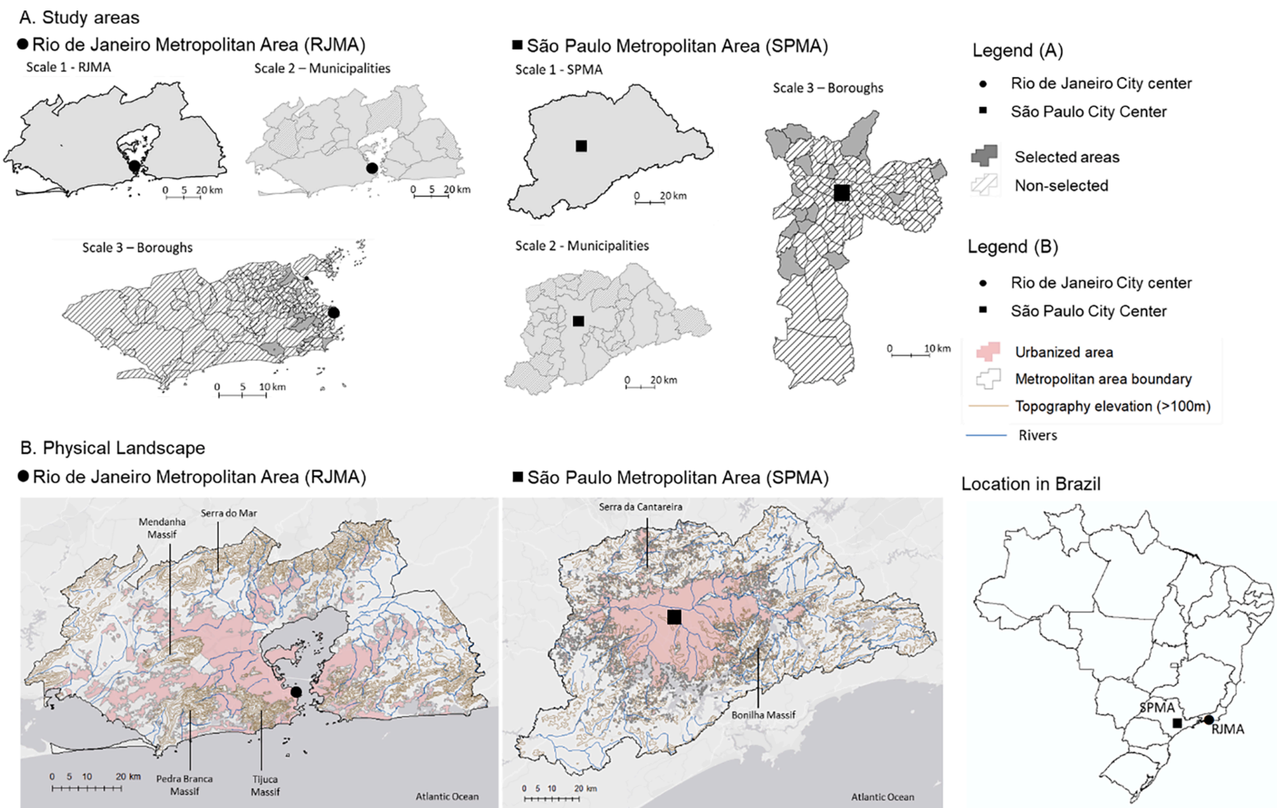


Fig. 1. Study areas and Physical characteristics. Fig. 1A shows the study areas in the three analytic scales for each city. Fig. 1B shows the topography elevation, rivers and urbanized areas for both Metropolitan Areas. The topography and hydrography dataset are from IBGE (2016) and the built-up area is from IBGE (2015).

the windward slopes of the three granite-gneiss massifs located within or on the border of the municipality of Rio: Tijuca, Pedra Branca, and Gericinó-Mendanha. Total annual rainfall reaches 2,200 mm at the Sumaré weather station in the Tijuca Massif. Precipitation levels decrease in the plains, especially those to the north of the massifs, with a minimum of around 900 mm observed at Irajá and Penha, in the extreme north of the municipality (Dereczynski et al., 2009). São Paulo, by its turn, has a humid subtropical climate (Cfa) with rainfall mostly concentrated in the summer and spring. The spatial variation of precipitation is much lower than in Rio, with the highest levels occurring in the southern watersheds (1,950 mm) and the lowest levels in the most densely built-up areas in the central, western, and eastern zones of the city (1,363 mm) (Marcuzzo, 2016).

2.2. Analytic scales

This study examines nested urban areas through three scales (spatial extents). The first level is the metropolitan areas of Rio de Janeiro and São Paulo. The second level comprises the individual municipalities within the metropolitan areas with the highest combined susceptibility to flooding and landslides, accounting for 14 municipalities in Rio de Janeiro and 22 in São Paulo. Finally, the third level refers to the boroughs with the highest combined susceptibility to flooding and landslides (14 boroughs in Rio de Janeiro and 15 in São Paulo).

Rio de Janeiro and São Paulo have different denominations for the intraurban administrative boundaries. Although the two municipalities use different labels for intraurban units – *bairros* in Rio and *distritos* in São Paulo – in this paper, we refer to them indiscriminately as “boroughs” as they have similar administrative characteristics.

2.3. Data sources, concepts, and variables

We used two data sources with national coverage. The first is the 2010 census, the latest one made available by the Brazilian Institute of Geography and Statistics (IBGE, 2010). We retrieved the data at the census tract level, defined as an area for which data can be collected by an individual officer, containing an average of 300 households. The second data source is the map of susceptibility to landslide and flooding produced by the Brazilian Geological Service (CPRM, 2014). The map was produced at the 1:25.000 scale for 526 municipalities, covering approximately 88 million people in the whole country.

In this study, we assume susceptibility to refer to “the tendency of an area to undergo the effects of a certain hazardous process (e.g., floods, earthquakes, tsunamis, subsidence, etc.) without taking into account either the moment of occurrence or potential victims and economic losses” (Domínguez-Cuesta, 2013, p. 988). We consider two hazardous processes associated with climate change: landslides and flooding. Landslides are catastrophic mass movements that generally take place in highly sloped terrain, “usually triggered by high-intensity rainfall events or else accumulated rainfall [occurring over days or weeks], conditioned by predisposing factors intrinsic to the soil” (CPRM, 2014, p. 11). Based on the interpretation of high-resolution orthophotos, the CPRM technicians mapped susceptibility using landslide scars as the primary indicator and other influencing factors such as slope geometry and the underlying geological structure. Flooding can be defined as “the temporary rise in the water level relative to the regular riverbed in a given drainage basin, commonly due to increased water flow caused by prolonged rainfall events and high accumulated rainfall” (CPRM, 2014, p. 12). The CPRM technicians mapped susceptibility to flooding by considering the hydrology, rain-flow rates, and other environmental variables such as soil type and vegetation (see CRPM, 2014). Both susceptibility types were mapped according to three classes of intensity: low, medium, and high. In order to enhance analytical sharpness, we considered only the areas of high susceptibility.

As to the socio-economic dimension, we used two variables, both of which were calculated from census data: per capita income (values in

USD, considering the exchange rate in December 2010, when US$1.00 was worth BRL1.66) and race/color (percentage of white people). The use of the latter is justified by the insidious legacy of slavery, which was abolished very late in Brazil (1888). Racism and the lack of public policies to integrate formerly enslaved people have left these groups with no access to land and adequate housing, condemned to live in the most precarious urban areas (Valladares, 2005). Table 1 summarizes the four variables used in this study.

2.4. Areal-Weighted interpolation (AW)

We used R Stats' package areal to pair the two datasets (census and susceptibility mapping). To transpose the susceptibility data into the census tract polygons, we applied the areal-weighted interpolation algorithm. This assumes that the variable is evenly distributed through the spatial unit, thus calculating the estimated value for the overlapped polygon (see Fig. 2). This method enables the harmonizing of all variables within each cell at each scale. Then we calculated the proportion of the tract's area classified as high susceptibility to flooding and landslides.

2.5. Correlation and K-means clustering

First, we ran a Spearman Rank Correlation to understand the relationship between the variables in each scale and geographical area (i.e. city). However, since susceptibility data is zero-inflated, classic statistical methods such as correlation and regression are not reliable because the data do not fit standard distributions. To deal with this problem, we resorted to k-means clustering, a multivariate analysis method that has been widely used to explore spatial inequalities (Siqueira-Gay et al., 2017; Yohan et al., 2020; Zhai et al., 2020). It groups observations into clusters, maximizing the internal homogeneity of each cluster. For this, it uses the "principle of iterative relocation", meaning that the algorithm works by doing rounds of clustering to guarantee that the "within-cluster" sums of squared errors are the lowest possible (Anselin, 2020). The calculations are based on Hartigan and Wong's (1979) algorithm. In this study, we ran the clustering analysis by using the R Stats' package K-means.

Using the harmonized values per cell, we applied the k-means technique to assess the relationship between susceptibility and socio-economic variables for each scale in both cities. Then, we analyzed the clusters spatially to understand how they are distributed across urban space and determine whether the clustering patterns are replicated across scales. A limitation of our approach is that we had to use the same number of clusters (k) for all scales and cities. This analytical requirement stems from our need for comparability across scales and geographical areas. Usually, the optimal number of clusters for each scale and city would have been calculated – for which there are several techniques available – as this increases the statistical homogeneity internally to each cluster. Nevertheless, the most suitable number of clusters should reflect the research problem and the characteristics of the input data. In the pursuit of comparability and the specific research objectives of this study, we considered some alternatives to obtain the optimal k. Applying the elbow method, it varied between three and six. Then, we calculated the k-means for the two metropolitan areas for three, four, five, and six clusters. With the four variables at play and considering the zero-inflatedness of our data, the best k revealed itself to be four, which indeed maximized intra-cluster similarity and inter-cluster dissimilarity. With three clusters, tracts with high susceptibility to flooding were not well separated from low susceptibility. With five clusters, higher-income observations with similar values for other variables were split into two groups. With six clusters, we had lower-income with high-susceptibility to landslide split into two groups. The optimum option of four clusters provided the following structure:

- Cluster 1: Low values for all variables;
- Cluster 2: High values for income and white people and low value for susceptibility variables;
- Cluster 3: High susceptibility to flooding and low values for other variables;
- Cluster 4. High susceptibility to landslide and low values for other variables.

In order to facilitate the comparison, the optimal number was fixed as four for all areas and scales. However, we did analyze the level of "compactedness" of each cluster (bss/tss) to guarantee this would not generate any misgrouping of observations. Cluster compactness is measured as the ratio between cluster sum squares and the total sum of squares, varying between 0 and 100%. The greater the value, the more statistically similar are the observations (i.e. census tracts) within each cluster (Bienvenido-Huertas et al., 2020). Therefore, we opted to include in our analysis only those areas with compactness higher than 60% in a four-cluster scenario, which means that the clusters have at least 60% of similarity between observations. This approach allowed us to make comparisons across scales and cities while making sure clustering had good quality (see Table 2).

Table 1
List of selected variables for the study. Sources: Census database (2010) provided by the Brazilian Institute of Geography and Statistics (IBGE) and high susceptibility dataset provided by the Geological Brazilian Service (CPRM) (2015).

Variables	Description	Method	Unit
1. Per capita income = i (R $)	v1. Total monthly income of permanent private dwellings v2. Population living in permanent private dwellings	$i = \frac{v1}{v2}$	USD
2. Percentage of white people = p	v1. Residents v2. Residents self-declared white	$p = \left(\frac{v2}{v1}\right)*100$	%
3. Percentage of cell area highly susceptible to flooding = fr	f. Geospatial polygons of high susceptibility to flooding (km^2) a. cell area (km^2)	$fr = \frac{f}{a}*100$	%
4. Percentage of cell area highly susceptible to landslide = lr	l. Geospatial polygons of high susceptibility to landslide (km^2) a. cell area (km^2)	$lr = \frac{l}{a}*100$	%

3. Results and discussion

3.1. Correlation

The spearman rank correlation between the socio-economic and susceptibility variables shows different results across scales (Fig. 3). Firstly, at the metropolitan extent, in both cities, results are very close to zero. This means that there is no relationship between susceptibility and socio-economic variables, suggesting the inexistence of environmental injustice at this scale. At the municipal scale, no clear pattern can be observed. There are some areas where the correlation is negative, indicating that lower-income and non-white people are more prone to living in high-susceptibility tracts. At the same time, there are areas for which the correlation is positive, indicating the inexistence of environmental injustice.

3.2. K-means

These data cannot be analyzed solely through correlation, primarily because of the zero-inflated values, which affects the reliability of the results. The k-means technique offers a solution to this problem by creating groups with similar observations. In other words, this technique tends to group values very close to zero (or similar values) in the same cluster. The k-means clustering results are presented in parallel

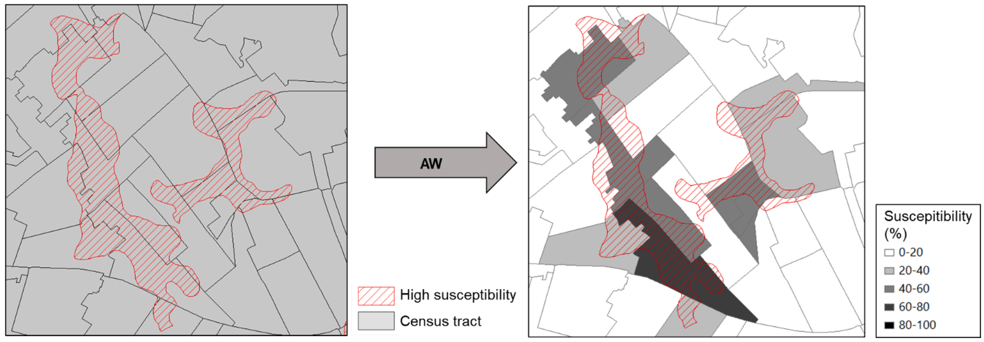


Fig. 2. Scheme of the areal weighting interpolation method. This method was applied to overlap the two databases used (census and susceptibility). The first image represents all databases overlapped. The second image represents the result of AW method, showing the percentage of high susceptibility in each census tract.

Table 2
Number of clusters and the compactedness of 4 clusters (bss/tss) for each area.

Extent	bss/tss (%)	C1	C2	C3	C4	Total
RJMA	69.7	3656	2810	12170	461	19097
Belford Roxo	62	162	161	382	15	720
Duque de Caxias	60.7	503	203	475	26	1207
Guapimirim	62.3	34	5	33	2	74
Itaboraí	61.5	71	75	250	1	397
Itaguaí	69.7	15	47	80	1	143
Japeri	63.2	8	66	71	4	149
Maricá	61.2	55	98	121	17	291
Mesquita	66.5	99	89	117	9	314
Niterói	70.6	197	256	328	88	869
Nova Iguaçu	64.7	82	215	897	26	1220
Paracambi	68.5	25	9	17	5	56
Queimados*	56.4	31	55	114	7	207
Rio de Janeiro	71.1	1577	2276	6101	204	10158
São Gonçalo	64	376	438	986	55	1855
São João de Meriti	60.7	268	1	445	5	719
Copacabana	66	115	237	24	11	387
Andaraí	80.7	16	30	23	3	72
Bonsucesso	72.8	14	9	12	2	37
Engenho Novo	74.7	14	37	13	4	68
Itanhangá	71.9	15	8	19	1	43
Jardim Botânico	73.9	4	24	5	3	36
Penha	80.6	9	56	42	17	124
Penha Circular	80	15	37	29	5	86
Rio Comprido	75.1	13	29	29	4	75
Rocinha	61.1	4	26	34	16	80
Tauá	82.5	7	18	17	8	50
Tijuca	80.8	51	182	30	21	284
Vicente de Carvalho	83.1	5	18	10	5	38
Vila Isabel	78.4	21	77	25	13	136

Extent	bss/tss (%)	C1	C2	C3	C4	Total
SPMA	64.8	964	8778	18782	443	28967
Sao Paulo	68.5	483	5938	11214	180	17815
Barueri	73.7	28	20	216	10	274
Biritiba_Mirim	72.7	1	15	12	3	31
Caieiras	71	3	18	86	8	115
Cajamar*	59.8	3	1	69	11	84
Cotia	60.8	9	32	181	4	226
Diadema	62.6	11	137	348	8	504
Embu	61	31	42	319	9	401
Embu_Guacu	62.6	5	24	45	3	77
Ferraz_de_Vasconcelos	72.1	4	47	154	2	207
Guararema	69.9	2	9	14	10	35
Francisco_Morato	67	7	39	134	18	198
Itaperica_da_Serra*	56.4	13	15	169	29	226
Itapevi	62.9	14	10	155	8	187
Itaquaquecetuba*	56.7	23	83	277	5	388
Maripora*	56.9	6	36	72	13	127
Maua	68.8	42	116	300	37	495
Mogi_das_Cruzes	64.9	21	100	274	7	402
Osasco	68.5	42	331	538	7	918
Ribeira_Pires	62.4	9	36	95	24	164
Rio_Grande_da_Serra*	59.7	4	11	25	15	55
Santa_Isabel	64.9	3	24	25	5	57
Santana_de_Parnaiba	76.5	9	40	53	3	105
Santo_Andre	60.7	66	582	448	22	1118
Sao_Bernardo_do_Campo	71.3	38	566	518	43	1165
Suzano	66.6	12	115	225	4	356
Taboa_da_Serra	69	29	64	159	8	260
Anhanguera	67	3	11	56	8	78
Campo Limpo	68.5	7	74	239	5	325
Casa Verde	75.9	5	51	75	1	132
Cidade Lider	69.5	6	59	92	6	163
Itaim Paulista	69.6	22	69	258	4	353
Jacana	70.2	9	74	61	3	147
Jaguare	84	3	65	35	1	104
Jardim Angela	65.9	4	149	204	27	384
Morumbi	64.2	6	104	14	2	126
Pedreira	69.1	2	62	161	14	239
Perus	70.1	3	49	59	5	116
Pirituba	66.8	11	114	127	4	256
Tremembe	73.7	17	83	169	9	278
Vila Andrade	78.1	4	142	64	10	220
Vila Sonia	61.4	10	114	130	2	256

* Areas excluded because the bss/tss is lower than 60%

Boroughs

Municipalities

Metropolitan Area

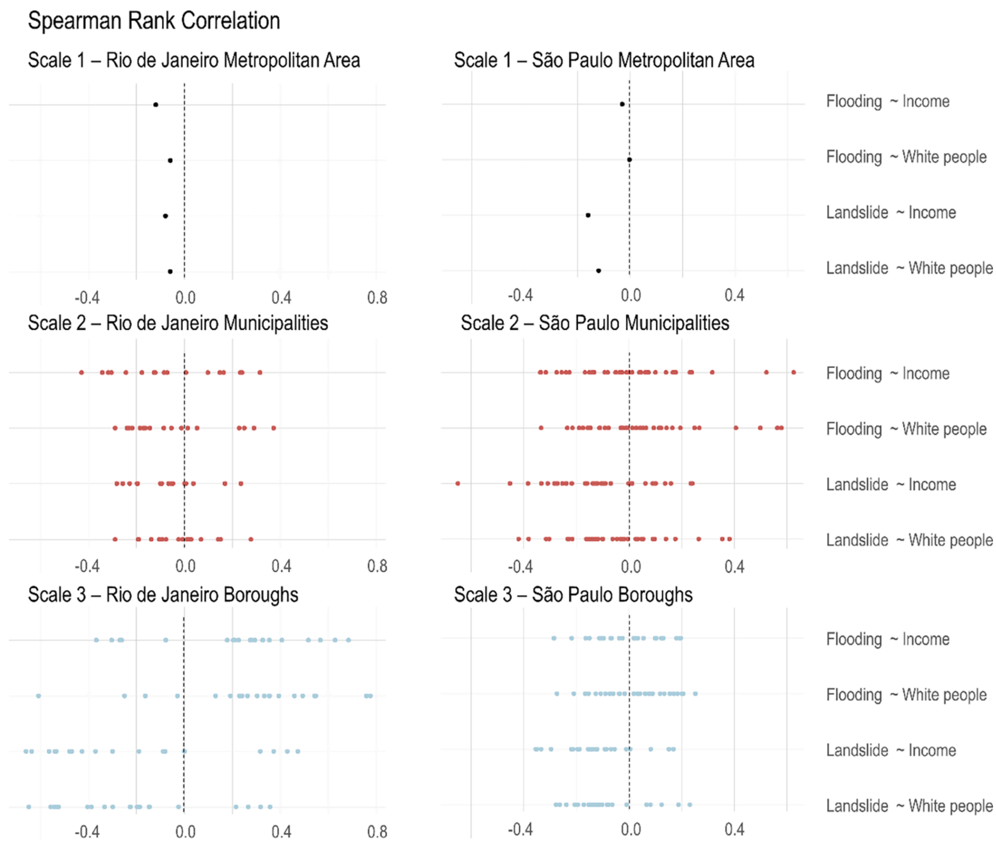


Fig. 3. Spearman rank correlation for each area studied. Each dot represents an area. X axe displays the correlation values.

coordinate charts for each of the three analytical scales (Figs. 4 and 5). The variables were homogenized between 0 and 1 to render them more easily comparable. In all scales, the k-means clustering divide the observations into the four groups described in the Material and Methods section.

3.3. Scale 1 – Metropolitan area

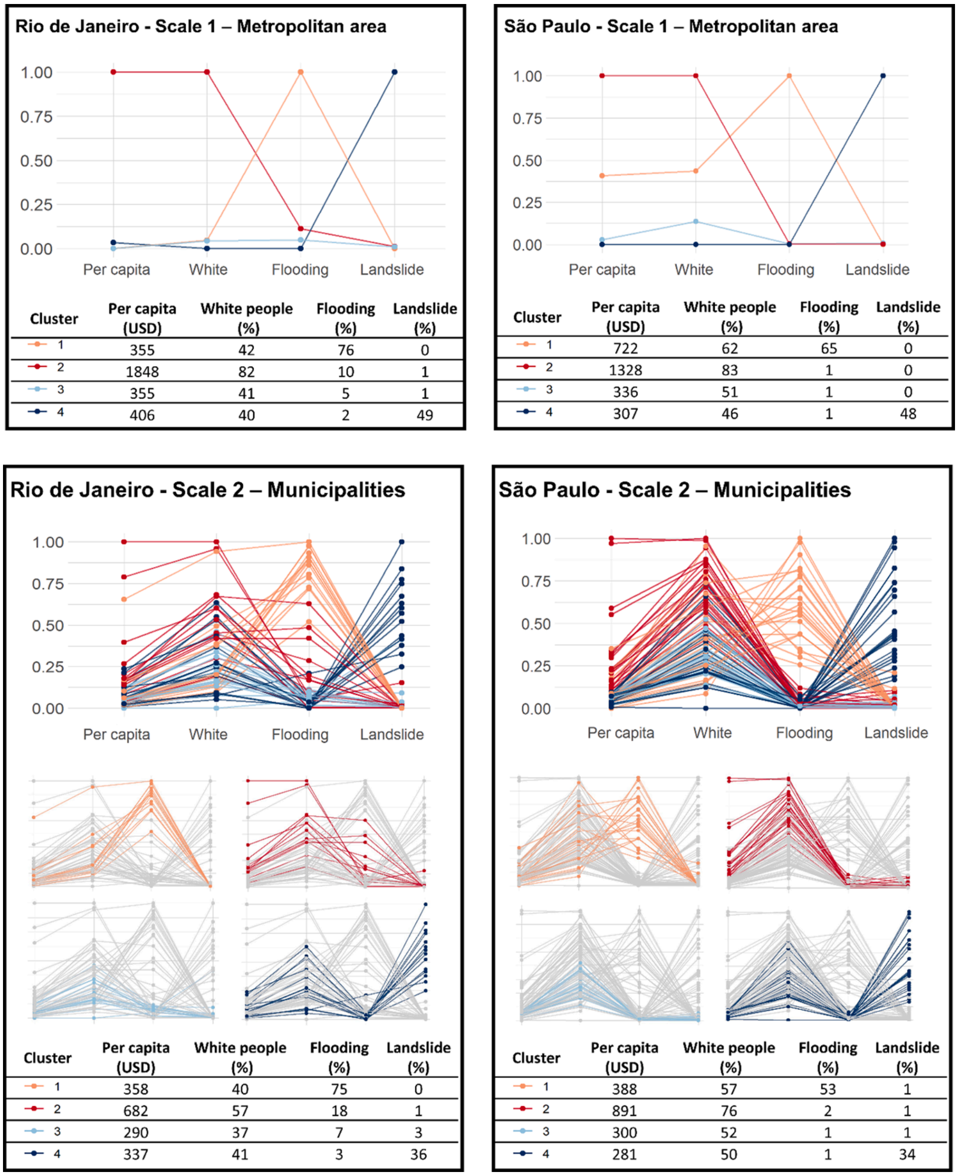
At Scale 1 (metropolitan areas), the division into four clusters show that the percentage of white people seems to be associated with per capita income, a relationship well documented for Brazilian cities (Carvalho & De Carvalho Cabral, 2021; França, 2017; Telles, 1992, 2006). In the Rio de Janeiro Metropolitan Area (RJMA), Cluster 1 features the highest susceptibility to flooding (76%), the lowest income (USD 280), and a moderate percentage of white people (42%). Cluster 2 has the highest income (USD 1848), the highest percentage of white people (82%), low susceptibility to landslide (1%), and counterintuitively, moderate susceptibility to flooding (10%). Cluster 3 encompasses tracts with low income (USD 355), a moderate percentage of white people (41%), low susceptibility both to flooding (5%), and landslide (1%). Finally, cluster 4 encompasses the tracts most affected by landslide susceptibility (49%), featuring low income (USD 406) and the lowest percentage of white people (40%). The overall pattern of RJMA can be summarised as follows: two clusters (1 and 4) with high susceptibility and high presence of non-white, low-income groups, one cluster (3) of low susceptibility tracts with a robust presence of non-white, low-income groups, and one cluster (2) with high per capita income, a high percentage of white people, and moderate susceptibility. The point to be highlighted here is that while minority groups are expected to be severely exposed to environmental susceptibility, the same cannot be said about well-to-do people. This can be partly explained by the local idiosyncrasies of urban environmental history.

RJMA has a complex urban landscape featuring mountains, plains, forests, and the sea. Bounded to the north by the Serra do Mar cordillera, the built-up fabric spreads over marine-fluvial plains interspersed with the three massifs mentioned above (Fig. 1B). From the late nineteenth century on, the historical pattern of urban settlement has been of well-to-do neighborhoods in low-lying areas near the sea and deprived neighborhoods in more inland portions of the plain, especially around train stations, and more recently, the *favelas* on mountainsides (Abreu, 1987, 1994). The 10% of flooding susceptibility in the higher-income cluster can be partly explained by the presence of affluent residents in seafront sites.

For the Sao Paulo Metropolitan Area (SPMA), the results are similar. Cluster 1 is the most affected by flooding (65%), though income is higher than in RJMA (USD 722), also featuring a higher percentage of white people (62%). This reflects the historical geography of urbanization, with the initial settlement established near the confluence between the Tietê and Pinheiros rivers remaining over time as the highest-income area of the city (Becceneri et al., 2019; Villaça, 1998). Cluster 2 combines the highest income (USD 1328) and the highest percentage of white people (83%) with low environmental susceptibility. Cluster 3 has the lowest income (USD 336), a moderate percentage of white people (51%) and low susceptibility. Cluster 4 combines the highest susceptibility to landslide (48%), low income (USD 307), and the lowest percentage of white people (46%). Compared to the RJMA, cluster 4 has lower values for income. As the mountains in SPMA tend to concentrate in peripheral areas, the income tends to be lower than in RJMA, where the mountains and hills dot the entire city, including the central area where income is higher (Fig. 3).

3.4. Scale 2 - Municipalities

The analysis conducted at Scale 2 (municipalities) shows a similar pattern. In Fig. 2, the charts feature the values for each cluster in each municipality, and the summary tables below show the average values for



Rio de Janeiro - Scale 1 – Metropolitan area

Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	355	42	76	0
2	1848	82	10	1
3	355	41	5	1
4	406	40	2	49

São Paulo - Scale 1 – Metropolitan area

Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	722	62	65	0
2	1328	83	1	0
3	336	51	1	0
4	307	46	1	48

Rio de Janeiro - Scale 2 – Municipalities

Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	358	40	75	0
2	682	57	18	1
3	290	37	7	3
4	337	41	3	36

São Paulo - Scale 2 – Municipalities

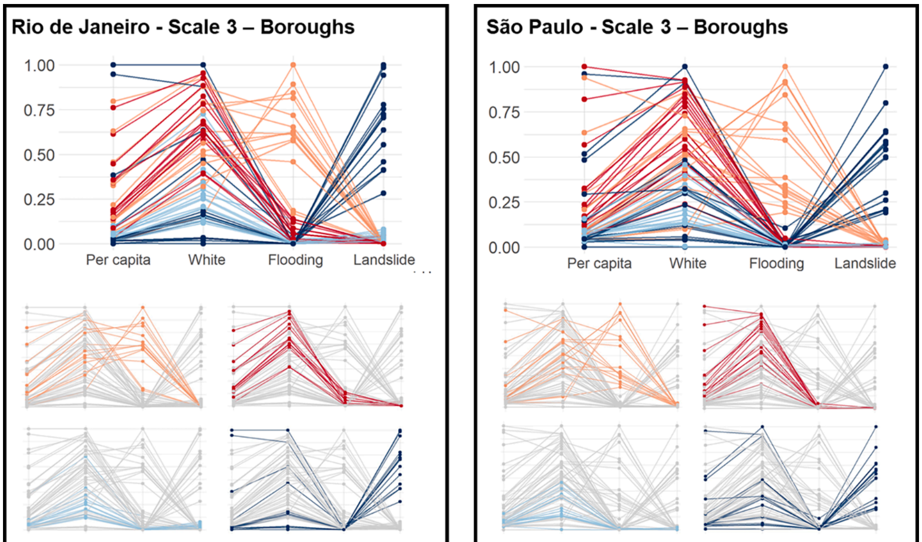
Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	388	57	53	1
2	891	76	2	1
3	300	52	1	1
4	281	50	1	34

Fig. 4. Parallel Coordinate charts showing the k-means clustering analysis for Rio de Janeiro and São Paulo Metropolitan Areas and Municipalities. Source: Census database (IBGE, 2010) and high susceptibility provided by (CPRM, 2015). The top graphs present the combined clustering results, while the bottom graphs present individual clusters.

the municipalities. In RJMA, Cluster 1 features the highest susceptibility to flooding (75%), having a low per capita income (USD 358) and a moderate percentage of white people (40%). Cluster 2 has the highest income (USD 682), the highest percentage of white people (57%), while susceptibility to flooding is light to moderate (18%). Income is considerably lower than the one found for the metropolitan area. The peripheral municipalities that, on the first analysis, appeared to be homogeneously poor now present their own higher income clusters, reducing the mean. Cluster 3 shows low susceptibility to environmental hazards, the lowest per capita income (USD 290), and the lowest percentage of white people (37%). Cluster 4 features the highest susceptibility to landslide (36%), presents low income (USD 337), and 41% of white people. Similar results were found for the SPMA, with the same exceptions already mentioned.

3.5. Scale 3 - boroughs

Although the results obtained at Scale 3 (boroughs) suggest a replication of the same pattern observed in the previous two levels, a even more detailed analysis reveals key differences (Fig. 4). First, the per capita income values are much higher than those obtained at coarser scales, a direct result of the criteria used to select boroughs – namely, those with the highest combined susceptibility, which happens to include some of the wealthiest areas in the city. Except for Cluster 3, all the others can be described as middle to high income, which is at odds with the findings in most of the environmental justice literature (more on this ahead). In both cities, Cluster 1, which features the highest susceptibility to flooding (62% in Rio de Janeiro and 43% in São Paulo), has higher average values for per capita income (USD 959 in Rio de Janeiro and USD 730 in São Paulo) and higher percentages of white people (65% in Rio de Janeiro and 61% in São Paulo) than those obtained in coarser scales. Cluster 2 shows the same pattern, with the highest income, the highest percentage of white people, and low susceptibility to hazards. The same happens with Cluster 3, which also features low susceptibility to hazards, low income, and the lowest percentage of white people. Cluster 4 has the highest susceptibility to landslide (59% in Rio de Janeiro and 42% in São Paulo) but – similar to Cluster 1 – features medium per capita income (USD 752 in Rio de



Rio de Janeiro - Scale 3 – Boroughs

Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	959	65	62	0
2	1089	70	6	1
3	384	40	2	3
4	752	41	1	59

São Paulo - Scale 3 – Boroughs

Cluster	Per capita (USD)	White people (%)	Flooding (%)	Landslide (%)
1	730	61	43	1
2	972	72	1	0
3	327	47	0	1
4	646	54	1	42

Fig. 5. K-means clustering analysis for Rio de Janeiro and São Paulo boroughs. Source: Census database (IBGE, 2010) and high susceptibility to flooding and landslide provided by CPRM (2015). The top graphs present the combined clustering results, while the bottom graphs present individual clusters.

Janeiro and USD 646 in São Paulo) and a moderate percentage of whites (41% in Rio de Janeiro and 54% in São Paulo).

A similar result can be observed when considering susceptibility variables combined with social and racial variables (Fig. 6). However, there is a difference in socio-racial composition relative to the kind of susceptibility to which people are predisposed. While flooding seems to be more equally distributed across the urban population, landslides are more associated with poor, non-white people. This pattern is particularly noticeable at the borough scale, probably due to geomorphological characteristics and the high social status attached to waterfront neighborhoods. While residence on steep, unstable slopes is mostly – though not exclusively – left to those with no alternatives, living near the ocean is a choice open to a considerable portion of the urban population.

This partial statistical change at the borough scale also can be visualized through a spatial multiscalar lens. When analyzing the spatial pattern of clusters (Fig. 7), our multiscalar approach allows us to see the kaleidoscope of homogeneity and heterogeneity. Areas that appear homogenous at Scale 1 become heterogeneous at the other scales. At Scale 1, the central municipalities (Rio de Janeiro and São Paulo) concentrate close to the central business district a significant part of the tracts with high income, a high percentage of white people, and a low percentage of susceptibility to hazards (Cluster 2). At Scale 2, the pattern changes and we can see Cluster 2 appearing in other peripheral municipalities. The zoomed-in areas (Z1, Z2, and Z3) are clearly different when Scales 1 and 2 are compared. Scale 3 is the one in which the pattern changes more intensely. Boroughs that appeared as homogenous areas at Scale 2 reveal at Scale 3 a complex clustering segmentation. Although the high susceptible clusters (1 and 4) change little, clusters 2 and 3 change substantially.

When the scale changes, some tracts "transition" to other clusters. This shifting is more pronounced when comparing Scale 2 (Municipalities) with Scale 3 (Boroughs) than when comparing Scale 1 (Metropolitan Areas) with Scale 2. The Chord Diagram in Fig. 8 helps us understand these changes and the proportions of clusters in each scale. Although the changes in high-susceptibility clusters are almost negligible (1 and 4), Clusters 2 and 3 – which represent high and low income (with a high and low percentage of whites, respectively) – do change considerably. The largest number of shifting tracts occurs in the "transition" from Cluster 2 at Scale 1 to Cluster 3 at Scale 2 (6% in Rio de Janeiro and 2% in São Paulo); see Fig. 8A and 8C. This means that part of the high-income tracts at Scale 1 turn into low-income at Scale 2. These changes are much more noticeable when we compare the tracts on Scale 2 and Scale 3. The biggest transition occurs with Cluster 2 tracts, which at Scale 3 transition to Cluster 3: 14% in Rio de Janeiro and 16% in São Paulo (Fig. 8B and 8D). This shows that income "positionality" is scale-dependent. Moreover, it is important to note the difference in proportions of clusters in each scale. As suggested by its spatial distribution, cluster 2 has a higher proportion of tracts at Scales 2 and 3 (Fig. 7).

These results reveal the complexity of assessing environmental justice across spatial frames. Corroborating Baden et al. (2007), we found that smaller spatial scopes tend to unsettle the well-known associations between socio-economic marginality and hazard exposure. When analyzed at our smallest frame, the census data show that a low- to middle-income, non-white resident in certain neighborhoods has pretty much the same chances of being exposed to flooding as a high-income white resident. In other words, the traditional parameters of socio-economic inequality seem to lose their grip on the structure of environmental justice. This forces us to consider the possibility that living in areas nominally exposed to environmental risk might not reflect a real vulnerability but the competence of local residents – either current or past ones – to employ technical and political power in order to minimize the costs of specific urban sites while profiting from their amenities. As Collins et al. (2018, p. 321) argued, "While socially elite residents may voluntarily expose themselves to flood hazards in their pursuit of environmental amenities, they are often able to externalize risks by harnessing a disproportionate share of the flood mitigation resources redistributed by state and market institutions to support flood, preparedness, response, recovery and reconstruction."

This discussion applies mainly to the case of Rio de Janeiro. (In São Paulo, most of the boroughs selected for analysis at Scale 3 due to the presence of both flooding and landslide are predominantly inhabited by lower-middle- and middle-class people.) Some of the boroughs selected in Rio are notorious for the robust presence of upper-middle- and upper-class residents: Copacabana, Jardim Botânico, Gávea, São Conrado, and

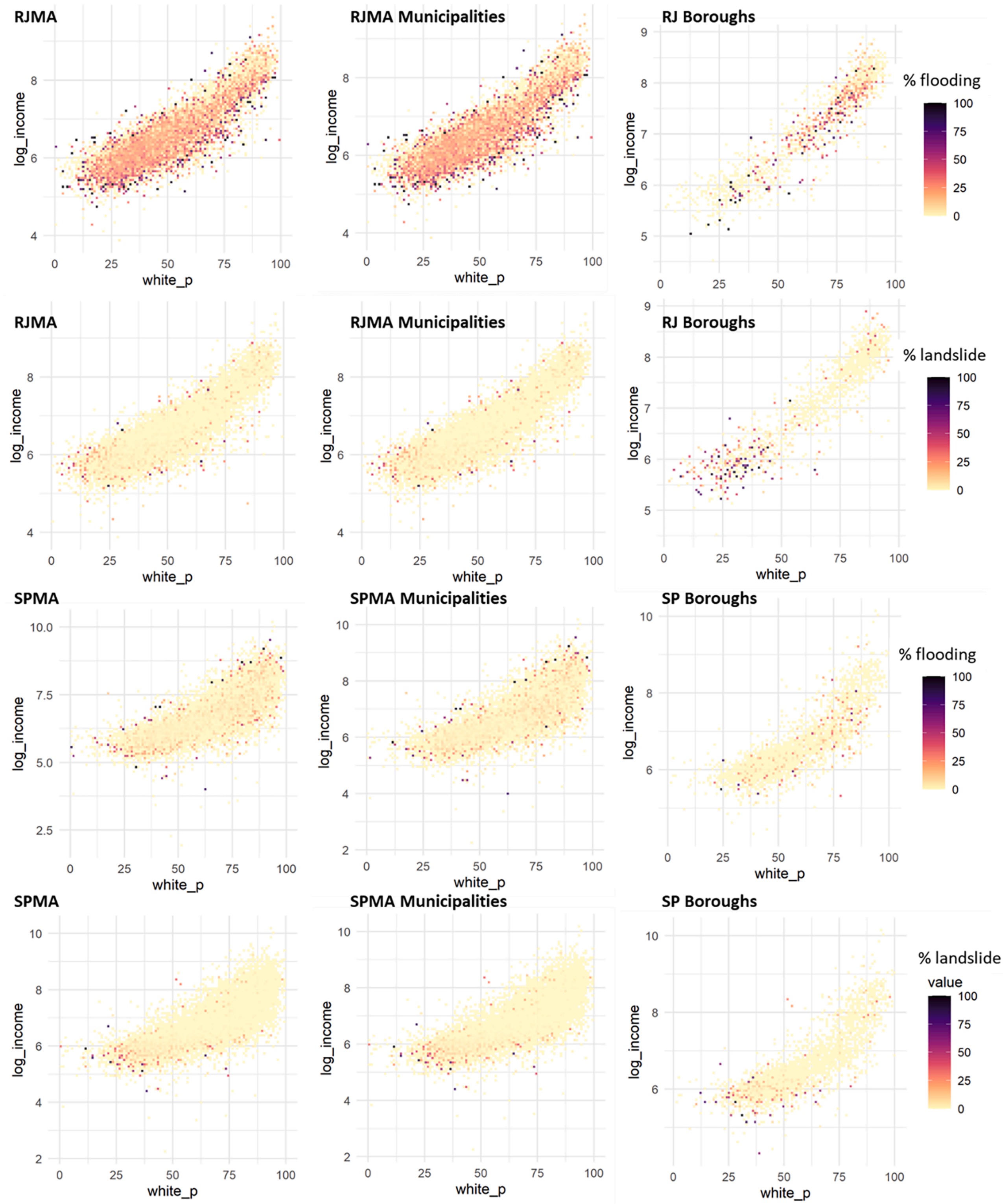


Fig. 6. Scatterplot showing three variables. Y axe displays income, x axe displays the percentage of white people. Each dot displays susceptibility variables (in colour).

Itanhangá. All of them are located at the interface between the high granite-gneissic massifs and the coastal plain, geomorphological environments subject to flooding due to the sudden change in topography. The deforestation of hillsides potentializes the risk by increasing runoff, thus making larger sediment loads (together with garbage) converge on storm drains (Cambra & Coelho Netto, 1997). The stormwater network is a crucial infrastructure in making these areas habitable today, having been instrumental in allowing real estate development companies to profit from the reclamation of these plains in the past.

Copacabana is a textbook example. Virtually isolated until 1892, when the opening of a tunnel made it accessible from the city, in 1906 Copacabana was the first area to receive a sewage system with total separation between stormwater and household wastewater (Abreu, 1987; Marques, 1995). Led by powerful capitalist interests, which

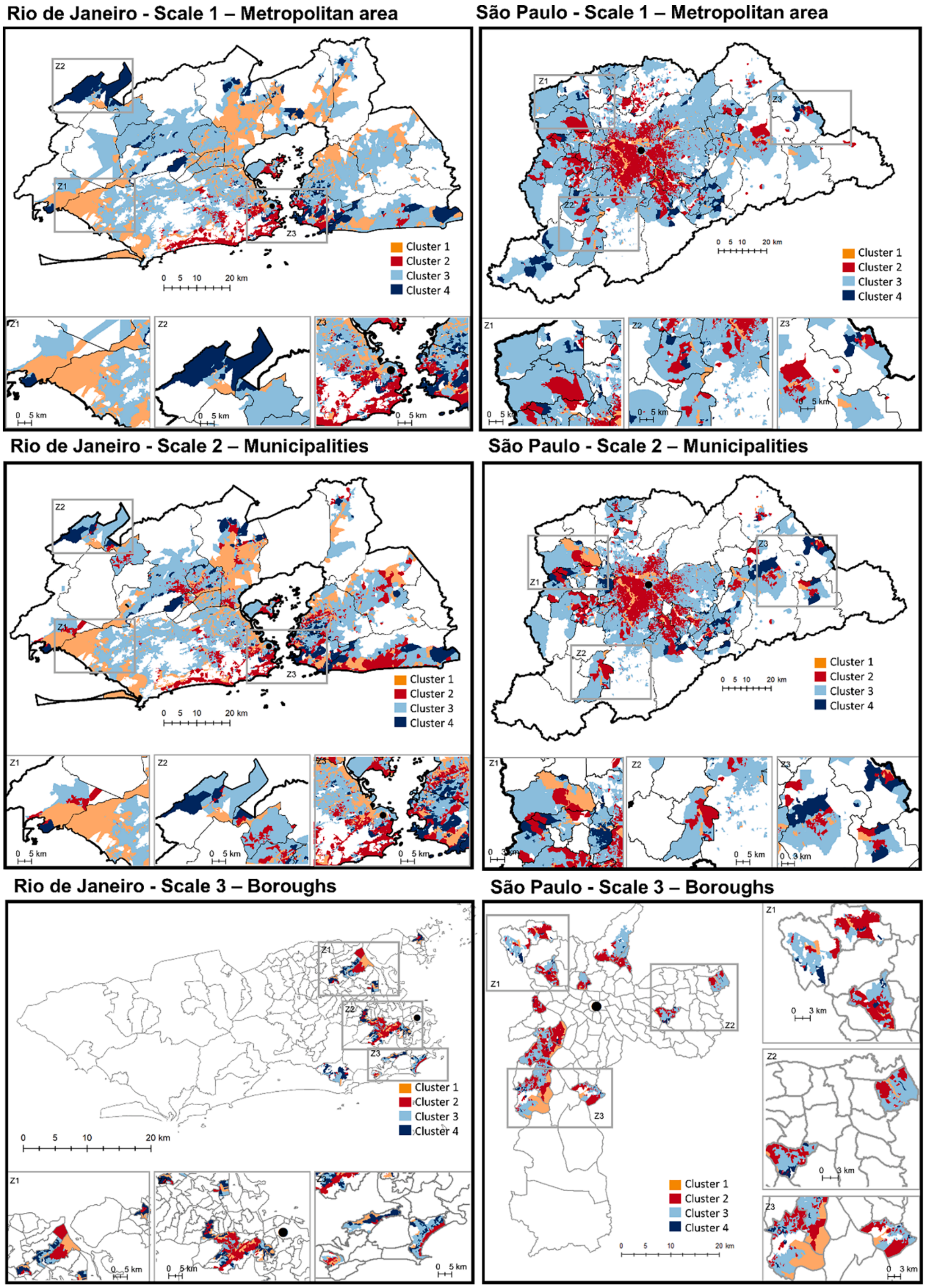


Fig. 7. Mapping k-means clustering analysis for Rio de Janeiro and São Paulo.

fiercely explored the market value of the new aesthetic valorization of seafront landscapes, this urban frontier grew swiftly to become Rio's most famous upscale neighborhood in a couple of decades. However, from the mid-twentieth century, the neighborhood's socio-economic profile began to change, as newly-opened frontiers to the west (Ipanema and Leblon) attracted the new generations of urban privileged. But the slight increase in the number of middle- or even lower-middle-class non-white residents did not seriously erode the neighborhood's old political prestige. The inhabitants of Copacabana continue to be closely assisted by the state so they can live in a geomorphologically challenging environment close to one of the most beautiful urban beaches in the world. State and municipal governments spend resources to maintain the stormwater network in the "Little Princess of the Sea" and other high-end areas to the detriment of other neighborhoods and municipalities, especially in the suburbs – some of which are not yet served with separate networks for stormwater and wastewater to this day (Britto & Quintslr, 2020; Oscar Júnior, 2018).

Thus, multi-scale analyses are crucial to understanding unequal risk (Collins, 2010), among other things, because they help to clarify the differences between nominal and real risk. The scale-dependence revealed by our results highlight the fact that biophysical susceptibilities are only abstract indicators of risk. The biophysical impossibility of human settlement is rare, especially in urban areas; instead, urban landscapes feature a range of environmental costs that people have to

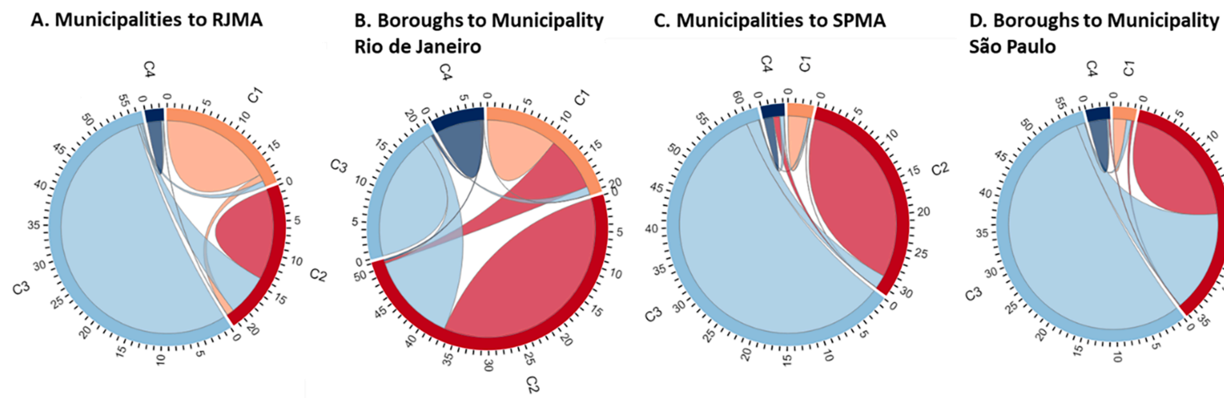


Fig. 8. Chord Diagram showing the shifting of clusters across scales. A and C show the changing of the clusters at the Municipality Scale to the Metropolitan Scale for Rio de Janeiro and São Paulo, respectively. B and D show the changing of the clusters in (selected) Boroughs scale to Municipality Scale for Rio de Janeiro and São Paulo, respectively. (See interactive version for further information on how to read it).

meet to become residents. Susceptibility polygons like the ones used in this study are indicators of such differential costs, not vulnerability to risks – which could be defined as the level of social inability to meet those costs. One can certainly live on low-lying plains or steep hillsides as long as one has enough income and political influence to secure the infrastructure and economic safety net needed to face the biophysical challenges. Hazard events may represent a risk of death for minority groups living in precariously self-built hillside sheds but not for high-income white residents living in risk-proof mansions. The quality of construction is one of the most important factors determining the capacity to resist hazard events: anecdotally, houses collapsing down the hill after major storms is a sporadic occurrence in upscale areas in Brazil but not in favelas, even though susceptibility levels are similar. Although both sites are classified as landslide-prone, the geomorphological risk is only nominal for high-income white residents, as in practice it has a low capacity to cause human and material losses.

4. Conclusion

This study corroborates the environmental justice literature by showing that the most vulnerable to landslide and flooding hazards in São Paulo and Rio de Janeiro are non-white, low-income people. However, we also showed that the spatial extent of analysis does impinge on statistical patterns, though the effects are complex to interpret. On the one hand, some of our results suggest that the structure of environmental injustice is scale-free. The clusters are very similar in the metropolitan and municipal scales, pointing to a fractal-like structure (Carvalho, 2018) in which unjust patterns created by uneven development are "reinforced across multiple scales simultaneously" (Bezdecny, 2018, p. 74). In landscape ecological terms, one could say that metropolitan areas and municipalities are the "scales of effect", that is, the spatial scopes in which socio-economic marginality is strongly coupled with environmental susceptibility. On the other hand, the borough scale reveals a different picture, one in which well-to-do white people are just as exposed to hazards (especially flooding) as non-white, middle- to lower-middle-class people – at least nominally. Drawing on Collins et al. (2018), we argued that this is a result of an elite self-exposure to risk, which is supported by socio-spatially unjust distribution of risk-mitigation infrastructures.

In sum, this study suggests that geographical extent is crucial for urban environmental inequality assessments, particularly when these inform policy and management decisions, as different scopes of analysis shape the relations between socio-economic positionality and the level of vulnerability to environmental hazards. Our results should be interpreted alongside those of studies exploring the effects of varying data resolution, most of them showing that different grain sizes give rise to different statistical patterns (see references in the introduction). Future research efforts should pay more attention to the usefulness of qualitative methods, which can help illuminate the underlying processes generating the patterns made visible by quantitative analyses (Collins et al., 2018; Hernandez et al., 2015). The historical geographies shaping the distribution of social groups in cityscapes and the differential environmental costs associated with each kind of site are among these processes. Together with multiscalar statistical methods, the historical investigation of urban political ecologies promises to help form a more comprehensive picture of the role of spatiality in environmental justice patterns.

Our findings also have implications for urban planning. Although environmental susceptibility might be argued to be the same, different socio-economic positions – sometimes in the same borough – entail unequal capacities of choice and resilience. Policy-makers should consider this lest their policies reinforce rather than mitigate environmental injustices at smaller scales (Liao et al., 2019). Differentiating between nominal and real risks is easier at smaller scales such as boroughs. Compared with environmental susceptibility variables, socio-economic and racial variables are more prone to vary across scales, thus unveiling heterogeneity in areas that seemed to be homogeneous under wider geographical lenses. These more complex spatial mosaics tend to augment accuracy when targeting areas for governmental intervention. Given that climate change makes hazard events increasingly recurrent, while at the same time public resources remain limited, policy-makers should consider multiscalar approaches to assess and tackle environmental injustice.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2022.104369.

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