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# Data integration to determine vulnerability to climate change

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**Abstract.** Statistics has been traditionally based on administrative boundaries (country, states, etc.) and, in few cases, on operational boundaries (enumeration areas, output areas). Climate hazards, however, disregard these boundaries. Statistics based on the geography of climate hazards need to be considered. The level of granularity of statistical data is quite low in most cases but a reduction in the size of aggregation units is necessary to meet the geography needs of climate hazards. Nowadays, these tasks are easier to perform due to the technological advances in GIS and its growing use in national statistical offices.
This paper discusses a case study in Brazil that uses aggregate Population Census microdata in small and regular geographical units to characterize the population settled in areas susceptible to geological hazards and flooding on the northern coast of São Paulo.
The paper finds that Census data, combined with data on the geography of climate hazards, can significantly improve our understanding of hazards and vulnerability, but many steps are necessary before this result can be achieved. The existence of georeferenced statistical or environmental data is not enough. A common spatial unit or basis for both data types is required so that data integration can be simple, quick, and effective.

Keywords: Data integration, population grid, census, vulnerability, climate change

## 1. Introduction

The impacts caused by climate change have become the greatest challenge of the twenty-first century, and their consequences are felt by most of the world's population. There are no areas that are free of this risk, and headlines about another severe weather event are always observed. The effects of climate change on human health are ever more present. Changes in the frequency and intensity of precipitation affect agriculture; they cause floods in some places and droughts in others. Landslides, storm surges, and windstorms are also becoming more frequent [1].

Climate change threatens urban infrastructure and quality of life, among other things, in poor and rich countries alike [2]. The greatest impacts are felt in cities, since most of the world's population lives in urban areas [3,4]. The combination of the characteristics of the physical environment and those of the constructed environment, both of which are intertwined with the socioeconomic conditions present in large urban areas, indicates local vulnerabilities to the effects of climate changes [5]. Thus, it can be said that cities are the focus of risk and that they are not prepared to face these impacts [6].

In studies on population and climate change, risk assessment is particularly useful for planning and responses to severe weather events [2]. Thus, it is important to develop methodologies and indicators to locate and characterize both areas of greater risk and the more vulnerable population groups. Among the challenges to be considered, a looming issue is the difficulty in reconciling sociodemographic data with environmental data [7,8].

The present article incorporates a set of efforts to identify and characterize populations that are in situ-

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ations of risk. Furthermore, it seeks to contribute to advances in the types of relationships that sociodemographic variables have with other layers of information in the conduct of spatial analysis on human dimensions of environmental change. Specifically, we overlaid Population Census with environmental data related to susceptibility to severe weather events classified according to physiographic features, such as landslides in highlands and on hillsides, flooding in lowland areas, and erosion in coastal areas. A statistical grid with Census data from the Brazilian Institute of Geography and Statistics (IBGE) is used to perform the spatial integration with the data that represents susceptibility categories as defined by the Geologic Institute.

The use of statistical grids to organize demographic data created through the use of a hybrid method that makes use of aggregation and disaggregation techniques is new in Brazil. It offers significant potential for environmental analysis, though applications similar to those used in this article are still scarce and should be explored further.

The case of the municipality of São Sebastião presented in Section 4 is highly appropriate for the proposal of integrating statistical data with physical/environmental data in order to perform studies on vulnerability to climate change. This municipality is located on the coast of São Paulo, the most populous state in Brazil, and its physiographic features vary, from very steep hillsides to lowland beaches. Coastal zones are the areas of greatest risk in the world; they may be most significantly affected by climate change [9], which includes rise in sea levels and a greater frequency of severe weather events such as river floods, flash floods, and mudslides [1,10]. Thus, this article is of global relevance and can be replicated using other areas that face the same risks.

## 2. Vulnerability to climate change

Climate change refers to the alteration in weather patterns over time. It is identified through changes in average values or in the variability of weather properties. In the broader definition given by the Intergovernmental Panel on Climate Change (IPCC) [10], changes that are both natural and man-made in origin are considered. Meanwhile, in the stricter definition given by the United Nations Framework Convention on Climate Change (UNFCCC) [11], only changes caused by human activity are considered.

According to the fifth report of the IPCC [10] and based on the scientific literature published since the previous report in 2007 [1], the last few decades have presented more impacts that may be attributed to climate change: higher atmospheric and oceanic temperatures, positive temperature and rainfall extremes, more frequent heat waves, altered precipitation distribution patterns, and more intense tropical weather such as cyclones. These modifications will impact water and food supplies, human activity, population settlements, the spread of disease, and risk and disaster patterns. They also have the potential to disturb human society [12].

To understand the different dimensions of climate change, the concept of vulnerability is used. It can be defined as the degree to which a system is susceptible to the adverse effects of climate change or is capable of handling these adversities [10].

Among the many regions that will suffer from the effects of climate change, particular attention should be paid to coastal areas where large cities are located, largely because of the factors involving the exploitation of marine resources, as well as connectivity, transportation, and, more recently, tourism and leisure [2,3]. In addition, close to 13% of the world's population is concentrated in these areas. These areas have also experienced high rates of urbanization and population growth without adequate urban planning, all of which makes them especially vulnerable to climate change [2,14].

Two traditional qualitative approaches to analyzing vulnerability to climate change involve the measurement of vulnerability. One is the most frequently employed approaches in environmental studies and uses physical factors associated with susceptibility to analyze geographic areas [15]. The other, which is more commonly applied in the social sciences, uses social and economic indicators and analyzes individuals, households, or social groups [16]. Because the impacts of climate change are directly correlated with both the physical space and the human occupation of this space, an approach that integrates physical and social conditions has been suggested as the most appropriate [17,18].

However, the integration of interdisciplinary data, acquired on many different scales and utilized to analyze many different phenomena, is not a simple task. Thus, it is important to develop analytical methodologies that enable the quantification of vulnerability to climate change and which include the identification of areas and populations at different levels of exposure, sensitivity, and adaptation potential. This task is complex, and the first challenge is to integrate the interdisciplinary information [19] available on specific spatial units into each of the disciplines involved.

## 3. Spatial units

Since the end of the 1980s, there has been a growing interest in the human dimensions of environmental change. The focus of this interest has been to integrate methodologies and data from the natural sciences and the social sciences [20]. However, these disciplines typically use different analytical units since the phenomena and characteristics of the biophysical sciences are measured in a way that is not directly comparable with sociodemographic phenomena and characteristics. For example, the data collected from Population and Housing Censuses is historically guided by administrative units, whereas environmental data relies on geographic units based on the nature of the phenomenon or on the process being considered.

Weather events occur on different and simultaneous scales and always within units that cannot be linked to administrative units. The first point in the understanding of the human dimensions of environmental change should be a common spatial unit for the integration of data, since most environmental events do not occur on the same spatial and temporal basis as socioeconomic or demographic events. Thus, finding a common unit that enables the data to be integrated and that researchers can use to work independently of any political or administrative units is an important step [7].

In recent decades, technological advancements have improved knowledge on the relationship between environment and population, particularly through the incorporation of geotechnologies and the use of space as an integration plane [21]. This challenge was partially resolved using dasymetric techniques in order to generate population totals using auxiliary data. For example, the Center for the International Earth Science Information Network (CIESIN) of Columbia University developed the Gridded Population of the World (GPW) and the Global Rural-Urban Mapping Project (GRUMP) [22].

Variables other than population totals are currently being estimated using more sophisticated techniques, but despite their advantages, such as the production of annual estimates, these data are highly dependent on the quality and availability of auxiliary data [23,24].

Since the 2000 Census round in Brazil, the IBGE has increased its use of geotechnological techniques at all stages of the Census process. This has made it possible for the agency to obtain Census results for non-traditional geographic areas. One approach that has been employed in many countries, first in those of Northern Europe [25] and more recently in others such as Spain [26] and Brazil [27], is the use of one-kilometer-squared or smaller cells available in a regular grid structure in order to aggregate Census data. This approach allows for the cells in the grid to be put together to form any geographic space; it also allows grids to be grouped into cells of a larger dimension in order to meet assessment needs on different scales. The greatest challenge to the broader adoption of this technique by statistical institutions is confidentiality, since the decrease of the size of an aggregated spatial unit significantly increases the disclosure risk [29].

The generation of a statistical grid came about through a hybrid approach defined by Bueno [28] and combines aggregation and disaggregation techniques according to the availability of spatial data. The aggregation approach uses Census microdata and their locational attributes. The approach has been put into practice through the direct incorporation of the geographic coordinates of households in rural areas, of street block segments in urban areas, and of enumeration areas with dimensions lower than that of the grid cell. The disaggregation approach has been used in cases where the use of aggregation was not possible. The disaggregation approach utilizes spatial and/or statistical methods, with or without ancillary data, for the spatial reallocation of data, that is, existing data is transferred from one spatial unit to another. The ancillary data used were classes of land use/coverage (in the case of rural areas) and road system (in the case of urban areas).

Although generally Censuses are performed only once every ten years, the advantage in their use is the regular and harmonious production of a minimal set of variables for practically all countries. The variables obtained from Censuses supply basic information about the quantity, location, and main characteristics of housing units. They also consider population statistics on sex and age. This is the basic information necessary for determining risks associated with environmental issues. To meet the need for more detailed variables, Census data can be combined with local surveys or with administrative data [8]. In addition, even though Census data is known to be scattered across large units in many different countries (which hinders detailed analysis), they have the advantage of covering a wide geographic area. Even so, the use of Census data in climate change adaptation studies has been limited, and its potential has been underestimated [8].

To demonstrate how population Census data can be integrated with environmental data to aid in studies on vulnerability to disasters caused by severe weather events, we have performed a case study that will be outlined in the following section.


Fig. 1. Location of the municipality of São Sebastião in the state of São Paulo and location of the state of São Paulo in Brazil.

Table 1
Population volume organized by susceptibility category

| Susceptibility | Population | |
|---|---|---|
| | inh | % |
| Very high | 1,237 | 1.70 |
| High | 26,872 | 36.84 |
| Moderate | 22,527 | 30.89 |
| Low | 22,299 | 30.57 |
| Total | 72,935 | 100.00 |

## 4. Case study

The goal of the following case study was to illustrate the integration of statistical and environmental data in order to supply information for studies and analysis on the interaction between human activity and environmental processes.

The largest Brazilian cities are located along the coast. Therefore, significant population concentration can be found in the coastal regions of Brazil. Close to 25% of the country's population is concentrated in coastal areas, in 7% of the municipalities and 16 metropolitan regions (2010 data). This situation has increased progressively due to three guiding developmental forces: urbanization, industrialization, and tourism [30,31]. The state of São Paulo, which is the largest in the country in terms of its economy and population, is home to a large population along its coast. Part of this population occupies areas of lower economic value. These areas are located on the slopes of the Serra do Mar mountain range and are considered areas at risk of mudslides and landslides caused by severe rainfall.

The municipality of São Sebastião was selected for the integration of land movement susceptibility data and landslide/flooding data with housing and population characteristic data. This city is located on the northern coast of São Paulo within an area of great regional and national economic importance. The region includes ports and oil and gas pipelines. It is also a tourist hub that attracts substantial visitors on weekends and summer holidays. Figure 1 shows the location of São Sebastião within the state of São Paulo, as well as the location of São Paulo within Brazil.

In this city, natural disasters involving landslides often occur, largely due to the surrounding geophysical characteristics – approximately 50% of the total area of the city is formed by escarpments with 25 to 60-degree slopes and at altitudes between 200 and 2,000 meters [32]. Another factor that contributes to the high frequency of these disasters is unregulated population growth, which has led to the occupation of these slopes and hillsides.

### 4.1. Data and method

The first set of data used in the case study comes from a PhD thesis conducted by Bueno [28]. It is a grid

Table 2
Age group organized by susceptibility category

| Susceptibility | 0–9 (inh – %) | 10–19 (inh – %) | 20–64 (inh – %) | Over 65 (inh – %) | Total (inh – %) |
|---|---|---|---|---|---|
| Very high | 148 | 186 | 573 | 65 | 972 |
| | 15.23 | 19.14 | 58.94 | 6.69 | 100.00 |
| High | 4,357 | 4,683 | 15,275 | 881 | 25,196 |
| | 17.29 | 18.59 | 60.62 | 3.50 | 100.00 |
| Moderate | 3,331 | 3,749 | 13,447 | 1,259 | 21,786 |
| | 15.29 | 17.21 | 61.72 | 5.78 | 100.00 |
| Low | 2,986 | 3,578 | 13,702 | 1,638 | 21,904 |
| | 13.63 | 16.34 | 62.55 | 7.48 | 100.00 |
| Total | 10,822 | 12,196 | 42,997 | 3,843 | 69,858 |
| | 15.49 | 17.46 | 61.55 | 5.50 | 100.00 |

Note 1: p-value $< 0.05$ for the Chi-square Test. Note 2: Total population is lower than shown in Table 1 due to suppressed values to meet confidentiality issues.

Table 3
Household Income group organized by susceptibility category

| Susceptibility | no income (hh – %) | $<$ 3 MW (hh – %) | 3–5 MW (hh – %) | $>$ 5 MW (hh – %) | Total (hh – %) |
|---|---|---|---|---|---|
| Very high | 15 | 259 | 17 | 8 | 299 |
| | 5.02 | 86.62 | 5.69 | 2.68 | 100.00 |
| High | 257 | 6,995 | 323 | 267 | 7,842 |
| | 3.28 | 89.20 | 4.12 | 3.40 | 100.00 |
| Moderate | 208 | 5,944 | 426 | 359 | 6,937 |
| | 3.00 | 85.69 | 6.14 | 5.18 | 100.00 |
| Low | 168 | 5,944 | 635 | 499 | 7,246 |
| | 2.32 | 82.03 | 8.76 | 6.89 | 100.00 |
| Total | 648 | 19,142 | 1,401 | 1,133 | 22,324 |
| | 2.90 | 85.75 | 6.28 | 5.08 | 100.00 |

Note 1: p-value $< 0.05$ for the Chi-square Test. Note 2: Income group = average monthly income per household (private and collective).

Table 4
Type of private household occupancy organized by susceptibility category

| Susceptibility | Owned (hh – %) | Rented (hh – %) | Provided by third parties and other (hh – %) | Total (hh – %) |
|---|---|---|---|---|
| Very high | 2,387 | 341 | 27 | 2,755 |
| | 79.60 | 11.37 | 9.03 | 100.00 |
| High | 5,005 | 1,888 | 935 | 7,828 |
| | 63.94 | 24.12 | 11.94 | 100.00 |
| Moderate | 4,533 | 1,714 | 684 | 6,931 |
| | 65.40 | 24.73 | 9.28 | 100.00 |
| Low | 4,363 | 1,737 | 1,142 | 7,242 |
| | 60.25 | 23.98 | 15.77 | 100.00 |
| Total | 14,139 | 5,373 | 2,788 | 22,300 |
| | 63.41 | 24.09 | 12.50 | 100.00 |

Note 1: p-value $< 0.05$ for the Chi-square Test.

with demographic data aggregated in cells with dimensions of approximately $1 \times 1$ km in rural areas and of approximately $200 \times 200$ m in urban areas. The demographic variables used were total population, sex, age, per-capita household income expressed as multiples of the Brazilian monthly minimum wage (MW), household occupancy status, and type of household. Brazil's monthly minimum wage in 2010 was R$510, equivalent to US$290 according to the exchange rate at the time.

Although this data are not official, they were calculated based on the confidentiality rules used by the IBGE, the agency responsible for performing the Population Census in Brazil. According to the IBGE, the organization of data aggregated into enumeration areas requires a minimum of five households occupied in the geographic unit so that the data for these enumeration areas is not discarded for confidentiality reasons [33].

The second set of data was on the classification of susceptibility to certain disasters, which was collected according to specific physiographic features. In other words, landslides were analyzed in highlands and on hillsides, susceptibility to flooding was analyzed in lowland areas, and coastal erosion was considered on beaches [34].

The risk susceptibility classification polygons were overlaid on the grid cells containing the Census data. This allowed for the use of a spatial derivation, the result of which provided the population volume and demographic characteristics for each feature/category association.

### 4.2. Results

The analysis indicates that approximately two thirds of the total population resides in lowland areas, whereas one third resides in highlands and on hillsides. As shown in Table 1, population volume is well distributed throughout the low, moderate, and high susceptibility categories; there is a slight predominance of high susceptibility. The very high susceptibility category presents an insignificant population volume (less than 2%), whereas the high susceptibility category encompasses 40% of the municipality's population.

Table 2 shows that all age categories (except the elderly) are present in the susceptibility categories at a similar rate. The quantity of elderly residents in the high susceptibility category is lower than the other categories, but there is no evidence to explain the reason for this difference. However, the slight variation in the absolute quantity of elderly residents may lead to large relative variations, given the fact that this group is already small relative to the others.

It can be seen in Table 3 that the income group that includes residents receiving up to three times the monthly minimum wage is the one that presents the greatest relative number of households in each susceptibility category. The frequency of this group is similar among all of the categories. The households that reported having no income were found to be most frequent in highlands and on hillsides constituting the highly susceptible category. This result suggests that these households are located in areas with little real estate value as a result of both the risks involved and the lack of infrastructure. The occupation of these areas may be legally prohibited; for urban or environmental reasons, they are more likely to be used for squatter settlements, such as slums. Households that reported the highest income (more than five times the minimum wage) are most commonly located in areas of moderate and low susceptibility.

Table 4 shows that most households are either owned or rented, with little difference in terms of susceptibility category and the exception of the highest susceptibility category. In this category, there was a greater frequency of households owned by the householder and a lower frequency of rented households. This indicates that there is a different real estate market in those areas in comparison to the other areas of the city.

Overall, the results obtained in the municipality of São Sebastião corroborate the findings of other studies: the population that is most vulnerable to climate change is also an economically vulnerable social group [7,36].

## 5. Conclusion

Given the fact that environmental transformations caused by climate change can no longer be undone, it is necessary to focus our efforts on the understanding and reduction of vulnerabilities so that we can successfully adapt to this new reality.

Part of this process includes knowledge of the population exposed to the risks and dangers involved in climate change and an understanding of the mechanisms that lead to this exposure, while still considering the fact that different individuals will react to dangers in different ways. For this, however, we need to have methods that make it easier to combine data from different disciplines in such a way that interdisciplinary analysis becomes a feasible task. However, the existence of georeferenced data will not suffice; there must be a layer that functions as a spatial unit or basis for the aggregation of all of this data. The use of a regular grid system is a real possibility, and the empirical case study outlined in this article demonstrates the effectiveness of this approach.

The techniques used in the case study of this article can be applied to other contexts, in addition to other geographic divisions, as long as adequate data are available. In this specific case, statistical institutions must adopt small geographic units – preferably regular units, akin to the ones used in this article – to aggregate Census data. There is also a need for more investment in studies and research for the development of techniques that enable us to overcome the existing limitations involving disclosure risk control.

Data integration using a statistical grid as a common spatial unit has been found to be promising, since it allows for analysis from a social, economic, and demographic perspective that also consider the physical and environmental aspects of the land. This is relevant in cases of floods or landslides, which are most frequently caused by severe weather events.

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One limitation that must be carefully considered is the scale of the data. Physical and/or environmental surveys are often performed on a regional scale (map scales between 1:250,000 and 1:50,000) or on a local scale (map scales above 1:10,000) [35]. Meanwhile, although the Census data was collected at the very accurate level, it was aggregated into demographic spatial units and hence lost its accuracy. The difference between the environmental mapping polygons and the demographic data polygons can be very large, a factor that caused many of the susceptible areas in the empirical case study to present an area approximately equal to or smaller than the grid cells. In practice, this causes a small quantity of the cells to be completely inside a single susceptibility polygon. Spatial selection methods must then be used for data integration (contain, completely contain or have their centroid in). However, we must be aware that these techniques generate uncertainties and may lead to imprecise results. They should therefore be seen as estimates.

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