Chapter 115

Mapping social vulnerability for the development of environmental disaster preparedness and mitigation strategies

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Mariane Paulina Batalha Roque
Department of Rural Economics, Federal University of Viçosa, Viçosa, MG, 36570-900, Brazil.
mariane.roque@ufv.br

José Ambrosio Ferreira Neto
Department of Rural Economics,
Federal University of Viçosa, Viçosa, MG, 36570-900, Brazil.

Wilson da Cruz Vieira
Department of Rural Economics,
Federal University of Viçosa, Viçosa, MG, 36570-900, Brazil.

ABSTRACT
There is a growing interest in research on understanding social vulnerabilities and how they are measured, however, the lack of standards and criteria for evaluating them is still one of the great challenges to be faced. This we have developed an open access R software tool to map social vulnerability, with based on official data at the level of the Brazilian census tract. The performance of the tool was evaluated in the context oof the Paraopeba River Basin, which in 2019 suffered a major socio-environmental impact, caused by the collapse of a dam in Brumadinho, in southeastern Brazil. The proposed methodology is based on concepts and indicators internationally validated and adapted to the conditions of Brazil. The results indicate regional differences significant in the basin. The most vulnerable municipalities are in the lower part of the basin to the north, while the southern basin is less vulnerable. The tool developed can be used by the polylithium formulators, for example researchers and other stakeholders to determine social vulnerability in other regions.

Keywords: Social Vulnerability Index, Brumadinho, socio-environmental disaster, Software R.

1 INTRODUCTION

The concept of social vulnerability has gained increasing attention from academia (Tasnuva et al., 2020). However, Brazil still lacks structures and indicators to evaluate it in its distinct dimensions, including territorial dimensions (Cutter et al., 2003; Birkmann, 2013; Tate, 2013; Hummell et al., 2016; Cutter et al., 2003; Hao et al., 2010; Guo; Kapuco, 2020; Chao et al., 2021).

Index-based approaches are increasingly recognized for their ability to synthesize spatially complex concepts such as social vulnerability (Chakraborty; Tobin; Montz, 2005;

Schmidtlein et al., 2008; Anderson et al., 2020). The importance of measuring social vulnerability lies in the fact that it allows the identification and quantification of the most vulnerable groups in society, who are commonly the most likely to be affected when a disaster occurs (Hummell et al., 2016; Deria et al., 2020; Chao et al., 2021).

There is a considerable volume of studies on the development of social vulnerability indices (Morrow, 1999; Atkins et al., 2000; Cutter et al., 2003; Flanagan, et al., 2011; Zandta et al., 2012;

Bergstrand et al., 2014; Coast; Marguti, 2015; Renova Foundation, 2018; Anderson et al., 2019; Brazil 2020), however most of them focus on theoretical and conceptual descriptions of the variables used.

Others , although more empirically detailed and with a greater methodological approach, provide little attention to the possibilities of practical application in concrete realities (Spielman et al., 2019; Chao et al., In addition, some available research often neglects, for example, the scales of mappings, not allowing the representation of social vulnerability at the local level (Holand; Lujal, 2012; Garbutt et al., 2015; Hummell et al., 2016). Finally, little attention has been devoted to the use of data and open source technology (Garbutt et al., 2015) in the construction of social vulnerability indexes.

This aspect is especially problematic as the success in the measurement of vulnerability is associated with the robustness of the variables employed in a given reality and scale of action and the replication of the methods used.

Although several studies and methodologies are available to map social vulnerability, up to the we do not know the existence of accessible tools to generate and replicate social vulnerability. We face this challenge by outline ing a tool for planning and supporting decision-making in environment R, for calculation and spatialization of the Social Vulnerability Index (IVS). The empirical basis used was the Paraopeba River Basin, which in 2019 faced one of the largest environmental disasters in the world, caused by the rupture of the B1 dam in Brumadinho. In addition to environmental impacts , part of the social problems arising from that tragedy is still unknown, since previously existing vulnerabilities have been added to others resulting from the collapse of the resulting in numerous challenges for the local community and the environment (CPRM, 2019; From Lima et al., 2020; Ramos et al., 2020).

This work comprised two parts: (1) the development of the algorithm and its use for preparation and mitigation applied in the Paraopeba River Basin; and (2) the construction of an index, replicable to other regions of the country. The R-language algorithm outlined here is robust, relatively simple, and can be updated over time.

This study is organized as follows: in addition to the Introduction (Section 1), in Material and Methods (Section 2), we present the study area and describe the stages of the research and its methodological design vulnerability index mapping in environment R. In Results and Discussion (Section3), we present and discuss the results of the tool (Section 3.1) and the internal consistency of the index and economic and infrastructure indicators for the Paraopeba River Basin (Section 3.2). In Conclusion (Section 4), we present the main notes of the study.

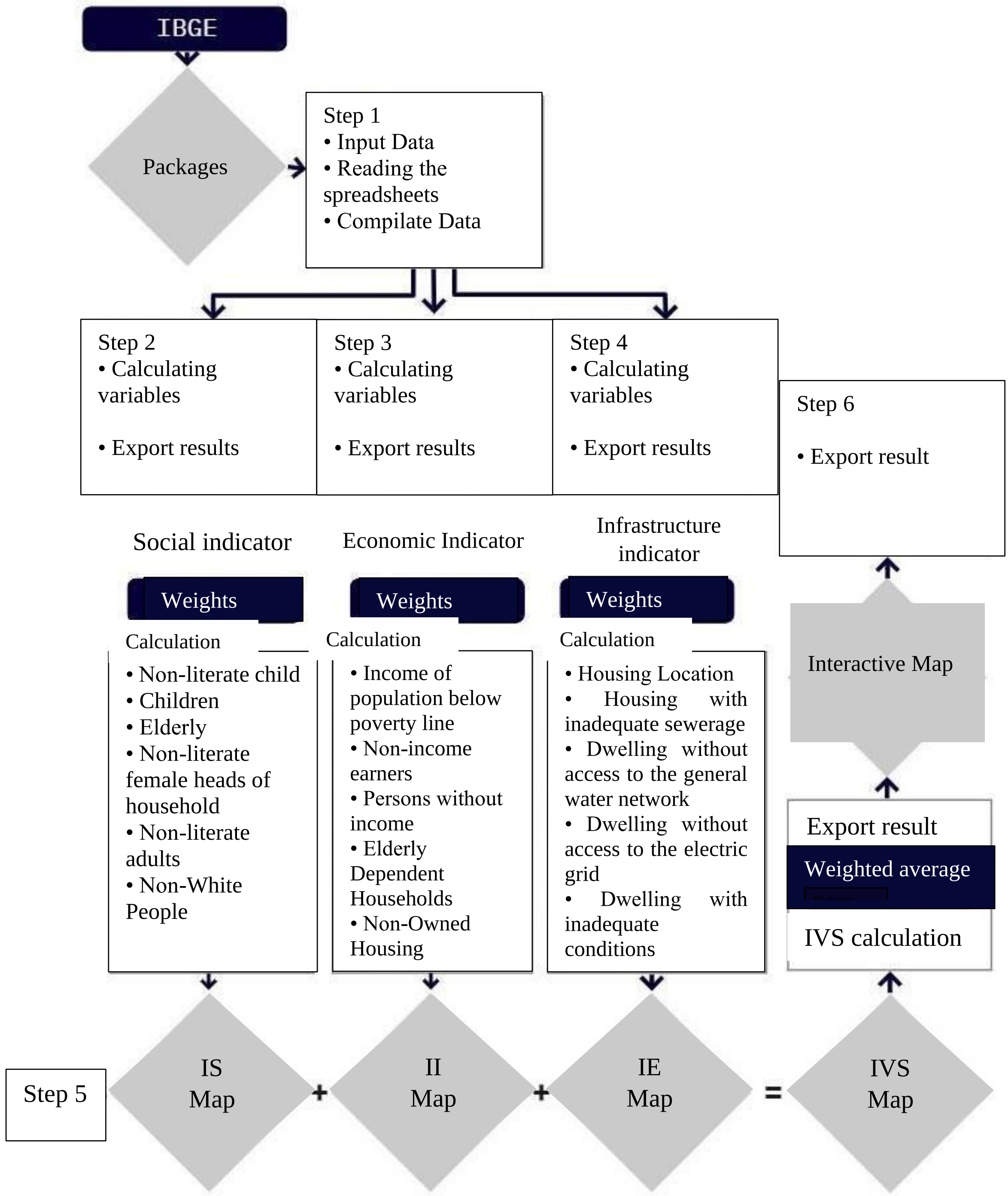
2 MATERIAL AND METHODS

2.1 . DATABASE AND SELECTION OF IVS VARIABLES

We extracted, in IPUMS International, data from the Brazilian Census Survey, publicly available on site https://international.ipums.org/international-action/samples, base year 2010. We've compiled 1,537 original variables of the Brazilian Census data set at census tract level for the 48 municipalities of the basin, which were subsequently reduced to 501, then to 31 and, finally, transformed into 16 variables, using percentage functions, as the variables were described in the literature (Sherrieb et al., 2010; Burton, 2014). Data from the Demographic Census counted 3,732 census tracts for the 48 municipalities in the basin.

As provided for in Law No. 5,534, some sectors had their data omitted to comply with the guidelines for information confidentiality , as the number of observations was not sufficient to preserve the Informants. For the set of variables selected for this study, see Figure 1. The social vulnerability variables used were adapted from previous studies by Cutter et al. (2003; 2010), Cutter, Finch and Burton (2008), Morrow (2008), Sherrieb et al. (2010), Costa and Marguti (2015), Bergstrand et al. (2014), Qin et al. (2017), Renova Foundation (2018) and Brazil (2020).

Figure 1: Methodological structure of the script.



Note: The structure created for the R script and presented in the figure above is based on a study by Lapworth and Kinniburgh, 2009.

2.2 CONSTRUCTION OF THE IVS

The variables were normalized using a min-max rescheduling scheme to create a set of indicators in a similar measurement range. This rescheduling is a method in which each variable is decomposed in an identical interval between 0 and 1 (where 0 corresponds to the worst case scenario and 1 to the (Cutter et al., 2010; Sherrieb et al., 2010; Burton, 2014; Qin et al., 2017). The 16 variables were grouped into three indicators. The Analytical Hierarchical Process (AHP) was used to calculate the score of each variable (Cutter et al., 2003; 2010; Cutter; Finch; Burton, 2008; Morrow, 2008; Sherrieb et al., 2010; Coast; Marguti, 2015; Qin et al., 2017; Renova Foundation, 2018; Brazil, 2020). Scores of the 16 variables collected from the 3,732 census tracts were then calculated within the following indicators (Figure 1): social, consisting of six variables; four variables ; and six variables to create combined variables calculated to produce the IVS. It is important to note that all variables assumed different weights, according to their importance, the expert opinion and the unique characteristics of the basin. The SVC was then calculated by the arithmetic mean social, economic and infrastructure indicators. Unlike variables, which had weights for social, infrastructure and economic indicators were not assigned weights, which means that they have the same importance in the overall sum for the IVS and the same contribution to the entire Paraopeba Basin. For the identification of the least and most vulnerable locations, the variation of the index and its indicators were specialized in five classes, at equal intervals ranging from 0 (very low vulnerability) to 1 (very high vulnerability).

2.3 ALGORITHM CONSTRUCTION

Software R is an open source language for statistical analysis (Sousa et al., 2019), developed in 1993 by Ross Ihaka and Robert Gentleman of the Department of Statistics at the University of Auckland, New Zealand (Lapworth; Kinniburgh, 2009; Sousa et al., 2019). The script was created and executed using r (version 3.6.1) (https://cran.r-project.org/bin/windows/base/old/3.6.1/).

We use the A Grammar of Data Manipulation (dplyr) (François; Henry; Müller, 2021), Simple Features for R: Standardized Support (sf) (Pebesma, 2018), Read, Write, Format Excel (xlsx) (Dragulesc; Arendt 2020), Thematic Maps in {R} (tmap) (Tennekes, 2018), Thematic Map Tools (tmaptools) (Tennekes, 2021), ColorBrewer Palettes (RColorBrewer) (Neuwirth, 2014) and Elegant Graphics for Data Analysis (ggplot2) (Wickham, 2016), to compile and obtain variables, indicators and vulnerability index and for viewing the results in standard file format, such as .xls, .png and html. Provide guidelines according to the studies by Souza et al. (2019), to assist in the development of the index for other regions. It should be emphasized that users can also modify some parameters of the routine used to obtain the IVS. The script is available as a supplement to this article in supplemental material.

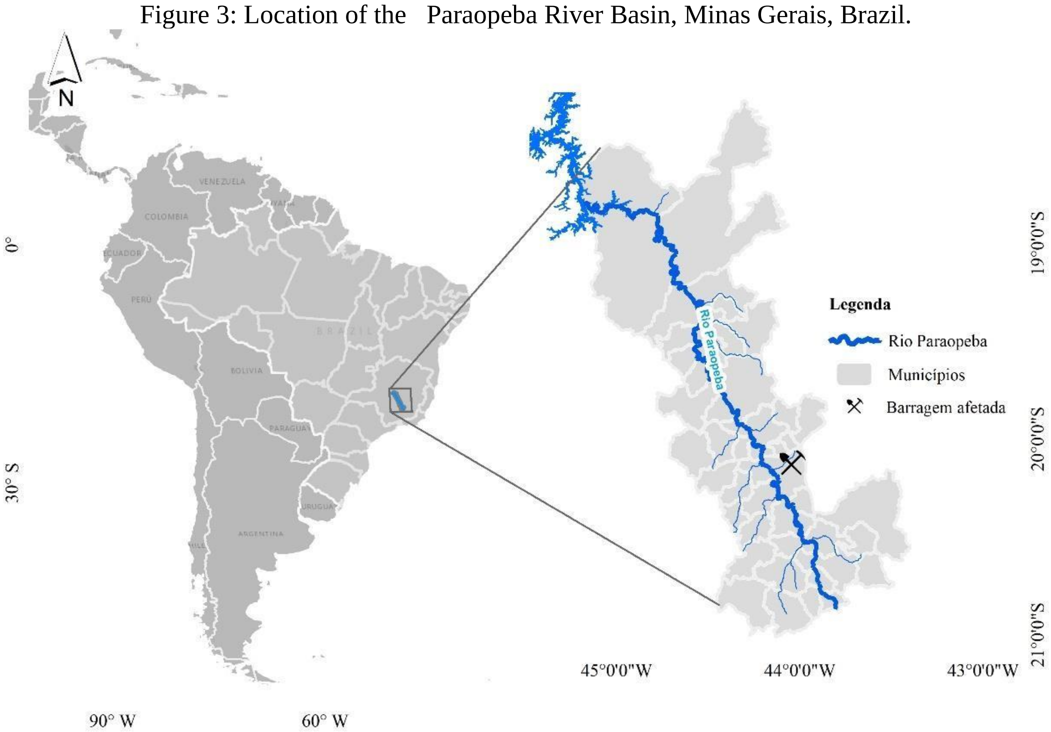
For access to the script with the detailed routine of all the steps and adjustments necessary for its replication to other areas , see https://github.com/MarianeRoque/indicedevulnerabilidadesocial.

2.4 CASE STUDY

The Paraopeba River Basin (Figure 3), located in the Southeast, is inserted in the São Francisco, one of the most important basins in Brazil and South America (CBHSF, 2020; Vergilio et al., 2020). The Paraopeba River rises in the municipality of Cristiano Otoni and collapses into the Três Marias Dam, municipality of Felixlândia (CBHSF, 2020). It is a strategic basin for the development of a vast region, marked by large socioeconomic disparities (Souza et al., 2021), covering 48 municipalities, its population density is 93.24 inhabitants/km² and the total population is 1.3 million inhabitants (CBHSF, 2020).

The basin is located in an environmentally sensitive area , transitioning from the only two hotspots in the Brazil: Cerrado (in Alto Paraopeba) and Atlantic Forest (in Baixo Paraopeba) (Roque; Grandson; Faria, 2022; Polygnane; Lemos, 2020). In this basin, several economic activities are developed, and among the using water resources are the generation of electricity , public supply and irrigation and mining (CPRM, 2019; Vergilio et al., 2020).

Figure 3: Location of the Paraopeba River Basin, Minas Gerais, Brazil.



Caption: Blue: Paraopeba river, Gray: Municipalities, Tools: Affected dam

In January 2019, one of the largest socio-environmental disasters occurred in Brazil, caused by the collapse of Dam B1, in the Feijão stream, tributary of the Paraopeba River, in the municipality of Brumadinho, MG (De Lima et al., 2020). The catastrophic event resulted in the death of approximately 260 people (VALE, 2021). The B1 dam was built in 1976 and decommissioned in 2016. It belongs to the Paraopeba Mining complex in the Iron Quadrangle, located in southeastern Brazil. It's an area economically active, related to iron mining (Robertson et al., 2019; Vergilio et al., 2020; Souza et al., 2021).

3 RESULTS AND DISCUSSION

3.1 . DEVELOPMENT OF THE ALGORITHM FOR THE AUTOMATION OF IVS

In this study, the tool developed for the elaboration of the SU comprised an expressive social data from the Brazilian Census, according to the studies by Cutter et al (2003), to identify the communities that tend to be potentially more vulnerable to the impact of disasters, due to their socio-economic and infrastructure characteristics in the Paraopeba River Basin. We use official data, available to the entire national territory, which allows a broad replication of the technique in the whole country.

Some social, economic and demographic patterns lead certain groups of people to live in of greater vulnerability (Godschalk, 2003; Garbutt et al., 2015). Mapping social vulnerability is one of the solutions to achieve the most comprehensive and integrated results of reality (Flanagan et al., 2011; Zandta et al., 2012). The elaboration of the algorithm, and consequently its application to the basin, is an alternative for stakeholders to identify the characteristics of these communities that can be positive and , or negatively , the possible impactstemming from the disaster , the scale of which allowed these actions to reveal clusters with varying levels of vulnerability.

The packages used in the algorithm canbe used in any database, simply by save them as recommended by their respective authors (Sousa et al., 2021). They were made modifications, with different functions , so that the input files could be used without any adjustment. More complete information about R codes , for reading each worksheet of interest , can be be found in the material available on https:// github.com/MarianeRoque/indicedevulnerabilidadesocial.

The data of the Demographic Census by census tract account, in the compilation of the year 2010, approximately 3,000 variables for each federative unit in the country (IBGE, 2010). For the state of Minas Gerais, a federative unit where the Paraopeba River Basin is located, we have all the previous information for about 32,565 sectors, divided into 26 worksheets. Any manual correction database, however small , may lead to limitations of this script, noasly in relation to the difficulty, as other researchers need to redo the same steps. After obtaining of each variable, the function was used to elaborate the three vulnerability indicators . Catafalque function also allows the eventual replacement of the weights assigned to each variable. In this case, it is sufficient to perform the data substitution in the script. Figure 4 illustrates the spatial distribution of vulnerabilities for each indicator in the Paraopeba Basin. The functions employed for each indicator have the same R code pattern and allow the parameters to be changed to replace the color of each vulnerability class (for more details , see supplementary material).

The results of the indicators and vulnerability index were generated in the spreadsheet format and also specialized in maps (see Methodology, for more details). However, for the IVS, a map which can be saved as an html file, was also generated. The following code was used to create the interactive map. For the html file and the full code for the IVS, see https://github.com/MarianeRoque/indicedevulnerabilidadesocial.

The generated vulnerability index interactive map can be opened on a computer , with a browser operations such as zooming and zooming and dragging can be performed (Chen et al., 2021).

The class of vulnerability and the municipality to which the census tract belongs can be verified by the mouse cursor over the sectors of the map. In developing this script, we seek to promote development and use of social vulnerability indices , but also facilitate their use decision-making by different parties, by means of an interactive map.

3.2 MAPPING OF THE IVS TO THE PARAOPEBA BASIN

First we present a tool for the elaboration of the IVS. To this end, we used the Paraopeba as an empirical basis, to discuss the internal consistency of the SVC. The three maps shown in the Figure 4a-c represents the results for each of the three indicators used.

Table 2 presents the bmean and standard deviation values of the social indicator, economic indicator and infrastructure indicator.

These three indicators of vulnerability are fundamental because they cover key aspects of society.

Figure 4d shows the IVS map showing the variation and distribution of vulnerability from the three indicators. Table 2 shows the mean and standard deviation for the SSI.

Table 2 Description of statistics for the IVS and its indicators

Description	Average	Standard deviation	Minimum	Maximum
IS Social Indicator	0.50	0.15	0.00	1
IE Economic Indicator	0.37	0.11	0.00	1
II Infrastructure Indicator	0.21	0.19	0.00	1
IVS Social Vulnerability Index	0.34	0.10	0.09	0.78

Note: For the sectors without information, their substitution was made by the median of the surrounding sectors.

Previous studies show that social vulnerability in the Paraopeba Basin is driven by contrast between developed and underdeveloped areas, the result of intense urbanization processes and industrialization, as well as historical patterns of occupation since the colonial period (Hummell et al., 2016; Castro; Pereira, 2019; Polygnane; Lemos, 2020). However, despite the existence of clusters with medium and high social vulnerability observed along the Paraopeba River, near its source, in the region of Baixo Paraopeba, the vulnerability is even worse. It is in this region that the worst indicators of the basin, with population rates close to 9.0% in São José da Varginha and 10.0% in Esmeraldas, and sanitary sewage tending to 13.2% in Felixlândia and 25.2% in Esmeraldas (IBGE, 2010; 2021). The Middle Paraopeba, a metropolitan region that has the state capital and has been intense economic growth in recent decades (Castro; Pereira, 2019), nod. is the region with the best socioeconomic indicators in the basin.

The tool to generate the IVS enabled the determination of vulnerability, at the sector level, to 3,571 of the 3,732 census tracts, 4.3% of census tracts had their data omitted to preserve the (see Methodology, section 2.2, for more details). The algorithm and its use for the vulnerability mapping allowed estimating and spatializing areas with very low, low, medium, high and very high vulnerability. The results of the IVS showed that about 30% of its are inserted in the classes from medium to high vulnerability and 70% are inserted in the lower classes and, or, very low vulnerability. Table 3 summarizes the results of the SVC and the indicators for each class.

Table 3: Percentage of Social Vulnerability Index (SIS), Social Indicator (IS), Indicator

Description	Too low	Low	Medium	High	Too High
IS Social Indicator	2.6		148.6	29.0	1.5
IE Economic Indicator	3.9		633.6	2.4	0.1
II Infrastructure Indicator	66.9		117.6	4.8	0.4
IVS Social Vulnerability Index	2.8		626.8	3.3	0.0

Note: For the sectors without information, their substitution was made by the median of the surrounding sectors. Thus, statistics refer to data without missing values.

The SSIV tends to highlight, as observed by other authors (Holand; Lujal, 2012; Garbutt et al., 2015), areas of greater vulnerability, so those areas with potentially more susceptible communities potential impacts. In addition to the index, its composition based on three vulnerability indicators (social, economic and infrastructure) provides municipalities with greater flexibility to visualize the existing internal differences. In so that they can choose different prevention strategies and, or, based on the information contained in each indicator , e.g . access and , or , the absence of basic services that should in principle be present in society and the greater presence of extreme and economically disadvantaged age groups. This data can also b overlapping the most strategic territorial divisions of each municipality. The algorithm was able to measure vulnerability , determining, based on the local scale, the areas most susceptible to the potential damage of these extreme events. Our findings emphasize the importance of measurement on the most refined scale for the possibility of mitigation actions in an adjustable way local specificities .

Among the indicators (Figure 4a-c), the vulnerability of EI to the middle classes to high vulnerability corresponded to 36.1% of the sectors; the results show that II was the indicator with the lowest number of sectors belonging to these same classes, with 22.8%, and IS presented the most belonging to these classes, with 79.1% of the sectors (Table 3). The IS was high mainly in the lower part of the basin, while the economic sector showed higher homogeneity of vulnerability, with higher portions at the low and high parts. The vulnerability related to infrastructure, on the other hand, is larger along the Paraopeba River and in the areas to the west. In however, most sectors presented a considerable portion of areas with medium to high vulnerability, for the three indicators (Figure 4).

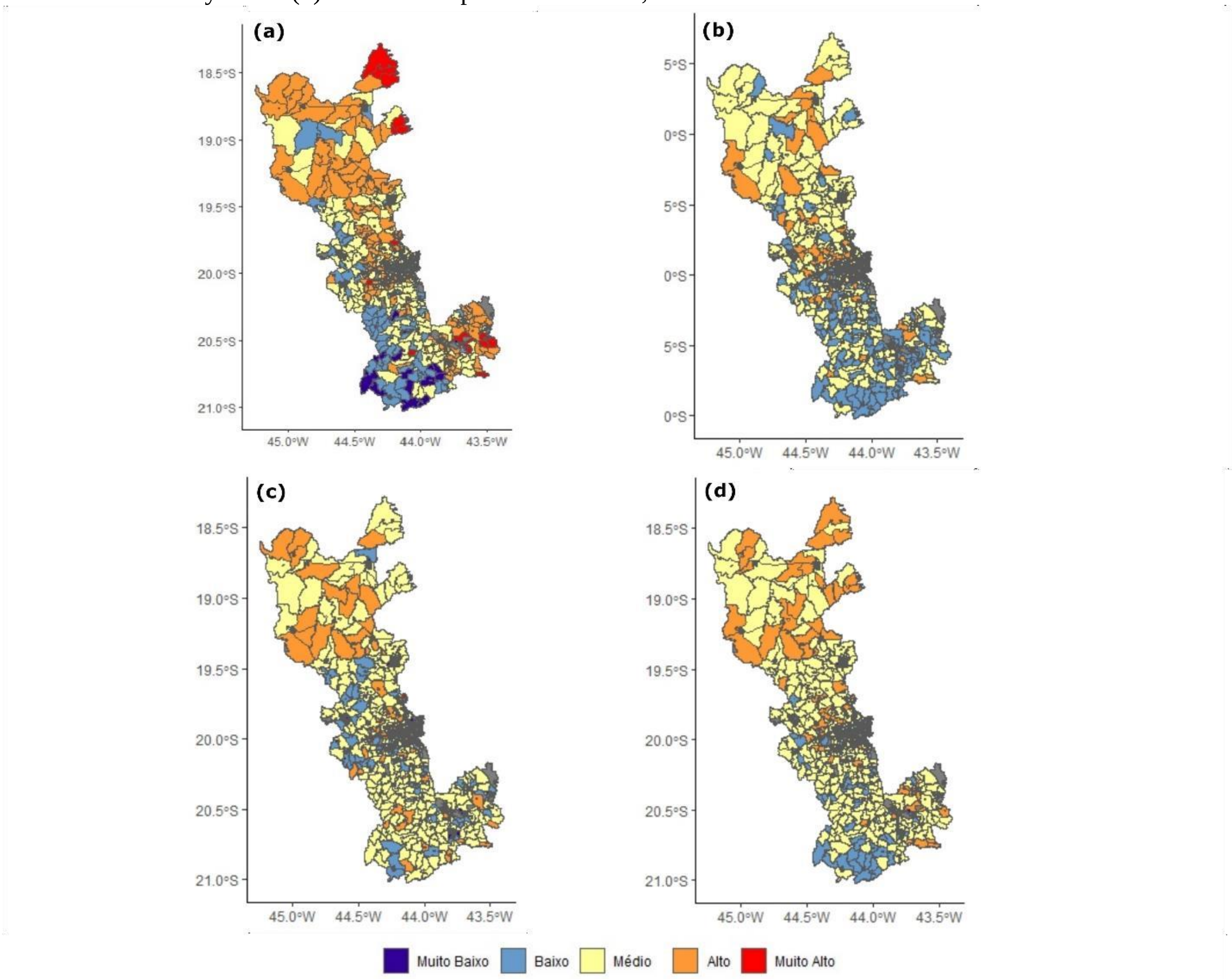
Our results differ in part and add up to these previous findings when we analyze the vulnerability index in the Paraopeba Basin. Hummell et al. (2016), unlike the observed in this study, found a higher proportion of lower classes and very low vulnerability in The Lower Paraopeba and a significant increase in vulnerable classes for the middle and lower parts of Paraopeba. The results of this study corroborate those obtained by Costa and Marguti (2015). Our conflicting findings may be associated with the use of different modeling techniques developed by Hummell et al. (2016), for example, the principal component analysis used in its studies, and the use of the AHP weighting process that we attribute to our research. The scale of action of the indexes prepared by Costa and Marguti (2015) and Hummell et al. (2016) is much smaller than that used in our research. Therefore, the results obtained here, even on a more detailed scale, were shown to be studies by Costa and Marguti (2015). In addition, we found that these researches at the municipal level have not produced similar results.

The enormous challenges associated with the increase in disasters around the world over the past decade, and the scale of impacts indicate the need to go beyond the physical and environmental component (Burton, 2014; Cutter et 22 al., 2020). In Brazil, environmental studies based on social approaches are still emerging in the debate environmental disasters. Therefore, the insertion of social aspects, including vulnerability, is research , programs and actions to prepare, respond to and mitigate disasters, not only in Brazil, but around the world in order to reduce disaster impacts.

Our algorithm, to date, is the most promising tool for obtaining this index. Stress that, as a future step, detailed studies to improve this tool are still needed.

This algorithm of planning and support for decision-making in environment R facilitated the acquisition and replication of the social vulnerability index. We hope that our tool will help policymakers decision to develop disaster management plans designed for communities with differentiated from vulnerability that are responding to, facing , and, or, recovering from disasters throughout the national territory.

Figure 4: Mapping social vulnerability to the Social Indicator (a), Economic Indicator (b) and Infrastructure Indicator (c) and the Social Vulnerability Index (d) in the Paraopeba River Basin, Brazil.



Caption: Purple: Very Low, Blue: Low, Yellow: Regular, Orange: High, Red: Very high.

4 CONCLUSION

We chose to use available , free and official secondary data to produce a tool that can be used by different stakeholders , such as companies and researchers , to identify communities that need additional assistance before, during or after an extreme event. Although there are other sources of data related to income, age, education, race, ethnicity of the population and available for the country, we chose to use only the data set of the Census Demographic, since, as ed by Deria et al. (2020), sources other than the data, in the studies may lead to discrepancies and changes in the margin of error, which may result in increased uncertainty about the overall accuracy of the dataset. The best-case scenario for achieving a high level of accuracy would be the collection of all data on site (Deria et al., 2020), which would make the task highly difficult and partly disadvantageous, as it would make it difficult to replicate the index.

The modeling presented provides a mechanism through which official country data related to the income, age, education , race and ethnicity of the population, as well as the situation of households, the condition of access , infrastructure and location, can be combined to create a vulnerability index that provide information, in a sufficiently precise resolution, to identify pockets of communities more or less vulnerable.

The script was uploaded to the GitHub repository, according to the studies by Souza et al. (2019). The results evidenced that the analysis employed here proved effective for understanding the more and less Vulnerable. Certainly, the algorithm can also be applied to other regions. This study demonstrates that it is possible to make a vulnerability assessment based on the census tract of the entire territory national. A possible future application of the script would be to allow the mapping of social vulnerability different regions and for different stakeholders.

The tool, as well as studies on indicators of social vulnerability in Brazil, is still in its initial stage. This algorithm promotes the use of social vulnerability indexes and has the be replicated to other regions, as well as facilitating their use in decision-making. Up to the is the most promising tool available , and allows the user to obtain the IVS and its indicators using a single script. The methods used are adaptable, and as they are included in the studies of Garbutt et al. (2015), the use of open source data and technology significantly reduces the costs of and allows all parties involved to easily coordinate and share information, improving knowledge about the local population in order to reduce vulnerabilities (Garbutt et al., 2015).

Supplementary data Script R, the official database of the Brazilian Census, tabulated results and figures are available in https://github.com/MarianeRoque/indicedevulnerabilidadesocial.

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