Natural Hazards (2025) 121:3123–3149
https://doi.org/10.1007/s11069-024-06920-7

ORIGINAL PAPER

Social vulnerability to long-duration power outages in Brazil

Jesse Dugan[1] · Edson Gonçalves[2] · Luciana Costa[2] · Joisa Dutra[2] · Rafael Souza[2] · Salman Mohagheghi[3]

Received: 8 May 2024 / Accepted: 9 September 2024 / Published online: 24 September 2024

Abstract

Natural disasters and extreme weather events have caused long-duration power outages in Brazil in recent years, partly due to the lack of resilience of the power grid. These outages can have disastrous impacts on the lives and livelihoods of the people who lose access to electricity. These impacts are most severe for socially vulnerable populations who struggle to prepare for or recover from a power outage. However, no index of social vulnerability specific to power outages in Brazil currently exists. To fill this gap, this paper develops an index of social vulnerability to long-duration power outages tailored to Brazil. Results are demonstrated on a case study of Rio de Janeiro using publicly available data to create indices of vulnerability in three dimensions of health, preparedness, and evacuation, as well as an index of overall vulnerability. The vulnerability maps are reported at the municipality, weighting area, and/or census tract levels. The results indicate that the most socially vulnerable regions are also highly susceptible to extreme weather events and natural disasters. The vulnerability maps can be used for targeted decision making in terms of infrastructural hardening, grid reinforcement, and preemptive event preparation as well as to inform risk-based resilient operation strategies. This study also discusses policy barriers and opportunities for vulnerability-informed resilience approaches in Brazil. Overall, this index is a valuable tool for policymakers and electric utilities to understand who is vulnerable during a power outage and to build a more equitable and resilient power grid.

Keywords Extreme events · Natural disasters · Power grid resilience · Power outages · Social vulnerability

✉ Salman Mohagheghi
smohaghe@mines.edu

1 Advanced Energy Systems Graduate Program, Colorado School of Mines, Golden, CO 80401, USA

2 Fundação Getulio Vargas, Center for Studies in Regulation and Infrastructure, Rio de Janeiro, RJ 22231-000, Brazil

3 Electrical Engineering Department, Colorado School of Mines, Golden, CO 80401, USA

1 Introduction

Brazil is prone to natural disasters, including floods, droughts, severe storms, and wildfires, which have increased in frequency and intensity over the recent years. According to the Integrated Disaster Information System (SIID—*Sistema Integrado de Informações sobre Desastres*), between 2013 and 2022, natural disasters affected 5199 out of 5,570 Brazilian municipalities (93%), forcing over 4.2 million people to leave their homes. These events resulted in damages to more than 2.2 million homes in 4334 municipalities (78% of the municipalities in Brazil), of which 107,413 homes were destroyed beyond repair. The South Region of Brazil was the most impacted, with 46.8% of homes damaged or destroyed. The financial losses associated with these natural disasters have been estimated at R$ 18.3 billion (SIID 2023).

Critical infrastructure in Brazil, particularly the power system, is vulnerable to these disasters, as demonstrated by two large-scale power outages in 2023. First, in August 2023, a blackout affected almost the entire country, interrupting 27% of Brazil's energy consumption; the lost load totaled 19 GW, impacting roughly 29 million consumer units, including homes, businesses, schools, and hospitals (Operador Nacional do Sistema Electrico 2023). Second, in November 2023, the region operated by Enel in the state of São Paulo was affected by high winds, which caused a large-scale outage; as a result, approximately 2.1 million customers were left without electricity for up to five days. According to Enel, this was the biggest weather event in the company's history, with wind speeds twice as high as originally predicted, and more than 2000 fallen trees prompted the replacement of roughly 240 km of medium voltage conductors (Investing.com 2023). These events will become more frequent as climate change increases the likelihood and severity of extreme weather events and the power grid continues to be operated closer to its stability limits (Panteli and Mancarella 2015).

These examples illustrate two fundamental and connected issues: (*i*) the lack of resilience of critical infrastructures in Brazil, especially the power grid, and (*ii*) the corresponding impact on the lives and livelihood of people, most of whom are unprepared or underprepared to face extreme events. Despite the recent large-scale outages, there is no incentive for Brazilian utilities to invest in power grid resilience. Brazil currently follows a price-cap regulation, where investments must be recognized periodically by the regulatory commission, and there are no clear rules about how to classify resilience investments in the Regulatory Asset Base[1]. Thus, utilities have no instruments to perform robust cost–benefit analyses to decide where and how much to invest in power grid resilience. Brazilian electricity utilities are only required to comply with reliability indicators related to short interruptions, including the frequency and duration of outages (Ministério de Minas e Energia 2024). This lack of focus on power grid resilience affects all customers across the country; however, the ability to respond to and recover from disasters (including long-duration power outages) varies based on socioeconomic factors (Thomas et al. 2013), and high inequality across Brazil has exacerbated this disparity. This disproportionate impact of large-scale power outages on socially vulnerable populations underlines the importance

[1] Regulatory Asset Base is the value of the assets in place, net from depreciation. It is combined with the weighted average cost of capital to compute the portion of a utility's allowed revenue related to the cost of capital for investors (shareholders and debtholders). It is a common practice for Price-Cap or Revenue-Cap regulations; the former being the classic type of regulatory model still used in Brazil for electricity distribution companies.

of adopting a vulnerability-based paradigm in the operation, modernization, and reinforcement of the power grid. Such an approach requires quantification of social vulnerabilities to power outages across the country to prioritize areas whose residents are most severely impacted and will therefore benefit the most from proactive resilience interventions.

Despite the need to quantify these vulnerabilities, no index of social vulnerability specific to power outages currently exists in Brazil. Previous studies have estimated the monetary costs of power outages to inform grid planning and operation decisions; however, these metrics are not available at appropriate geographic granularities to support localized power restoration decisions and do not account for the differing capabilities of social groups to respond to power outages. General social vulnerability indices have been developed for Brazil, but are not tailored to power outages specifically, and can therefore overlook factors that impact a resident's ability to respond to or recover from an outage.

This paper computes an index to measure social vulnerability to long-duration power outages in Brazil, using the state of Rio de Janeiro as a pilot region. The granularity level of the proposed index is at the municipality, weighting area[2] and/or census tract levels. Rio de Janeiro was selected due to its susceptibility to adverse effects caused by extreme weather events; since 1991, almost 6 million people have been affected by extreme weather in Rio de Janeiro, resulting in monetary losses of about R$ 7.5 billion (SIID 2023). Following the methodology presented by Dugan et al. (2023), the proposed vulnerability index comprises factors associated with health, preparedness, and the intention and means to evacuate during long-duration power outages. The proposed index will allow stakeholders to prioritize mitigation and risk management strategies for long-duration power outages and can be used in combination with grid data to better inform resilience investments and as a benchmark for required changes in local regulation. The main contributions of this paper are a model of social vulnerability to long-duration power outages tailored to Brazil and the development of vulnerability maps for the pilot region of Rio de Janeiro. The results will serve as a quantitative measure to aid in the understanding of how regional inequities can be combined with technical issues to support better decisions for both electric utilities and regulatory commissions.

The rest of this paper is organized as follows: Sect. 2 reviews the literature on social vulnerability indices in Brazil. Section 3 presents the methodology and the data. Section 4 provides the results and discussion for the state of Rio de Janeiro. Section 5 discusses applications of the proposed index and the policy barriers and opportunities that currently exist. Finally, Sect. 6 presents the concluding remarks.

2 Social vulnerability indices in Brazil: review of the literature

Previous work has adopted two main approaches to measure vulnerability to power outages in Brazil. The first approach is to estimate the social and economic costs that arise due to power outages through monetary measures, and the second is to develop general social vulnerability indices to measure how residents are impacted by disasters. However, no index of social vulnerability specific to power outages exists for Brazil.

[2] The Brazilian Institute of Geography and Statistics (IBGE) defines a weighting area as a group of contiguous census tracts, where the smallest size of a non-municipal weighting area is 400 occupied households.

As highlighted by a report from the Fundação Getulio Vargas Center for Studies in Regulation and Infrastructure (FGV CERI—*Fundação Getulio Vargas Centro de Estudos em Regulação e Infraestrutura*) (FGV CERI 2015), the estimation of the costs associated with long-duration power outages can be done in a variety of ways, for instance, using data from the System of National Accounts and the Input–Output Matrix (Eletrobras 1988), computable general equilibrium models (Botelho 2019), or contingent valuation techniques (Gonçalves and Grijó 2018). While all these macroeconomic modeling techniques offer invaluable information that can be used for long-term planning, they fail to provide a geographical granularity appropriate for social vulnerability analyses. This is because they aim to obtain an estimate, in monetary terms (R$/MWh), of the cost of 1 MWh of electricity not supplied to the system. At most, this value is differentiated by submarkets in the Brazilian electricity market, i.e., Southeast/Central–West, South, Northeast, and North, and/or by consumer types, i.e., residential, industrial, and commercial. This high-level approach is appropriate for large-scale decision-making for the Brazilian electricity system. For example, a chain of operations research models[3] exists that are used in the planning and in the operation[4] of the entire system, where this value, the "cost of the deficit", is used as an input, impacting decisions regarding the dispatch of different generation sources and the prices in the spot market (FGV CERI 2015). The value for 2024 is R$ 7810.62/MWh (~US$ 1600/MWh) (Câmara De Comercialização De Energia Elétrica 2024). However, the low granularity acts as a barrier to incorporating meaningful information about localized and regional social vulnerabilities—that are known to vary, sometimes significantly, over relatively small geographical areas—into grid operation and planning decisions. Furthermore, these approaches do not account for the varying capabilities of social groups to cope during an outage.

General vulnerability models have also been proposed and developed for Brazil to quantify the degree to which residents are impacted by large-scale events and hazards. Of note is the work that started in 2015 by the Institute of Applied Economic Research (IPEA—*Instituto de Pesquisa Econômica Aplicada*) and is known as the Social Vulnerability Atlas in Brazil (IPEA 2023). This platform displays a social vulnerability index (IVS—*Índice de Vulnerabilidade Social*) for the country, disaggregated by socioeconomic factors, and uses census tract data to build different human development units (UDH—*Unidade de Desenvolvimento Humano*) for the entire country. The UDHs are territorial sections located within metropolitan areas that can be part of a neighborhood, a complete neighborhood, or, in some cases, even a small municipality. The definition of the limits of the UDHs is understood based on their socioeconomic homogeneity, formed based on the Brazilian Institute of Geography and Statistics (IBGE—*Instituto Brasileiro de Geografia e Estatística*)[5] census tracts. The IVS for each UDH is derived as the arithmetic average of three sub-indices, namely IVS Urban Infrastructure, IVS Human Capital, and IVS Income and Labor. To calculate the sub-indices, 16 indicators are used, calculated based on variables from demographic censuses conducted by the IBGE for the years 2000 and 2010. To construct each dimension of the IVS, the indicators are standardized, with values ranging from 0 (indicating the ideal or desirable situation) to 1 (corresponding to the worst-case

[3] These models seek to minimize the cost of energy supply, including the cost of deficit. They are based on stochastic dual dynamic programming models and use different types of physical and market constraints.

[4] The Brazilian power grid has a single operator in charge of the entire country. There are no economic markets, and the operation is entirely centralized.

[5] IBGE is the entity responsible for collecting census and other types of socioeconomic data in Brazil.

situation) and assigned equal weights (IPEA 2023). There are a few academic studies that make use of this index as is or that propose more specific indicators. It is important to mention that similar indices, related to some states of the Brazilian Federation (e.g., the state of São Paulo), were previously developed by the IPEA (2015). A related study uses the same methodology but with data provided by local entities to develop and evaluate a social vulnerability index for the city of Porto Alegre (UFRGS 2022). Therefore, the IVS lays a strong foundation for further research into social vulnerability in Brazil.

In addition to the IVS, some studies have adopted the popular model of social vulnerability to environmental hazards from Cutter et al. (2003) to measure vulnerability in Brazil. Hummell et al. (2016) replicate the approach by Cutter et al. (2003) to develop a social vulnerability index to natural hazards (SoVI®) for Brazil and show how SoVI® concepts and indicators were adapted for the country. The index is constructed based on the place-based framework used in the development of the Social Vulnerability Index for the United States. Using principal component analysis (PCA), 45 city-level indicators were reduced to 10 factors that explain approximately 67% of the variance in the data, and some spatial patterns were identified, showing a concentration of the most socially vulnerable cities in the North and Northeast regions of Brazil, as well as the social vulnerability of metropolitan areas and state capitals in the South and Southeast regions. Similarly, Roncancio and Nardocci (2016) present a SOVI® index for the City of São Paulo, which, as previously described, suffered a long-duration power outage in 2023. With a focus on floods, which are common in the city in the summer months, the authors identified the main components of vulnerability as ‘urbanization level and vulnerable populations’, ‘favorable environmental and social conditions’, ‘alternative basic sanitation solutions’, ‘unfavorable social conditions’, and ‘development indicators’, explaining 21%, 18%, 14%, 10%, and 8% of the variability in the input data, respectively. The study also found that vulnerability increases in the center-periphery direction. The IVS and the SOVI® lay a strong foundation for research and analysis of social vulnerability to natural hazards in Brazil. However, although these studies are significantly more informative compared to the previously mentioned cost estimates, they are not tailored toward long-duration outages and may therefore not be appropriate or sufficiently informative for power system applications.

In addition to the SVI and the SOVI®, which are general social vulnerability indices, studies have developed models of vulnerability that are either tailored toward specific locations or use indicators focused on certain applications and hazards. Malta and Costa (2021) provide a general vulnerability index for the city of Rio de Janeiro that also considers environmental factors. The proposed methodology integrates 15 indicators in a multi-criteria decision analysis into a Geographic Information System, and the results indicate that socio-environmental vulnerability in Rio de Janeiro is aggravated by at-risk situations and environmental degradation. Goto et al. (2022) apply the SOVI® to the city of São Paulo, but, in contrast to Roncancio and Nardocci (2016), social vulnerability is evaluated at the neighborhood level. Results show that ‘demographic and average household size’ is the dimension that contributes the most to social vulnerability in the city of São Paulo. Other dimensions considered by Goto et al. (2022) are ‘precarious sectors’, ‘female managed households’, ‘renters’, ‘indigenous peoples’, ‘no income’, and ‘no basic infrastructure’. Ribeiro et al. (2022) evaluate the vulnerability and capacities of small Brazilian municipalities to reduce risks, especially those related to landslides and floods. A statistical analysis of a set of quantitative and qualitative indicators revealed that the social vulnerabilities and municipal capacities are mainly related to economic sectors, public policies, and city size. Batista and Brum (2023) present an application of the SOVI® methodology to Ribeira Medium Valley, a region under landslide risk in the state of São Paulo. Finally, de Souza et al. (2020) perform a vulnerability study associated with the COVID-19 pandemic. While these studies have provided valuable, localized vulnerability models that are well-suited for specific disaster events, no previous work has tailored a vulnerability index to long-duration power outages in Brazil.

As demonstrated by the review of the literature, there are shortcomings associated with the existing models and metrics that can potentially be used for assessing social vulnerabilities to power outages in Brazil. Models that focus on the social and economic cost of power outages fail to provide the necessary granularity level for an informative social vulnerability analysis. On the other hand, social vulnerability metrics that are defined specifically for Brazil are either too general or are focused on a particular natural hazard and are therefore not informative enough to be applied to power outages. Hence, they are not able to provide a complete picture of how long-duration power outages impact communities. Although many long-duration power outages are in fact caused by natural disasters, social vulnerabilities to them cannot be necessarily viewed from the exact same angle. This is in part due to lack of sufficient information and guidelines on how to respond to power outage events. While residents in natural disaster-prone communities generally have a (subjective) sense of the risks exposed to them and their families and a timeline for those risks, most either do not have the same level of information about power outages or may underestimate them. Further, many residents do not have access to reliable estimates of when power might be restored so they can plan accordingly. This means that, to have a comprehensive view of vulnerability to outages, the different aspects of vulnerability, particularly health vulnerabilities for those who decide to stay at their homes without access to electricity and evacuation vulnerabilities for those who wish to evacuate but do not have the means to do so, must be quantified and assessed separately, and not as an aggregate metric. This paper intends to fill these gaps by developing an index of social vulnerability that (*a*) is available at the municipality, weighting area, or census tract level, (*b*) is specifically tailored towards long-duration power outages, and (*c*) is customized for Brazil. The model is adapted based on the work presented by Dugan et al. (2023), where vulnerability is viewed from the angles of health, preparedness, and evacuation.

3 Methodology and data

Factors of social vulnerability specific to long-duration power outages are summarized in Fig. 1. The proposed methodology to construct a three-dimensional metric of social vulnerability to power outages is outlined in Fig. 2. Based on the factors from Fig. 1, data for each dimension of health, preparedness, and evacuation is sourced from publicly available datasets at the most granular level available. Each dataset is preprocessed so that values lie between 0 and 1, with larger values indicating higher vulnerability. Principal component analysis and an L1 norm model are used to develop a composite index for each dimension of vulnerability. An overall index of vulnerability is computed using Pareto ranking. Choropleth maps are then created in ArcGIS Pro to visualize how vulnerability varies across the geographic area. The proposed methodology is used to perform a case study of the state of Rio de Janeiro. The following subsections describe the data collection and preprocessing and the index development, including the principal component analysis and the Pareto ranking. Unless otherwise noted, all coding was performed in MATLAB.

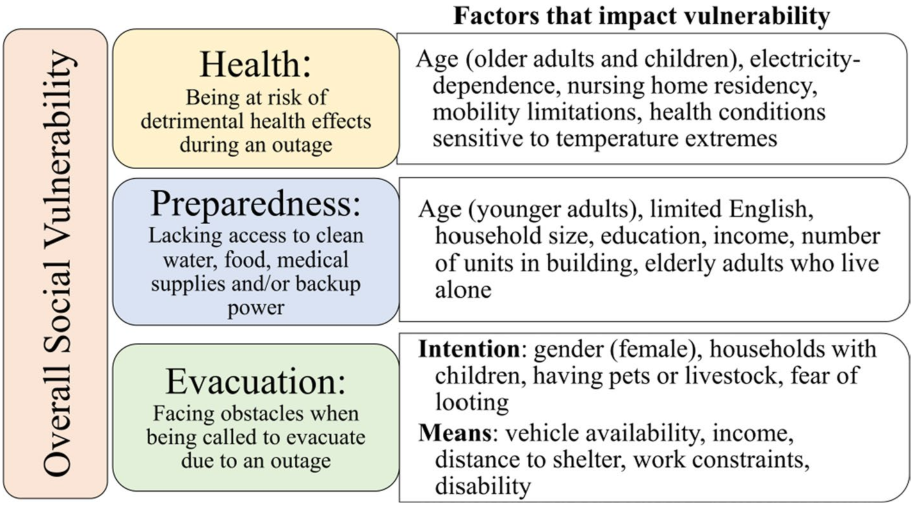

Fig. 1 Dimensions of vulnerability to power outages and the factors that impact them. Figure adapted from Dugan and Mohagheghi (2023)

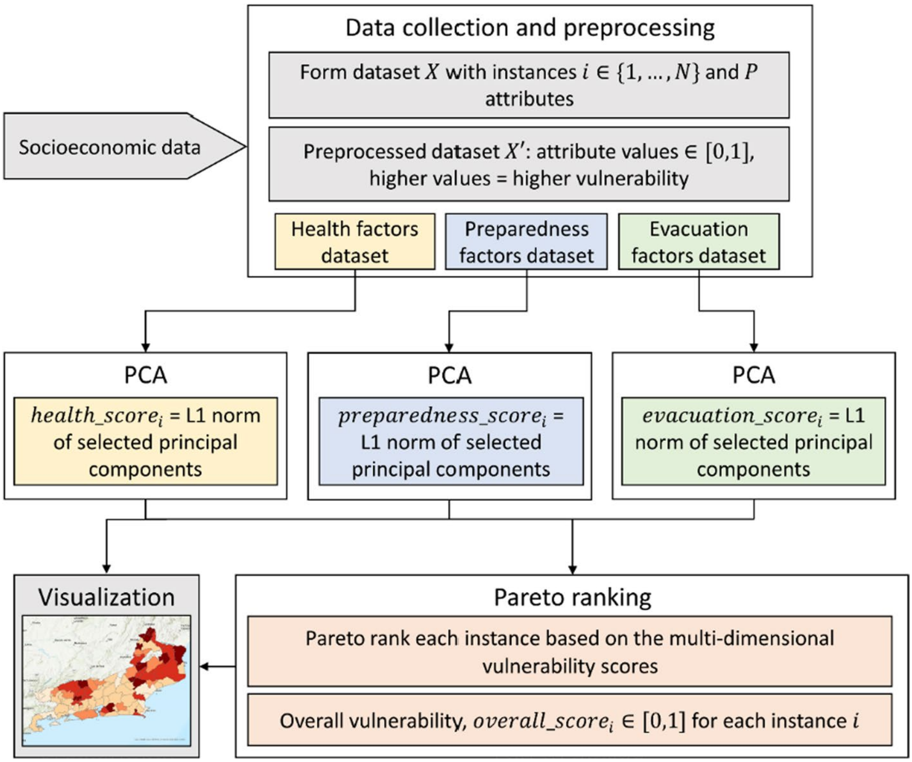

Fig. 2 Proposed methodology to evaluate social vulnerability to long-duration power outages

Table 1 Health vulnerability: factors and variables that contribute to health vulnerability during a power outage

Contributing factors	Variables
Age (above 65 or below 5)	Percent of population over 65 years old (+)
	Percent of population under 5 years old (+)
Mobility limitations	Percentage of population with an ambulatory difficulty (+)
Having an underlying condition sensitive to temperature extremes	Ischemic heart disease hospital admission per 100,000 people (+)
	Ischemic heart disease mortality rate per 100,000 people (+)
	Heart failure hospital admission per 100,000 people (+)
	Heart failure mortality rate per 100,000 people (+)
	Diabetes hospital admission per 100,000 people (+)
	Diabetes mortality rate per 100,000 people (+)
	Asthma hospital admission per 100,000 people (+)

A (+) indicates that the variable increases vulnerability. All variables are calculated at the municipality level for the year 2010

3.1 Data collection and preprocessing

Data are collected for the state of Rio de Janeiro at the smallest granularity possible for the year 2010[6]. Data sources used include the Rio de Janeiro State Department of Health (*Secretaria de Saúde*) (Rio de Janeiro Secretaria de Saúde 2023) and the Brazilian IGBE (IGBE 2010). Three scales of data are considered including municipality-level, weighting area-level, and census tract-level data. In the state of Rio de Janeiro, there are 92 municipalities, 538 weighting areas, and 27,769 census tracts. While census tracts allow for greater disaggregation of data, fewer variables are available at that level compared to the weighting area level, primarily to preserve privacy in tracts with small populations. Data related to health variables is only available at the municipality level.

Table 1 lists the variables and contributing factors for the health dimension that are publicly available at the municipality level from the 2010 census. Table 2 lists the variables and contributing factors for the preparedness dimension available at the weighting area level or the census tract level. Finally, Table 3 lists the variables and contributing factors available at the weighting area level or the census tract level.

Input datasets are formed for the health dimension at the municipality level, the preparedness dimension at both the weighting area level and the census tract level, and the evacuation dimension at both the weighting area level and the census tract level. Data instances with missing data are removed, resulting in 89 municipalities, 538 weighting areas, and 27,311 tracts included in the final analysis.

Each input dataset is preprocessed so that the variable values fall between 0 and 1 and higher values indicate higher vulnerability. This ensures that one variable does not artificially dominate another during the principal component analysis due to differing scales. Each instance, x, of variable X is normalized to x_{norm} following Eq. (1). If the variable contributes to decreased vulnerability (e.g., average income), the final value is subtracted from 1 so that higher values indicate higher vulnerability.

[6] As of February 2024, data from the most recent Brazilian census (2022) was not yet available.

Table 2 Preparedness vulnerability: factors and variables that contribute to power outage preparedness vulnerability

Contributing factors	Variables	Data granularity
Younger average age	Average age (−)	Weighting area, census tract
Linguistic isolation	Percentage of total population over 18 who are illiterate (+)	Weighting area, census tract
Households with children, larger households	Percentage of population under 6 years old (+) Average household size (+)	Weighting area, census tract
Low income	Average income (−) Percentage of population with per capita income under R$ 70 (+)	Weighting area, census tract
Living in multi-family housing	Percentage of households that are multi-family (+)	Weighting area, census tract
Low educational attainment	Percentage of adult population (25 and older) without a high school degree (+)	Weighting area

A (+) indicates that the variable increases vulnerability, while a (−) indicates variables that decrease vulnerability. All variables are calculated for the year 2010

Table 3 Evacuation vulnerability: factors and variables that contribute to evacuation vulnerability during a power outage

Contributing factors	Variables	Data granularity
Gender	Percentage of the population over 18 and female (+)	Weighting area, census tract
Households with children, larger households	Percentage of population over 18 (+) Average household size (+)	Weighting area, census tract
Low income	Average income (−) Percentage of population with per capita income under R$ 70 (+)	Weighting area, census tract
Having a disability	Percentage of population with any disability (+)	Weighting area
Work constraints	Percentage of population employed in educational instruction and library operations occupations (−) Percentage of the population employed in healthcare practitioners and technical occupations (−) Percentage of population employed in service occupations (−) Percentage of the population employed in natural resources, construction, and maintenance occupations (−) Percentage of the population employed in production, transportation, and material moving occupations (−)	Weighting area
Vehicle availability	Percentage of households with no vehicle available (+)	Weighting area

A (+) indicates that the variable increases vulnerability, while a (−) indicates variables that decrease vulnerability. All variables are calculated for the year 2010

$$x_{norm} = \frac{x - min(X)}{\max(X) - min(X)} \tag{1}$$

3.2 Index development

The social vulnerability index is developed as follows. Principal component analysis is applied to each input dataset to reduce the number of input variables based on the variable variances. Principal components are identified by computing the eigenvalues and eigenvectors of the covariance matrix of the input data. Each resulting principal component is a linear combination of the input variables within that dimension of vulnerability; they are constructed such that the first principal component accounts for the largest variability in the dataset. Principal components are all linearly independent and uncorrelated. The first m components are chosen such that they explain at least 85% of the variance in the input dataset. For each dimension of vulnerability, a composite score is calculated as the L1 norm of the first m principal components. If data instance i has m principal components with values $v_{i,p}$ the composite vulnerability score, s_i, is calculated as shown in Eq. (2).

$$s_i = \sum_{p=1}^{m} |v_{i,p}| \tag{2}$$

Previous work has used the L2 norm to find the composite score (Dugan et al. 2023); however, the L1 norm is more robust to outliers and is applied here due to the presence of valid and informative outliers in the input variables. The principal component analysis results, including the number of principal components chosen and the percent of variance explained by those principal components is given in Appendix A, Table 4. For visualization, the composite score is converted to a vulnerability level, described in Appendix A, Table 5.

Due to the presence of outliers, a second metric of vulnerability is computed to count the number of extreme values present in the principal components for each data instance. The values in each principal component are ranked in ascending order, all duplicate numbers are given the same rank, and a percentile rank is calculated based on Eq. (3), where N is the total number of data instances. Extreme values are defined as values at or above the 90th percentile. For each data instance, the final metric reports the total number of extreme values.

$$percentilerank = \frac{rank - 1}{N - 1} \tag{3}$$

Pareto ranking is used to compute an overall vulnerability score based on the L1 norm scores for health, preparedness, and evacuation vulnerability. This approach relies on the concept of dominance, and one data instance is said to dominate another if it is at least as vulnerable in all three dimensions. The Pareto ranking algorithm produces an overall score between 0 and 1, where 1 is the most vulnerable, and is described in Appendix A, Algorithm A1.

4 Results and discussion

The vulnerability scores are depicted using choropleth maps and this section presents selected results for each dimension of health, preparedness, and evacuation vulnerability as well the overall vulnerability scores. All maps are produced in ArcGIS Pro. Additional choropleth maps can be found in Appendix B and all results are available through ArcGIS Online (Dugan et al. 2024).

4.1 Health vulnerability

Figure 3 shows the health vulnerability results by municipality. No municipality in the state of Rio de Janeiro has a vulnerability level of 1 (lowest possible vulnerability). There is a concentration at a moderate level (level 3), which includes the most populated municipalities such as Rio de Janeiro and Niterói, that frequently experience long-duration power outages. According to the Brazilian Electricity Regulatory Agency (ANEEL—*Agência Nacional de Energia Elétrica*), Rio de Janeiro and Niterói are served by electric utilities with a poor classification in terms of continuity—an index created by the regulatory commission that considers both duration and frequency of outages[7] (Ministério de Minas e

[7] Rio de Janeiro and Niterói are the two most populous municipalities located in Rio de Janeiro state. These regions are served by two electricity distribution companies (Light and Enel, respectively) ranked 17th and 21st in a sample of 29 companies in regions with more than 400,000 consumption units.

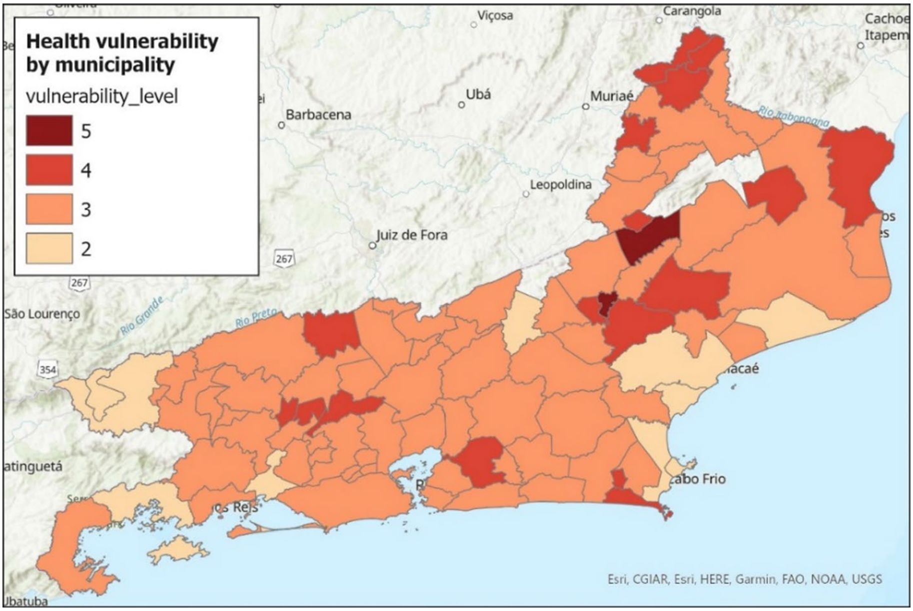

Fig. 3 Health vulnerability level for municipalities in the state of Rio de Janeiro

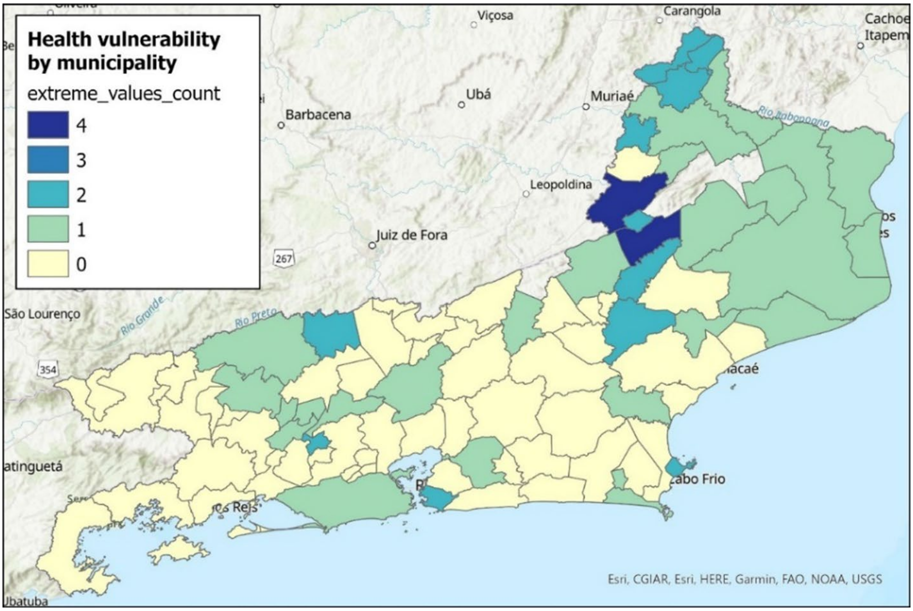

Fig. 4 Number of extreme values in the health vulnerability principal components for municipalities in the state of Rio de Janeiro

Energia 2024). The highest health vulnerability levels are seen in Itaocara and Cordeiro, which underlines the need and opportunity for improved public health assistance in these municipalities. According to the Ministry of Health, Cordeiro is ranked 84th and Itaocara 45th (out of 92) in terms of primary health care assistance (Ministério da Saúde 2023).

Figure 4 shows the extreme value counts (the number of principal components in or above the 90th percentile) associated with health vulnerability at the municipality level. These extreme values appear to demonstrate an expected pattern—municipalities with rank 4, i.e., Santo Antônio de Pádua and Itaocara, do not have a desirable level of primary public health coverage. According to the Ministry of Health, Santo Antonio de Padua is ranked 67th and Itaocara 45th out of a total of 92 municipalities in the State of Rio de Janeiro (Ministério da Saúde 2023). The process of aggregating the principal components into a single measure of vulnerability can mask locations that have very high values in certain input variables, but moderate or low values in others. For example, the municipality of Santo Antônio de Pádua has four extreme values but, as shown in Fig. 3, it has a health vulnerability level of 3, marking moderate vulnerability. Vulnerability levels and extreme value counts can be used in tandem to gauge which geographic areas might contain valid outliers and to adjust responses as necessary.

4.2 Preparedness vulnerability

Figure 5 shows the preparedness vulnerability results by weighting area. Here, there are a few regions with vulnerability levels 1 and 2, mainly in the City of Rio de Janeiro and its surrounding areas. Again, there is a high concentration of moderate level (level 3) and some critical areas (levels 4 and 5). This is not surprising due to the characteristics of some municipalities in the region of "Baixada Fluminense", for instance, cities such as Duque

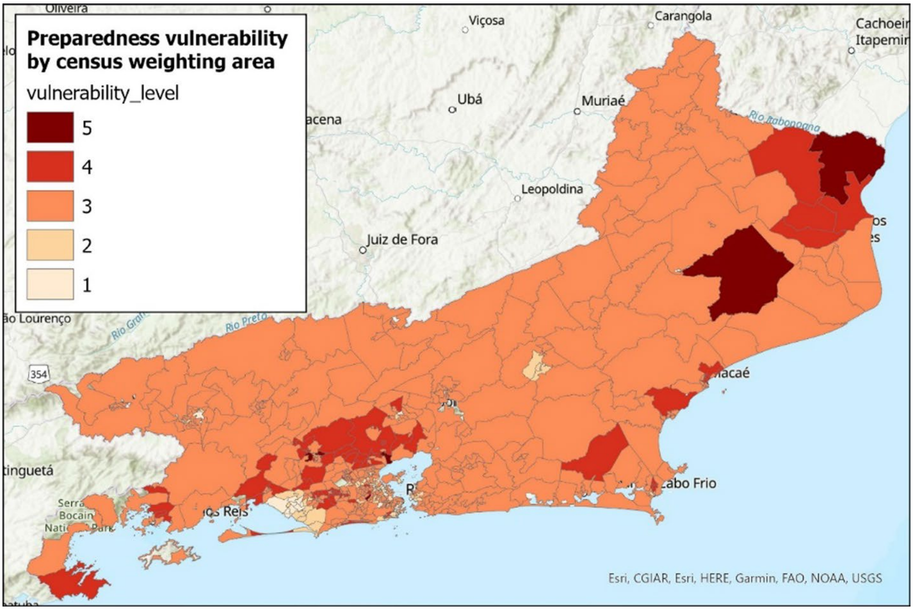

Fig. 5 Preparedness vulnerability level for census weighting areas in the state of Rio de Janeiro

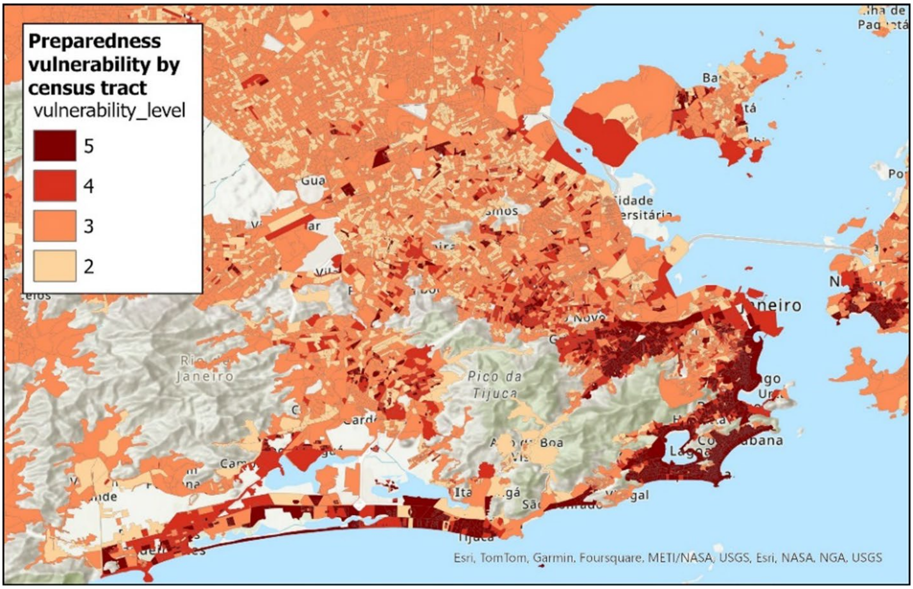

Fig. 6 Preparedness vulnerability by census tract for the city of Rio de Janeiro

de Caxias and Nova Iguaçu that present high inequality and poor infrastructure (Rio de Janeiro 2023). The Brazilian Portuguese name "Baixada Fluminense" can be translated to "a region in the state of Rio de Janeiro below sea level". This region suffers from flooding when there is an excessive increase in the water level in Guanabara Bay. Lack of maintenance in the drainage system of the rivers that cross "Baixada Fluminense" was one of the main reasons for the flooding in the region after storms in January 2024. According to the Hydrology Department at Coppe/UFRJ (Federal University of Rio de Janeiro, Engineering School), this system, which was built to protect "Baixada"[8] from these flooding events, has not undergone maintenance for at least 10 years (Agência Brasil 2023). The areas with the highest preparedness vulnerability levels include municipalities such as São Francisco de Itabapoana and Santa Maria Madalena. Coincidentally, many of these regions are associated with the highest number of disasters in the last 30 years, with Santa Maria Madalena, São Francisco de Itabapoana, and Campos dos Goytacazes leading in the frequency of events (SIID 2023). São Francisco de Itabapoana and Campos dos Goytacazes belong to the "Costa Doce" region of Rio de Janeiro State where flooding is a primary concern due to rising water levels of the Paraiba do Sul and Itabapoana rivers (Folha 1, Campos dos Goytacazes 2022). Santa Maria Madalena, located in the "Serrana" region[9], like other cities in same the part of the state, is threatened by landslides (DW Brazil 2023).

The census tract level allows for a more detailed view of vulnerability within an urban area, as demonstrated in Fig. 6, which shows preparedness vulnerability by census tract for the city of Rio De Janeiro. Here, one can see a strip of land near the sea with both levels 2

[8] The Portuguese word "Baixada" is translated as "below" or "at a lower level" in English.

[9] "Serrana" is a region surrounded by mountains. The root of the word "Serrana" comes from "serra", which means "mountain" in English.

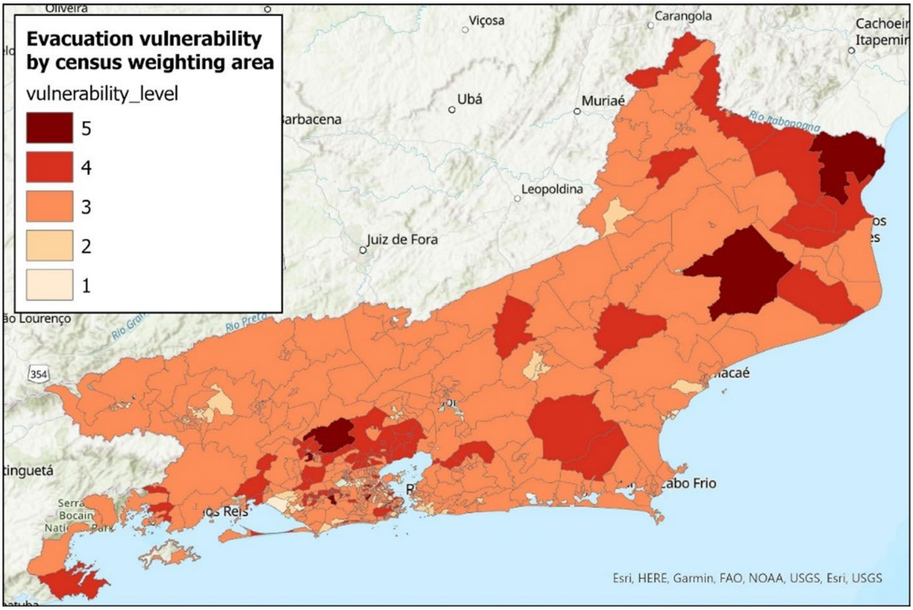

Fig. 7 Evacuation vulnerability level for census weighting areas in the state of Rio de Janeiro

and 5 for preparedness vulnerability. These are associated with the southern region of the city, characterized by the most affluent and traditional neighborhoods such as the famous Ipanema, Copacabana, and Leblon and, and at the same time, poor communities (the "favelas") with high population density.

4.3 Evacuation vulnerability

Figure 7 displays the evacuation vulnerability by census weighting area, which aligns largely with that of preparedness vulnerability, shown in Fig. 5. There is a high concentration at level 3, a few localities with the lowest level of vulnerability in the city of Rio de Janeiro, and the most vulnerable areas found in the Municipalities of São Francisco de Itabapoana and Santa Maria Madalena. Municipalities in the "Baixada Fluminense" area remain at level 4, which again highlights their vulnerability. It is interesting to highlight that vulnerability levels of 1 occur in the southern region of the city, with no apparent discrimination between the affluent and the poor parts of the area.

Figure 8 shows the extreme value counts (the number of principal components in or above the 90th percentile) associated with evacuation vulnerability at the census weighting area. When compared with the data provided by the SIID (2023), one can see that most of the past events have occurred in areas where people were not able to evacuate easily[10]. This is an important factor that must be considered in any mitigation strategies for power grid resilience.

[10] These areas correspond to regions that are surrounded by mountains ("Serrana"), mountainous regions ("favelas"), and areas bellow the sea level ("Baixada").

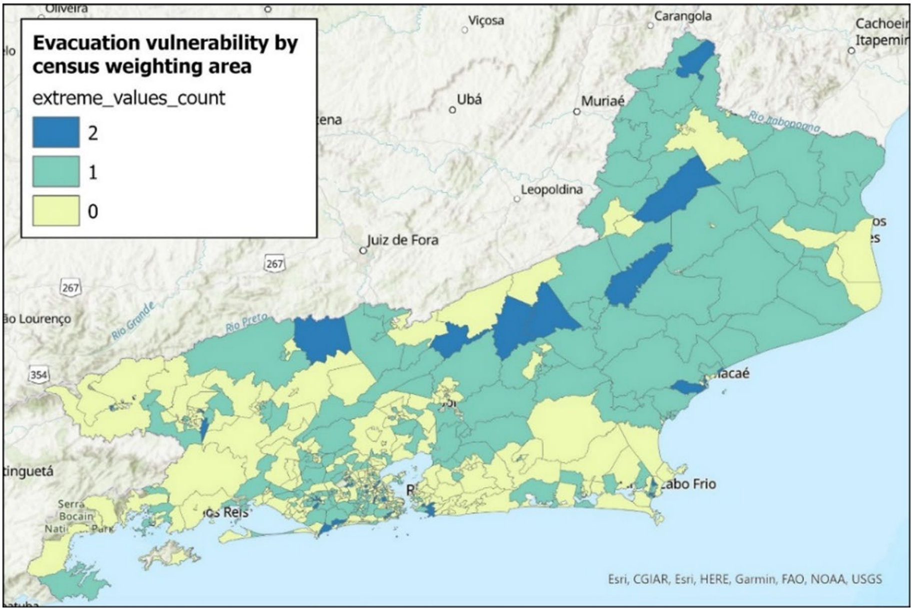

Fig. 8 Number of extreme values in the evacuation vulnerability principal components for census weighting areas in the state of Rio de Janeiro

4.4 Overall social vulnerability to long-duration power outages

The three L1 vulnerability scores are aggregated into an overall vulnerability score through Pareto ranking. Municipality-level health scores are applied to all weighting areas and census tracts within that municipality. The Pareto ranking results are translated to scores between 0 and 1, where 1 indicates the most vulnerable, and mapped in ArcGIS Pro. The results for the overall vulnerability scores at the weighting area level are presented in Fig. 9, which shows that, unlike the analysis of vulnerabilities for individual dimensions, when combined, the dominant pattern of moderate vulnerability (3) makes way to predominantly critical areas with high vulnerability scores (>0.6). In fact, most of the country has a vulnerability score above 0.6, which should be concerning for policymakers, governments, utilities, and regulators. In addition, the same consistent pattern as before emerges here where areas with the highest vulnerability are closely aligned with areas with the highest rate of disaster events in the last 30 years, as reported by the Integrated Disaster Information System and shown in Fig. 10 (SIID System 2023). The previously mentioned cities of São Francisco de Itabapoana, Campos dos Goytacazes, and Santa Maria Madalena must be highlighted again, with Duque de Caxias (located in the "Baixada Fluminense") and part of the city of Petropolis[11], that also appears as critical on Fig. 10. Finally, the high inequality in the city of Rio de Janeiro is exposed again—it is possible to see within the same surrounding region (the south region of the city) an overall score of less than 0.2 adjacent to those with scores close to 1.

[11] Petropolis has a chronic problem with floods and landslides, mainly in the summer season. It is another famous city in the "Serrana" region of the Rio de Janeiro State.

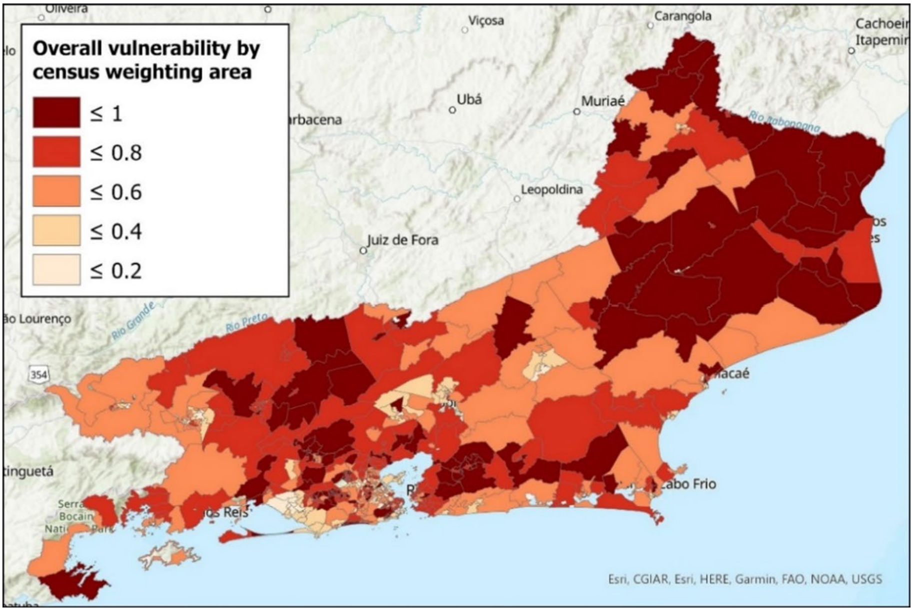

Fig. 9 Overall social vulnerability to long-duration power outages for census weighting areas in the state of Rio de Janeiro

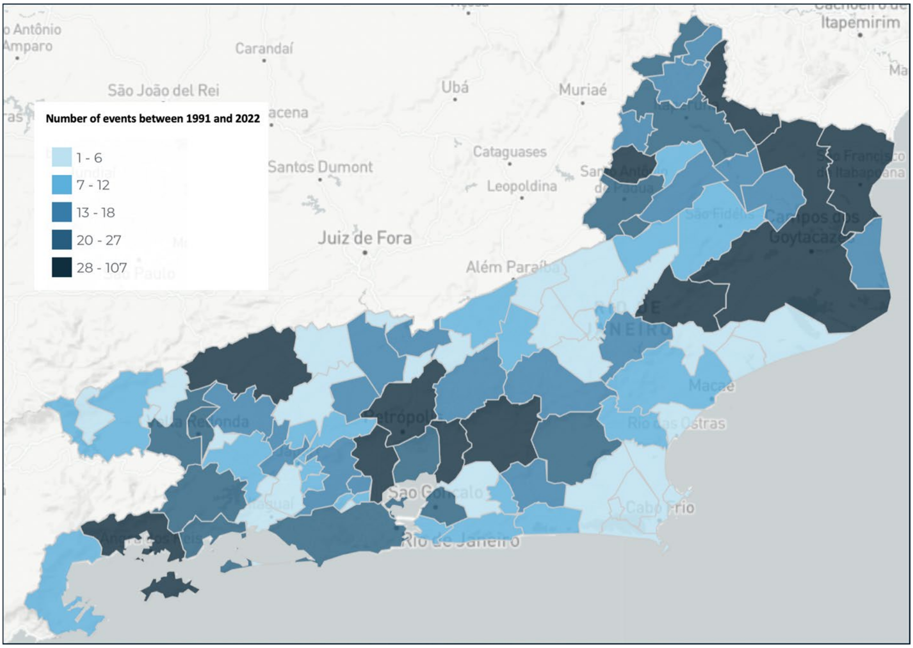

Fig. 10 Disaster occurrences in Rio de Janeiro municipalities. 1991–2022 (SIID 2023)

5 Applications and policy implications

5.1 Applications

The results of this paper indicate that areas with the highest levels of social vulnerability in Rio de Janeiro have also experienced high numbers of natural disaster events. One example is the city of São Francisco de Itabapoana, which ranks in the highest level of vulnerability and has experienced 34 disaster incidents since 1991 (SIID 2023). Addressing these disparities requires a vulnerability-informed resilience paradigm for grid operation, modernization, and reinforcement. This necessitates adopting a risk-based framework where the probabilities of outages and disturbances (the technical aspects) are balanced against the consequences of those events and their impact on the community (the societal impacts). The indices proposed in this paper can be used to inform the consequences of long-duration power outages, allowing for better-informed investment decisions and more equitable mitigation strategies.

Figure 11 illustrates various grid resilience measures according to their timeline, i.e., preventive (before the event), corrective (during the event), and restorative (after the event). When preparing the grid for disaster events, the proposed indices can be used by electric utilities to perform targeted and localized infrastructure hardening and reinforcements by allocating resources where they are needed the most. They can also employ preventative strategies, such as vegetation management or building levies, to protect communities that are the most vulnerable to outages. During a disaster event, the social vulnerability indices proposed in this paper can be used to update the electric utility's risk picture for any

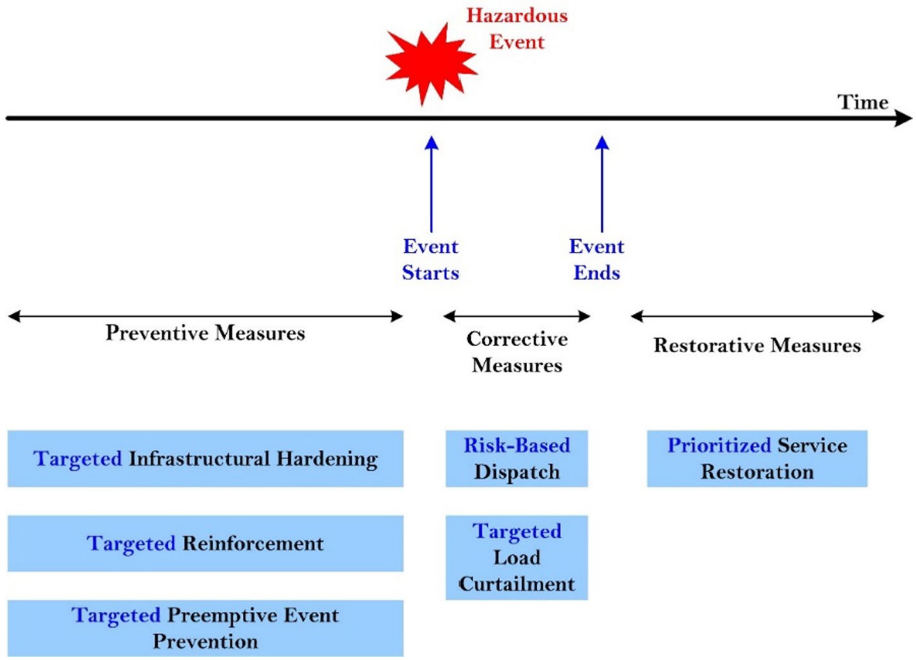

Fig. 11 Various grid resilience measures that can benefit from the proposed social vulnerability indices

security-constrained risk-based dispatch and/or to deprioritize load regions for emergency load curtailment. Lastly, equity-aware post-disaster electric service restoration can be implemented by prioritizing outage areas based on their estimated social vulnerability levels. Other vulnerability-informed disaster-related mitigation strategies include evacuating vulnerable residents during a long-duration outage, setting up community shelters, especially during extreme weather events, and investing in backup power at hospitals and other critical loads, among others. At the national scale, the National System Operator or the Energy Research Office, responsible for long-term energy planning in Brazil, can use this information to inform their policies and recommendations. Federal, state, and local entities involved in emergency management can also use these indices during disaster relief efforts to ensure that resources reach those who need them the most.

5.2 Policy implications

There is no publicly available tool or method used by the Brazilian government for prioritizing investments in the country. However, due to the recent events that impacted the Rio Grande Sul State, the federal government has started a new initiative to map the most vulnerable regions to assist with resource allocation related to natural disasters (Brazilian Government 2024). While this tool does not provide an index of vulnerability, it enables the monitoring of certain parameters that are generally related to vulnerability to natural hazards. In addition, the government recently issued a tool based on cost–benefit analysis as a non-mandatory guide to be adopted by decision makers in allocation of general investments (Ministério da Economio 2021). Despite these efforts, the most vulnerable regions do not necessarily receive the required investment to avoid or mitigate the impacts of large-scale disaster events. For instance, in Baixada Fluminense, where floods are recurrent, there are structures in place to mitigate the effects of these events. If maintained properly, these structures should be able to significantly increase flood resilience in an area where 3.5 million people live. However, in 2024, according to the government of the State of Rio de Janeiro, part of the infrastructure responsible for draining water in the Metropolitan Region was not operational, with only 2 drainage pumps (out of a total of 5) fully functioning at the time.

Unfortunately, areas or communities that are most impacted by disaster events are also the most affordable ones in terms of housing costs and rental fees. IBGE data indicates that many of these areas are associated with low income levels and income inequality (IBGE 2010). Yet, overpopulation and insufficient infrastructural investments make them especially vulnerable to the impacts of natural hazards and the long-term power outages that likely ensue.

Despite the numerous applications of this proposed index, barriers exist in Brazilian electricity policy that can hinder its adoption. First, while resilience investment strategies have been an issue on the agenda of ANEEL for 2024, societal concerns are yet to be explicitly included in energy policies set by the regulator. When conducting tariff reviews, some related parameters, such as the duration and frequency of outages, or information obtained from customer experience surveys run by electric utilities are accounted for; however, these aspects are mainly related to reliability, not resilience (ANEEL 2023). This absence of a specific regulatory framework for resilience is a potential barrier to including social vulnerability metrics into utility decision making, for instance when quantifying the consequences of outages in grid modernization studies by local utilities. Since the regulator does not have a methodology to recognize resilience investments in the Regulatory

Asset Base, there are no incentives to invest in and finance related research (FGV CERI 2023b). Even if a recommended framework is put in place, risk-based measures and resilience interventions may not result in an immediate or tangible return on investment (ROI) (ANEEL 2024). This makes it less likely for Brazilian utilities to adopt risk-based measures, particularly those facing financial challenges (Infra Agency 2023).

This highlights a second barrier of difficulty in balancing cost and energy equity. One way to address this issue is through the implementation of standardized cost–benefit analyses that consider metrics related to both financial and social rates of return (FGV CERI 2023a). This approach would consider the points of view of all stakeholders involved, including electric utilities that seek to maximize their profits, government and the regulatory commission that seek to maximize social welfare for both producers and consumers of electricity, and customers who seek to maximize their quality of life (FGV CERI 2023a). While the first two categories are well-understood, modeling and quantifying the customers' quality of life is challenging. To do this, one must be able to quantify the benefits gained by access to electricity during extreme events, for instance, the value of continuation of daily activities and customer convenience, as well as avoided costs (e.g., negative health impacts or psychological stress). Although monetary values may be assigned to these categories, such metrics are subjective at best. A more appropriate approach would be to seek a Pareto optimal solution that strikes a balance between financial profits, social welfare (from a market perspective), and quality of life. The latter can then be measured in terms of the number of customer-hours without electricity, weighted based on the social vulnerability indices proposed in this paper. The health vulnerability dimension is particularly relevant, as it can reflect the severity of potential health issues experienced by customers during an outage. Of course, investment decisions that are rooted in balancing cost and energy equity will likely result in solutions that are financially less attractive from an electric utility's perspective. Hence, such approaches must be driven by national and/or regional policies.

If resilience-based metrics that consider the social consequences of outages are available, electric utilities, under the supervision of the regulatory commission, can develop risk-based resilience plans and vulnerability assessment of their electricity service to guide prudent investments (FGV CERI 2023b). These plans, the associated cost–benefit analysis, and any progress must be shared with both the regulator and public. To further expedite the implementation of resilience strategies, the regulator can offer incentive mechanisms associated with the utilities' plans. It should be noted however that the rate of return on these investments can no longer be purely financial and must also include measures associated with quality of life and improvement in energy equity. A report from the FGV CERI (2023b) also proposed the creation of a special fund for access to resources by electric utilities in case of disasters. This can be set up by the regulator but also managed based on input from utilities, municipalities, local authorities, and the public.

Another important policy question is how a vulnerability-based paradigm can be encouraged at the federal, state, or municipality level in Brazil. Although the regulation of electricity distribution in Brazil is carried out by a federal regulatory commission, states, municipalities, and local authorities are involved in activities that can potentially impact grid performance during disasters and/or at times interfere with the utilities' planning and operation actions. For instance, municipalities have the power to legislate on matters of local interest, including pruning and cutting trees, but vegetation management is a crucial aspect of grid resilience against high wind events that must be initiated by or at least coordinated with electric utilities. Another example is related to grid infrastructural resilience through line hardening. Many utilities, especially those located in forested areas or regions that are prone to high winds or wildfires, have been moving to replace at-risk overhead lines with underground cables. In Brazil, such decisions are governed by local authorities such as the mayor's office. This again underlines the importance of including all stakeholders in the governance for resilience (Infra Agency 2023).

Although top-down approaches such as energy-justice-related policies and legislation can undoubtedly help the cause, bottom-up and grassroots efforts are the farthest-reaching solutions. While many community-based organizations (CBOs) and non-governmental organizations (NGOs) are actively involved in post-disaster relief and recovery efforts in Brazil, their inputs on grid resilience and challenges of access to electricity are not generally sought in a proactive manner. An effective first step to change this dynamic could be to inform and educate the public about their rights when it comes to equitable access to electricity, especially during or after disaster events. Further, CBOs and NGOs must be encouraged to participate more actively in the governance of grid resilience, which can be achieved through engagement in public hearings and public policy commenting periods. This promotes procedural justice, which is an important tenet of energy justice in which social feedback is incorporated into and informs energy-related projects. The indices of vulnerability proposed in this work can shed light on where some of the most urgent challenges and needs lie when it comes to long-duration power outages in Brazil.

5.3 Index generalizability

Indices and metrics such as the one proposed in this paper are generally developed in an unsupervised fashion, i.e., with no validation data. In the absence of testing data, variables and dimensions of social vulnerability are chosen heuristically and based on a detailed review of the literature as well as reports and case studies from past events (see Dugan et al. (2023) for more details). Because the variables and the structure of the model are determined with a focus on vulnerability to long-duration power outages, the proposed model is not necessarily generalizable to other types of events and disasters, even though many common themes and variables may emerge in all social vulnerability indices proposed in the literature. In case social vulnerability to a different type of disaster is being studied, the list of variables and possibly the three dimensions of vulnerability proposed here need to be reassessed and if necessary, modified.

Of course, the solution to this can be the development of a supervised model where the model structure and variables are determined using testing (validation) data. This can be survey data collected from the region under study. However, even with survey data, issues such as sample size, data sampling technique, data collection methods, sample biases, and survey response rate can affect the reliability and accuracy of the proposed model.

Another unique aspect to the model proposed in this paper is the fact that it is tailored towards Brazil. Most countries collect census data every few years and make it publicly available. However, although many socioeconomic and demographic variables collected are the same, there are differences in the types, categories, and definitions of some data points and variables. Hence, when applying the proposed index to another country or region, not all variables used in this study may be available, in which case revisions must be made to the model. It is also possible to consult multiple data sources, but care must be taken to ensure that the timeline of data collection and the granularity level are the same for all sources.

6 Conclusion

This study proposes the development of an index of social vulnerability to long-duration power outages in Brazil, using the state of Rio de Janeiro as a case study. Publicly available data are used to identify vulnerability during a power outage based on three dimensions of health, preparedness, and evacuation. Results are presented at the municipality, census tract, and/or weighting area levels. The results and corresponding vulnerability maps can help inform power grid resilience investments and analyses and aid the decision making of various stakeholders, including governments, regulators, utilities, and other entities responsible for the planning and operation of electricity in Brazil. Investments in power grid resilience, if aligned with a vulnerability-based paradigm, can help not only in risk mitigation against outages and disasters but also in decreasing the social inequities that are significant in Brazil. Future work will extend the analysis to the entire Brazilian federation and examine the relationship between current power grid operation practices and social vulnerability to power outages.

Appendix A: Additional details on index development

The number of input variables, number of principal components chosen, and percentage of variance explained by those chosen principal components are listed in Table 4.

Table 5 presents the mapping between composite vulnerability score, assigned vulnerability level, and the meaning of that vulnerability level. This process is applied to the health, preparedness, and evacuation vulnerability scores for visualization purposes.

Table 4 Principal component analysis results for each dimension

Dimension of vulnerability	Number of input variables	Number of principal components chosen	Percentage of variance explained by the principal components (%)
Health by municipality	10	6	88.57
Preparedness by census weighting area	8	3	89.56
Preparedness by census tract	7	1	85.27
Evacuation by census weighting area	12	5	87.98
Evacuation by census tract	5	2	87.53

Table 5 Vulnerability scores and corresponding levels

Value of composite vulnerability score	Assigned vulnerability level	Vulnerability level meaning
$S_i < \mu - 2\sigma$	1	Very low vulnerability
$S_i \in [\mu - 2\sigma, \mu - \sigma]$	2	Low vulnerability
$S_i \in [\mu - \sigma, \mu + \sigma]$	3	Moderate vulnerability
$S_i \in [\mu + \sigma, \mu + 2\sigma]$	4	High vulnerability
$S_i > \mu + 2\sigma$	5	Very high vulnerability

The Pareto ranking algorithm is described in Algorithm A1, where the input is the three L1 scores for each data instance and the result is the corresponding rank, where 1 is the most vulnerable. An exhaustive search is conducted to determine the set of non-dominated data instances. These are the most vulnerable and are ranked of $v = 1$, then removed from future searches. The rank value v is then incremented, and the search for non-dominated data instances is repeated until all have been ranked. To compute a final vulnerability score, the ranks are reassigned such that the most vulnerable tracts rank the highest and the least vulnerable tracts rank the lowest. The rankings are then rescaled based on Eq. 1 to produce overall scores between 0 and 1.

Algorithm A1: Pareto ranking by multi-dimensional vulnerability scores

Input: *multi-dimensional vulnerability scores for each data instance* $i \in I,\ I = 1..N$.
Output: *table containing the Pareto ranked data instances, rows are ranks from most to least vulnerable.*

Initialize: *vulnerability rank* $v = 1$, $S_v = \emptyset$
while $(N \neq \emptyset)$ ***do*** \\ *Not all instances have been ranked*
    for $i = 1..N$ ***do***
        Initialize: $S_i = \emptyset$ \\ *Set of instances that dominate* i
        for $j = 1..N$ ***do***
            if $(j$ *dominates* $i)$ ***then*** \\ *Dominates:* $score_j \geq score_i$ *in all dimensions*
                Add j *to set* S_i
        end for
    end for
    for $i = 1..N$ ***do***
        if $S_i = \emptyset$ \\ *If no instances dominate* i
            Add i *to set* S_v \\ *Assign it a rank of* v
            Remove i *from set* I
    end for
    $v = v + 1$ \\ *Increment rank*

Appendix B: Additional vulnerability maps

Figures 12, 13, 14, 15 present additional results for the vulnerability maps. Figure 12 displays the preparedness vulnerability by census tract. The same pattern of concentration of the moderate level (3) of vulnerability as seen in Fig. 4 is evident here.

Figure 13 displays the evacuation vulnerability level by census tract. Level 4 spreads to several parts of the state; however, the consistency with the results by weighting area (Fig. 7) remains and the most vulnerable locations are in the same municipalities as discussed for Fig. 7.

The extreme value counts associated with preparedness for the census weighting area is shown in Fig. 14. Due to low numbers of principal components (i.e., one and two for preparedness and evacuation vulnerability, respectively), the census tract-level extreme values results are less informative but are available on ArcGIS Online (Dugan et al. 2024).

Finally, the overall social vulnerability to long-duration power outages by census tract is shown in Fig. 15, which shows similar results to Fig. 9. This level of granularity preserves

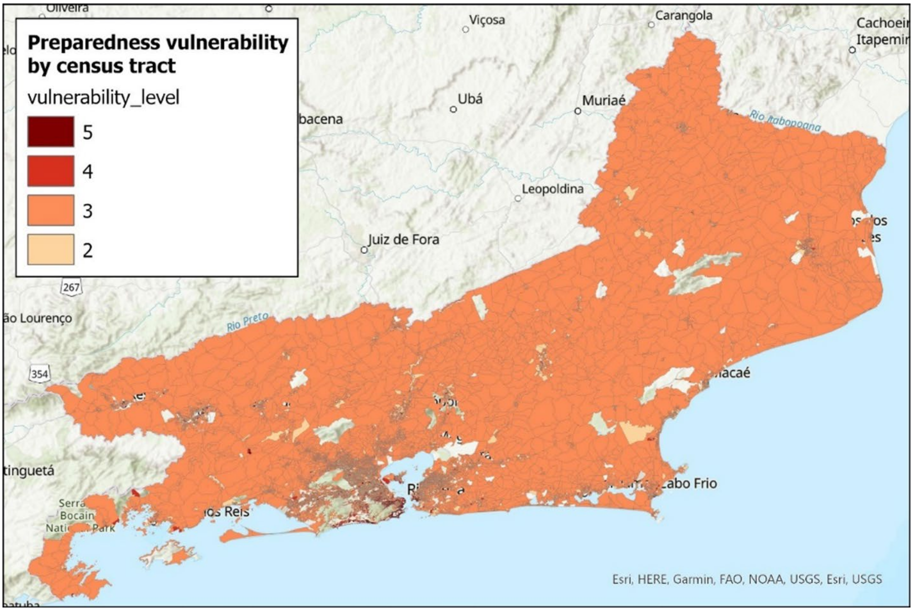

Fig. 12 Preparedness vulnerability level for census tracts in the state of Rio de Janeiro

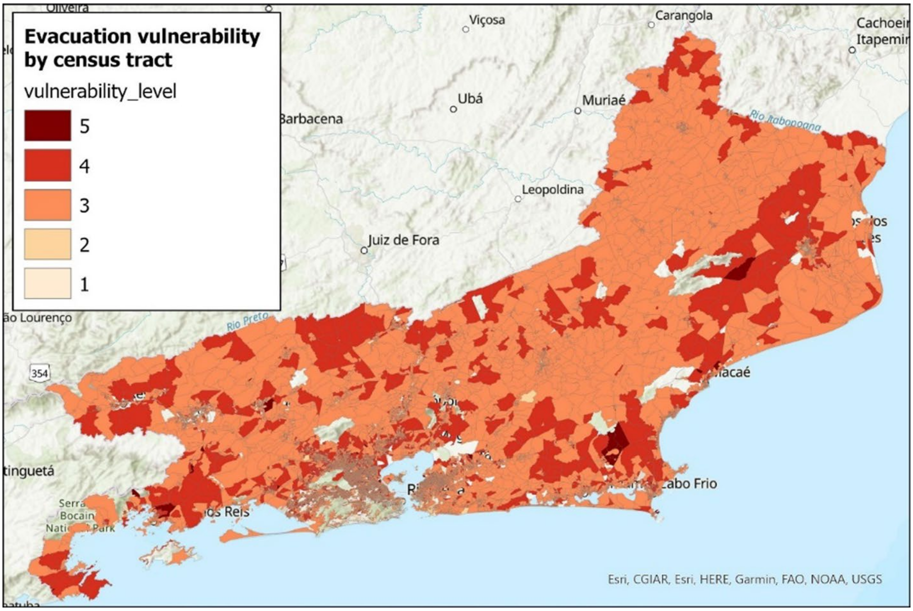

Fig. 13 Evacuation vulnerability level for census tracts in the state of Rio de Janeiro

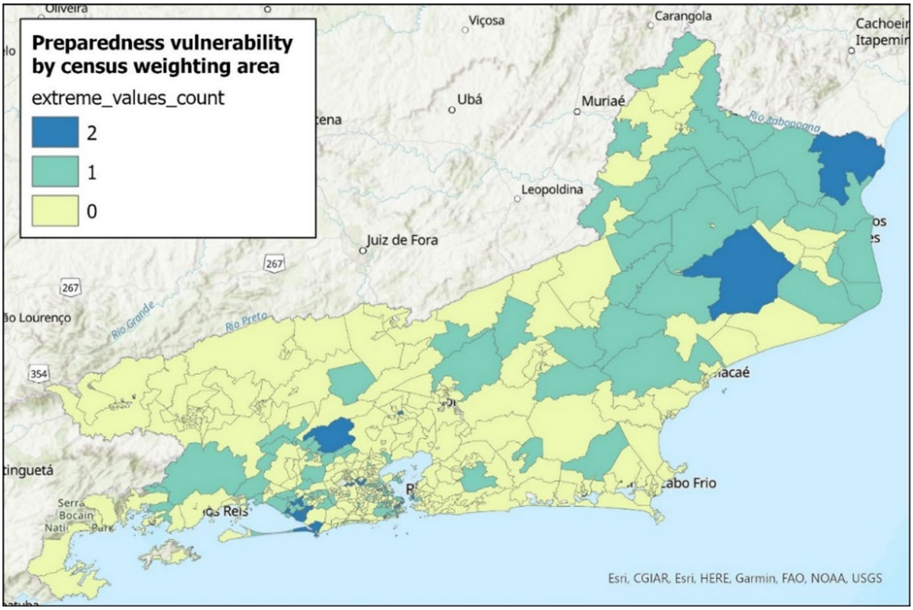

Fig. 14 Number of extreme values in the preparedness vulnerability principal components for census weighting areas in the state of Rio de Janeiro

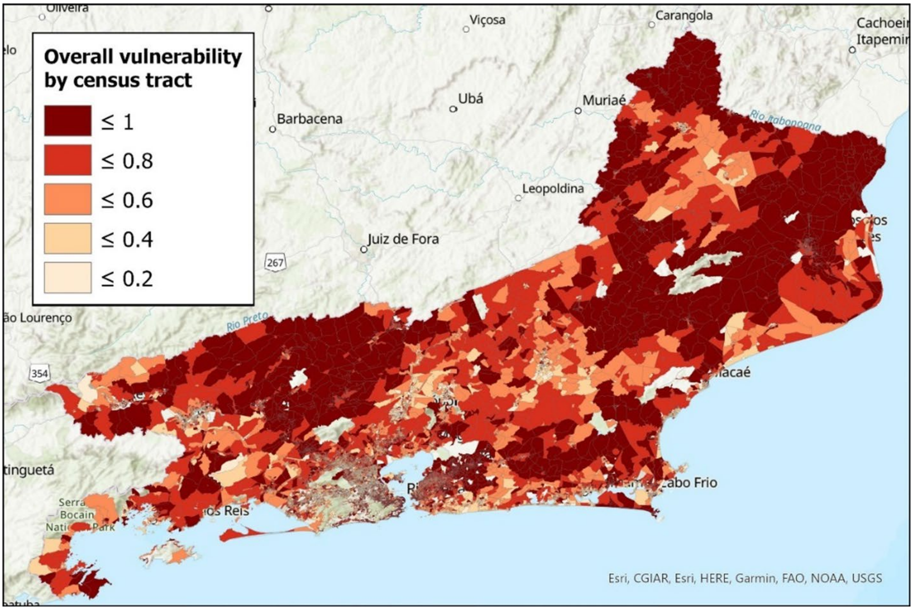

Fig. 15 Overall social vulnerability to long-duration power outages for census tracts in the state of Rio de Janeiro

the same critical regions, like the analysis by weighting areas, and is also consistent with the historical data from the SIID (2023).

Acknowledgements Edson Gonçalves wishes to acknowledge the financial support from the EPGE-FGV CAPES-Print program that facilitated his involvement in this project.

Author contributions All authors contributed to the study conception and design. The main idea for the paper was developed by Salman Mohagheghi. Material preparation, data collection, and analysis were performed by Jesse Dugan, Edson Gonçalves, and Luciana Costa. The first draft of the manuscript was written by Jesse Dugan, Edson Gonçalves, Luciana Costa, and Salman Mohagheghi. All authors read, made revisions to, and approved the final manuscript.

Funding The authors did not receive financial support from any organization for the submitted work.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Agência Brasil (2023) Falta de manutenção no sistema de drenagem causou inundação na Baixada. https://agenciabrasil.ebc.com.br/radioagencia-nacional/geral/audio/2024-01/falta-de-manutencao-no-sistema-de-drenagem-causou-inundacao-na-baixada#:~:text=O%20Instituto%20Estadual%20do%20Ambiente,%C3%A1gua%20da%20ba%C3%ADa%20de%20Guanabara. Accessed 7 May 2024

ANEEL (2023) Tariff regulation procedures for Brazilian electricity distribution companies.

ANEEL (2024) Public Hearing and proposal for studies – Power grid resilience, February 2024. https://antigo.aneel.gov.br/web/guest/tomadas-de-subsidios?p_auth=SO5vVbtt&p_p_id=participacaopublica_WAR_participacaopublicaportlet&p_p_lifecycle=1&p_p_state=normal&p_p_mode=view&p_p_col_id=column-2&p_p_col_count=1&_participacaopublica_WAR_participacaopublicaportlet_ideParticipacaoPublica=3843&_participacaopublica_WAR_participacaopublicaportlet_javax.portlet.action=visualizarParticipacaoPublica. Accessed 7 May 2024

Batista EF, de Brum Passini L (2023) Development and application of a social vulnerability index (SOVI) to landslide risk analysis in Ribeira medium valley, Brazil. Obs Econ Latinoam 21(5):2801–2829. https://doi.org/10.55905/oelv21n5-024

Botelho V (2019) Estimating the economic impacts of power supply interruptions. Energy Econ 80:983–994. https://doi.org/10.1016/j.eneco.2019.02.015

Brazil DW (2023) Um ano após tragédia de Petrópolis, risco continua. https://www.dw.com/pt-br/um-ano-ap%C3%B3s-trag%C3%A9dia-de-petr%C3%B3polis-risco-continua/a-64708203. Accessed 6 May 2024

Brazilian Government (2024) Plano Nacional de Proteção e Defesa Civil lança método para identificação de riscos de desastres e cenários prospectivos. https://www.gov.br/mdr/pt-br/noticias/plano-nacional-de-protecao-e-defesa-civil-lanca-metodo-para-identificacao-de-riscos-de-desastres-e-cenarios-prospectivos. Accessed 5 September 2024.

Câmara De Comercialização De Energia Elétrica (2024) Divulgação do Custo de Déficit e memória de cálculo referente ao ano 2024. https://www.ccee.org.br/web/guest/-/co-divulgacao-do-custo-de-deficit-e-memoria-de-calculo-referente-ao-ano-2024. Accessed 6 May 2024

Cutter SL, Boruff BJ, Shirley WL (2003) Social vulnerability to environmental hazards. Soc Sci Q 84(2):242–261. https://doi.org/10.1111/1540-6237.8402002

de Hummell BML, Cutter SL, Emrich CT (2016) Social vulnerability to natural hazards in Brazil. Int J Disaster Risk Sci 7:111–122. https://doi.org/10.1007/s13753-016-0090-9

de Souza CDF, Machado MF, do Carmo RF (2020) Human development, social vulnerability and COVID-19 in Brazil: a study of the social determinants of health. Infect Dis Poverty. https://doi.org/10.1186/s40249-020-00743-x

Dugan J, Byles D, Mohagheghi S (2023) Social vulnerability to long-duration power outages. Int J Disaster Risk Reduct. https://doi.org/10.1016/j.ijdrr.2022.103501

Dugan J, Mohagheghi S (2023) Assessment of social vulnerability to long-duration power outages in the United States. Proceedings of the 2023 IEEE Green Technologies Conference. https://doi.org/10.1109/GreenTech56823.2023.10173787

Dugan J, Costa L, Gonçalves E, Mohagheghi S (2024) Social Vulnerability to Long-Duration Power Outages in Rio de Janeiro. ArcGIS Online web map https://arcg.is/1e98Ti1

Eletrobras (1988) Comissão para estudo do custo do deficit. Relatório Final GCPS/SEC/CDEF/001/88
FGV CERI (2015) P&D estratégico ANEEL: Metodologia de elaboração da função de custo do deficit. https://repositorio.fgv.br/server/api/core/bitstreams/d922540c-786f-4d79-a89e-8c217ce49c3a/content. Accessed 6 May 2024
FGV CERI (2023a). P&D ANEEL com grupo CPF: Relatório com proposta de análise custo-benefício (CBA) para projetos de resiliência de redes elétricas de distribuição.
FGV CERI (2023b) P&D ANEEL com grupo CPFL: Relatório com sugestões de mudanças regulatórias
Folha 1, Campos dos Goytacazes (2022). Rios paraíba e itabapoana afetam comunidades de São Francisco de Itabapoana. https://www.folha1.com.br/na_foz/2022/01/1279124-rios-paraiba-e-itabapoana-afetam-comunidades-de-sao-francisco-de-itabapoana.html. Accessed 6 May 2024
Gonçalves E, Grijó JMM (2018) Estimando o custo do déficit energético a partir de modelos de valoração contingente no Brasil. XI CBPE Congresso Brasileiro de Planejamento Energético
Goto EA, Suarez AM, Ye (2022) Spatial analysis of social vulnerability in São Paulo City. Brazil Applied Geography. https://doi.org/10.1016/j.apgeog.2022.102653
IBGE (2010) Censo 2010. https://www.ibge.gov.br/. Accessed 7 May 2024.
Investing.com (2023) Enel diz que apagão em SP foi evento atípico, mas confirma falhas. https://br.investing.com/news/stock-market-news/enel-diz-que-apagao-em-sp-foi-evento-atipico-mas-confirma-falhas-1186152. Accessed 6 May 2024
IPEA (2015) Metodologia do atlas da vulnerabilidade social nos municípios brasileiros. http://ivs.ipea.gov.br/images/publicacoes/Ivs/publicacao_atlas_ivs.pdf. Accessed 6 May 2024
IPEA (2023) Atlas da vulnerabilidade social no Brasil. http://ivs.ipea.gov.br/index.php/pt/sobre. Accessed 6 May 2024
Malta FS, Costa EM (2021) Socio-environmental vulnerability index: an application to Rio de Janeiro, Brazil. International Journal of Public Health 66. https://doi.org/10.3389/ijph.2021.584308
Ministério de Minas e Energia (2024) ANEEL divulga os resultados do desempenho das distribuidoras na continuidade do fornecimento de energia elétrica em 2023. https://www.gov.br/aneel/pt-br/assuntos/noticias/2024/aneel-divulga-os-resultados-do-desempenho-das-distribuidoras-na-continuidade-do-fornecimento-de-energia-eletrica-em-2023. Accessed 7 May 2024
Ministério da Economio (2021) Guia Geral de Análise Socioeconômica de Custo-Benefício de Projetos de Investimento em Infraestrutura. https://www.gov.br/economia/pt-br/acesso-a-informacao/participacao-social/consultas-publicas/2020/arquivos/GuiaGeraldeAnliseSocioeconmicadeCustoBenefcio.pdf. Accessed 5 September 2024.
Ministério da Saúde (2023) Painel de indicadores de atenção primária a saúde https://sisaps.saude.gov.br/painelsaps/isf. Accessed 7 May 2024
Operador Nacional do Sistema Electrico (2023) Análise da perturbação do dia 15/08/2023 às 08H30MIN. https://storage.epbr.com.br/2023/10/RAP-2023.08.15-08h030min-versa%CC%83o-final.pdf
Panteli M, Mancarella P (2015) Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies. Electr Power Syst Res 127:259–270. https://doi.org/10.1016/j.epsr.2015.06.012
Ribeiro DF, Saito SM, Alvalá RCS (2022) Disaster vulnerability analysis of small towns in Brazil. Int J Disaster Risk Red. https://doi.org/10.1016/j.ijdrr.2021.102726
Rio de Janeiro Secretaria de Saúde (2023) Informações em Saúde. https://www.saude.rj.gov.br/informacao-sus/dados-sus. Accessed 28 November 2023
Rio de Janeiro (2023) Mapa da desigualdade da região metropolitana do Rio de Janeiro. https://mapa-da-desigualdade-casafluminense.hub.arcgis.com/. Accessed 28 November 2023
Roncancio DJ, Nardocci AC (2016) Social vulnerability to natural hazards in São Paulo, Brazil. Nat Hazards 84:1367–1383. https://doi.org/10.1007/s11069-016-2491-x
SIID (2023).https://s2id.mi.gov.br/paginas/index.xhtml. Accessed 28 November 2023
Thomas DSK, Phillips BD, Lovekamp WE, Fothergill A (eds) (2013) Social vulnerability to disasters, 2nd edn. CRC Press, Boca Raton. https://doi.org/10.1201/b14854
UFRGS (2022) Atlas de vulnerabilidade social de Porto Alegre. https://lume.ufrgs.br/bitstream/handle/10183/247149/001148201.pdf?sequence=1. Accessed 6 May 2024

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.