MARIANE PAULINA BATALHA ROQUE

VULNERABILIDADE SOCIAL E A CAPACIDADE DE RESILIÊNCIA EM ÁREAS SUSCETÍVEIS E AFETADAS POR DESASTRES AMBIENTAIS NA BACIA HIDROGRÁFICA DO RIO PARAOPEBA, MINAS GERAIS, BRASIL

Tese apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Extensão Rural, para obtenção do título de Doctor Scientiae.

Orientador: José Ambrósio Ferreira Neto

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José Ambrósio Ferreira Neto
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RESUMO

ROQUE, Mariane Paulina Batalha, D.Sc., Universidade Federal de Viçosa, dezembro de 2022. **Vulnerabilidade Social e a Capacidade de Resiliência em áreas suscetíveis e afetadas por desastres ambientais na Bacia hidrográfica do Rio Paraopeba, Minas Gerais, Brasil.** Orientador: José Ambrósio Ferreira Neto

Os impactos relacionados aos riscos naturais estão aumentando e se tornando uma grande ameaça em nível global, o que tem levado a uma reorientação de pesquisas e programas. Importantes estudos têm se centrado principalmente nos seus aspetos físicos, no entanto o grau de vulnerabilidade e de resiliência das populações envolvidas não depende apenas da proximidade da fonte da ameaça, nem da natureza física do desastre. Os fatores sociais desempenham um papel fundamental na determinação de estratégias que minimizem os impactos, assim como sua preparação, sua resposta e sua mitigação, consequentemente os esforços também devem envolver, em diferentes estágios, as comunidades locais. Este estudo teve como objetivo traçar um conjunto de métricas, validadas nacional e internacionalmente, para identificar, avaliar, correlacionar e especializar os índices de vulnerabilidade social e resiliência aos riscos ambientais na Bacia do Rio Paraopeba. Para tanto, foram avaliadas duas áreas de estudo: uma onde o desastre já aconteceu e outra onde ele pode acontecer. A primeira área foi onde ocorreu um grande desastre ambiental no Brasil, também considerado um dos maiores do mundo: o rompimento da barragem de rejeitos Córrego do Feijão, em Brumadinho, em 2019. A segunda é a barragem de rejeitos Casa de Pedra, em Congonhas, atualmente considerada a maior mina a céu aberto em áreas urbanas da América Latina. O Índice de Vulnerabilidade Social adotado nesta pesquisa foi composto por três indicadores (social, de infraestrutura e econômico), assim como o Índice de Capacidade de Resiliência (ICR) (institucional, comunitário e ecológico). O índice e os indicadores utilizados foram desenvolvidos em um software livre, e os mapas, em sistema de informação geográfica (SIG). As pontuações foram atribuídas usando o Analytical Hierarchical Process (AHP). Este estudo representou a primeira abordagem para obter e avaliar espacialmente a vulnerabilidade social e a resiliência a desastres na Bacia do Paraopeba e no Brasil, após enfrentar um dos maiores desastres ambientais do mundo. Os principais fatores impulsionadores da vulnerabilidade e da resiliência foram identificados e analisados. Constatou-se que os municípios mais vulneráveis estão localizados sobretudo no norte da bacia, enquanto os da região do sul são menos vulneráveis. Verificou-se que a resiliência é maior no sul e na região central do Paraopeba, e menor no norte no Baixo Paraopeba. Nossos resultados contribuem para entender onde as consequências serão mais ou menos graves caso ocorra um desastre, pois as vulnerabilidades e a capacidade de resiliência são condições inerentes à sociedade, e os impactos do desastre se somam aos já existentes, podendo servir de referência para que diferentes stakeholders ampliem suas estratégias com base em uma abordagem socialmente mais equitativa para preparar, corrigir e mitigar as consequências dos impactos de eventos extremos, no sentido de alcançar resultados mais inclusivos e permanentes.

Palavras-chave: Vulnerabilidade Social. Resiliencia. Geoprocessamento. Desastres socioambientais.

ABSTRACT

ROQUE, Mariane Paulina Batalha, D.Sc., Universidade Federal de Viçosa, December, 2022. **Social Vulnerability and Resilience Capacity in areas ausceptible and affected by environmental disasters in the Paraopeba River Basin, Minas Gerais, Brazil.** Adviser: José Ambrósio Ferreira Neto

The impacts related to natural hazards are increasing and becoming a major threat at the global level, leading to a reorientation of research and programs. Important studies have mainly focused on the physical aspects of natural hazards, however, the degree of vulnerability and resilience of the populations involved does not depend only on the closeness to the threat source nor on the physical nature of the disaster. Social factors play a key role in designing strategies to minimize, prepare, respond and mitigate impacts. Consequently, the efforts must also involve, in different stages, the local communities. This study aimed to define a set of nationally and internationally validated metrics, to identify, evaluate, correlate and spatialize indices of social vulnerability and resilience to environmental hazards in the Paraopeba River Basin. For this purpose, two areas of study were evaluated: one where the disaster has already happened and another where it may happen. The first area, Córrego do Feijão tailings dam in Brumadinho (MG), was where a major environmental disaster, also considered one of the biggest in the world, happened in Brazil in 2019. The second is the Casa de Pedra tailings dam, in Congonhas. Currently, it is considered the largest open pit mine in urban areas in Latin America. The Social Vulnerability Index (SVI), adopted in this research, was composed of three indicators (social, infrastructure, and economic), and the Resilience Capacity Index (RCI), was composed of three indicators (institutional, community, and ecological). The index and indicators used were developed using free software, and the maps were developed using a geographic information system (GIS). Scores were assigned using the Analytical Hierarchical Process (AHP). This study represented the first approach to spatially assess social vulnerability and disaster resilience in the Paraopeba Basin and Brazil, after facing one of the biggest environmental disasters in the world. The main drivers of vulnerability and resilience were identified and analyzed. It was found that the most vulnerable municipalities are mainly in the north of the basin, while those in the southern region are less vulnerable. It was found that resilience is greater in the south and central region of Paraopeba and smaller in the north, in Lower Paraopeba. The results contribute to understanding where the consequences will be more or less severe in case of a disaster since vulnerability and resilience are conditions inherent to society, and the impacts of the disaster add to the ones that already exist. The study provided a robust and replicable metric to identify areas that are more and less vulnerable and resilient to disasters in the Paraopeba Basin, which can serve as a reference for different stakeholders to expand their strategies based on a more socially equitable approach to prepare, correct and mitigate the consequences of the impacts of extreme events to achieve more inclusive and permanent results.

Keywords: Environmental Disasters. Resilience. Geoprocessing. Social Vulnerability.

SUMÁRIO

1. Introdução geral

A ocorrência de desastres ambientais e de outros eventos extremos tem impacto sobre o meio ambiente e o bem-estar das pessoas, demandando abordagens transdisciplinares que busquem integrar um amplo conjunto de dados biofísicos e socioeconômicos. Até meados do século XX, as ações e as estratégias de gestão dos impactos advindos desses eventos focavam apenas os aspectos ambientais. A preocupação com o componente social surgiu a partir da década de 1970, quando os pesquisadores e tomadores de decisão perceberam que as vulnerabilidades e os fatores associados a essa fragilidade também envolvem os sistemas socioeconômicos e que esses afetam a capacidade de resiliência das comunidades atingidas (JUNTUNEN, 2004; FLANAGAN et al., 2011). Embora os componentes sociais estejam recebendo atenção recente da academia e das políticas, dos planos e das ações de preparação, da resposta e da mitigação ambiental, os esforços ainda se pautam principalmente nos elementos biofísicos (JUNTUNEN, 2004; FLANAGAN et al., 2011; HUMMELL et al., 2017).

Nesse sentido, em vez de lidar de forma isolada com os impactos ambientais nas áreas afetadas ou suscetíveis a esses eventos, as diferentes fases de planejamento e tomada de decisão devem considerar a integração dos sistemas sociais e naturais (MILLER et al., 2010; BERGSTRAND et al., 2014; HUMMELL et al., 2017; FUNDAÇÃO RENOVA, 2018; CHAKRABORTY et al., 2020; DERIA; GHANNAD; LEE, 2020). A importância de incluir o componente social se ancora principalmente na constatação de que, apesar de as áreas afetadas por desastres ambientais ou suscetíveis a eles terem como cerne o desenvolvimento de ações e estratégias de gestão direcionadas a minimizar os impactos de âmbito ambiental, os esforços e, ou, as ações de preparação, resposta e mitigação envolvem, nas suas diferentes etapas, as comunidades locais.

Esse fato evidencia a relevância de abordagens integradas e a importância da compreensão abrangente acerca dos fatores associados à complexidade dos sistemas sociais locais. Portanto, a inclusão da dimensão social nos estudos sobre desastres ambientais pode ser considerada peça-chave para o desenvolvimento de estratégias pautadas em uma abordagem socialmente mais equitativa, para correção e mitigação de suas consequências (ZANDT et al., 2012; HUMMELL, 2013).

Muitos países já passaram por eventos extremos, sejam eles de ordem natural ou antrópica, cujos efeitos são sentidos de forma diferente entre regiões e populações com condições distintas de acesso a bens, serviços e recursos (ZANDT et al., 2012; FUNDAÇÃO RENOVA, 2018; DERIA; GHANNAD; LEE, 2020). Assim, os diversos graus de vulnerabilidade estão associados tanto à proximidade e ao nível de impacto dos eventos, como também às formas prévias de organização social e econômica das comunidades, expressas pelo conjunto de ativos, recursos e estruturas, cujo acesso ou insuficiência indicam a situação de desigualdade dessas populações envolvidas (FUNDAÇÃO RENOVA, 2018).

Essa desigualdade, por sua vez, reflete-se na capacidade ou incapacidade dessas comunidades de anteciparem e responderem a esses eventos, como também na recuperação deles, ou seja, os diferentes níveis de desigualdade social comprometem a vitalidade geral e a resiliência das comunidades afetadas por desastres ambientais (FLANAGAN et al., 2011; BERGSTRAND et al., 2014; FUNDAÇÃO RENOVA, 2018; RAN et al., 2019). O entendimento a respeito dos fatores que impulsionam a vulnerabilidade social, reflexo dos níveis diferenciados de desigualdade, é essencial nos estudos de programas, projetos e ações de preparação e recuperação, pois evidencia as distintas capacidades de envolvimento e participação das comunidades afetadas, ao fornecer um retrato mais fidedigno de sua realidade (FLANAGAN et al., 2011; BERGSTRAND et al., 2014; FUNDAÇÃO RENOVA, 2018; RAN et al., 2019).

As pesquisas sobre vulnerabilidade social e capacidade de resiliência emergiram como temas centrais para descrever a capacidade inerente dos sistemas de se preparar, absorver e responder aos impactos ocasionados por eventos extremos (ADGER et al., 2005; CUTTER; FINCH; BURTON, 2008; RAN et al., 2019). Embora esses conceitos sejam utilizados em vários campos e disciplinas, na presente proposta o foco perpassa pelas respostas aos desastres ambientais a partir de seu componente social. Alwang et al. (2001) ressaltam que a vulnerabilidade evidencia a suscetibilidade de grupos sociais ou da sociedade em geral a perdas potenciais, incorporando um conjunto de características e condições que tornam as pessoas mais ou menos vulneráveis ao lidar com eventos de risco. Os fatores que medem a vulnerabilidade social incluem a infraestrutura e as características demográficas e econômicas de diferentes comunidades (CUTTER et al., 2003; CUTTER; FINCH; BURTON, 2008; BERGSTRAND et al., 2014). A compreensão desses fatores que, por certo, moldam a exposição diferenciada aos impactos dos desastres ambientais mostra-se imprescindível para ajudar na recuperação das condições de vida das comunidades afetadas, de modo a otimizar os recursos e as estratégias necessárias para minimizar perdas e danos deles decorrentes (BERGSTRAND et al., 2014).

Enquanto a vulnerabilidade expõe as condições que tornam as comunidades suscetíveis a danos, a resiliência refere-se à capacidade que elas têm de absorver, persistir ou se adaptar às perturbações. Assim, neste contexto, a resiliência expressa a capacidade de uma dada comunidade absorver os impactos decorrentes de eventos extremos, expressando também a noção de reorganização e construção de novas estratégias, visando melhorar sua situação (FOLKE, 2006; RESILIENCE ALLIANCE, 2009). A vulnerabilidade social e a capacidade de resiliência das comunidades são cada vez mais entendidas como conceitos vinculados (CUTTER; FINCH; BURTON, 2008; BERGSTRAND et al., 2014).

A vulnerabilidade refere-se às características específicas do sistema social que existiam antes dos eventos ocorrerem e que contribuem para a quantidade de risco de exposição, como também para a intensidade dos impactos, enquanto a resiliência refere-se às condições que ajudam os sistemas sociais a resistirem e a se reorganizarem após os desastres (CUTTER; FINCH; BURTON, 2008; BERGSTRAND et al., 2014).

Além do entendimento dos fatores sociais que levam uma comunidade a ser vulnerável ou resiliente, os estudos têm mostrado também a importância de métodos que possam espacializar e quantificar as áreas socialmente vulneráveis e resilientes por meio da inclusão de ferramentas de mapeamento e obtenção de índices (FLANAGAN et al., 2011; BERGSTRAND et al., 2014). No entanto, esses estudos se concentram principalmente na utilização dessas ferramentas em escala municipal (COSTA; MATGUTI, 2015; CUTTER et al., 2013; HUMMELL et al., 2013). Por certo, essa escala não propicia o entendimento das especificidades presentes nos municípios afetados por desastres ou suscetíveis a eles.

O presente estudo buscou não apenas compreender quantitativamente a vulnerabilidade social e a capacidade de resiliência por meio de indicadores, mas também fornecer um mapeamento detalhado, passando de uma escala macro, dos municípios, para uma escala micro, expressa pelos setores censitários (para mais detalhes, ver IBGE, 2020). Essas abordagens se mostram determinantes para o entendimento dos contrastes nas condições de vida da população local, identificando aquelas que se encontram socialmente desfavorecidas, fornecendo, em escala detalhada, informações necessárias à definição das diferentes estratégias ao enfrentamento das externalidades decorrentes dos desastres ambientais.

Ligações conceituais, técnicas e empíricas entre vulnerabilidade e resiliência já foram discutidas por diversos pesquisadores (FRAZIER; THOMPSON; DEZZANI, 2014). No entanto, a relação empírica entre os indicadores de vulnerabilidade social e a capacidade de resiliência das comunidades é ainda pouco conhecida (SHERRIEB et al., 2010; BERGSTRAND et al., 2014). Logo, uma nova abordagem empírica a respeito desses indicadores pode contribuir para sua melhor compreensão e, ainda, para sua mensuração e quantificação, identificando os fatores subjacentes associados a essa fragilidade social. A avaliação dos impactos esperados durante a preparação e a posterior mitigação ajuda a compreender como as comunidades se diferem em relação à quantidade de danos ocasionados pelas perturbações advindas desses eventos extremos (CHAKRABORTY et al., 2020).

É esse amplo debate sobre vulnerabilidade social e capacidade de resiliência que orienta a construção dos artigos que compõem o presente material, trazendo como questão a ser respondida: *Como a análise da dimensão social, expressa em indicadores de vulnerabilidade social e de capacidade de resiliência, poderá ampliar as possibilidades de preparação de respostas e mitigação às externalidades decorrentes de desastres ambientais?*

Identificar os fatores responsáveis pelos diferentes níveis de vulnerabilidade, assim como a capacidade de resiliência, por meio de uma abordagem empírica em escala mais detalhada aumenta a probabilidade de encontrar soluções mais adequadas aos problemas decorrentes de desastres ambientais (HOLLING, 1973; WALKER et al., 2004; FOLKE et al., 2005; FOLKE, 2006; NELSON; ADGER; BROWN, 2007; COSENS; GUNDERSON, 2018).

Como apontado por Bergstrand et al. (2014), embora existam estudos que comprovem a alta correlação entre áreas muito vulneráveis e pouco resilientes, há outros que revelam a alta correlação entre elevados índices de vulnerabilidade e resiliência. Esse fato demonstra que as análises de resiliência e vulnerabilidade, apesar de serem conceitos vinculados, são distintas, portanto esses conceitos devem ser quantificados como indicadores separados, mas correlacionados nos estudos de preparação, reparação e mitigação.

Esta pesquisa teve como objetivo examinar essas experiências em dois contextos distintos. O estudo comparativo se justifica pela possibilidade de analisar diferentes cenários. A análise do primeiro cenário, de pós-desastre, tem o intuito de ampliar as possibilidades de reparação e mitigação dos danos, ao abarcar um grande desastre ambiental ocorrido no Brasil, em 2019, considerado também um dos maiores do mundo: o colapso da barragem de rejeitos Mina Córrego do Feijão (FERNANDES et al., 2016; ZHOURI et al., 2016; DE LIMA et al., 2020). O segundo cenário, que retrata áreas em condições normais, ou seja, que não foram afetadas por desastres, refere-se à barragem de rejeitos Mina Casa de Pedra, localizada em Congonhas, também na Bacia do Paraopeba, considerada atualmente a maior mina a céu aberto em área urbana da América Latina (CSN, 2020). O objetivo deste segundo cenário é indicar critérios de ação, a fim de aumentar a capacidade de áreas suscetíveis se prepararem para o enfrentamento de eventos extremos. A unidade de análise foi formada pelos municípios inseridos na Bacia Hidrográfica do Rio Paraopeba, no estado de Minas Gerais, Brasil.

1.1 Objetivo

Avaliar as contribuições dos componentes sociais categorizados por indicadores de vulnerabilidade social e de capacidade de resiliência nos municípios expostos a desastres ambientais ou suscetíveis a eles, inseridos na Bacia Hidrográfica do Rio Paraopeba. Assim, o estudo está setorizado com o delineamento de quatro objetivos específicos:

(i) elaborar o Índice de Vulnerabilidade Social (IVS) e o Índice de Capacidade de Resiliência (ICR) para as áreas afetadas e suscetíveis a desastres;

(ii) identificar, analisar e espacializar os fatores sociais responsáveis pelos diferentes níveis de vulnerabilidade social e de resiliência nos contextos de preparação e pós-desastre nos municípios inseridos na Bacia do Rio Paraopeba;
(iii) identificar, analisar e espacializar a relação entre diferentes níveis de vulnerabilidade social e de resiliência para as comunidades inseridas na Bacia do Rio Paraopeba; e
(iv) desenvolver um script[1] em linguagem R para o cálculo do Índice de Vulnerabilidade Social (IVS), para permitir a replicação em outras realidades.

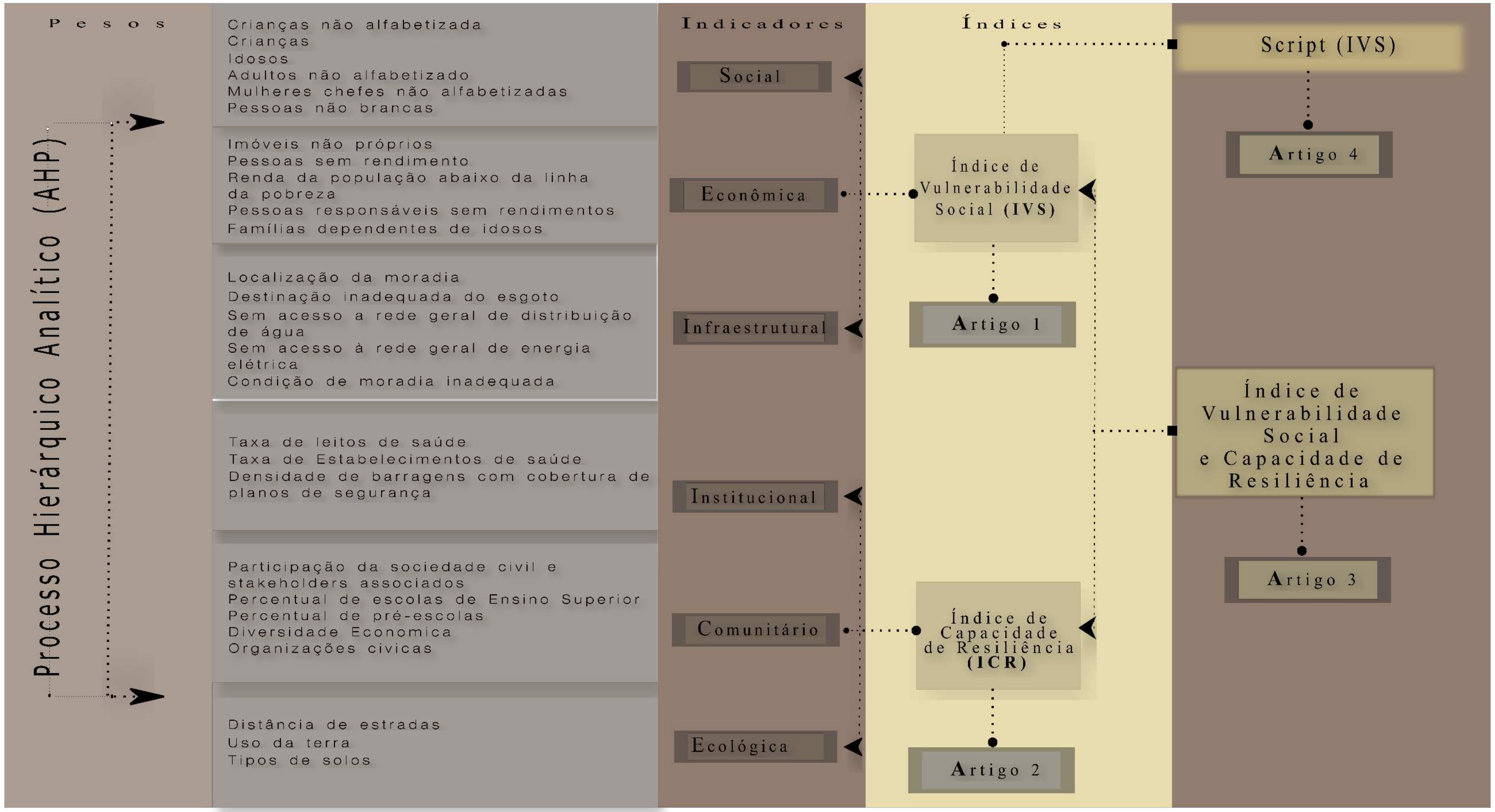
Na presente tese são apresentados quatro artigos, que ajudam a atingir integral e, ou, parcialmente os quatro objetivos propostos (Figura 1). Os Artigos 1 e 2 cumprem integralmente o objetivo 1, de elaboração do IVS e do ICR. Os Artigos 1, 2 e 3 contribuem para o cumprimento integral do objetivo 2, ao identificar, analisar e espacializar os fatores responsáveis pelos diferentes níveis de vulnerabilidade social e de resiliência no contexto da preparação e da mitigação de desastres ambientais. O Artigo 3 apresenta a articulação entre os dois índices: o IVS e o ICR, cujo objetivo é ser a base para a preparação de respostas e de mitigação de desastres ambientais, para cumprimento do objetivo 3. No Artigo 4 apresentamos o script em ambiente R, para mapear a vulnerabilidade pautada nos aspectos sociais, que pode ser usada pelos formuladores de políticas, por pesquisadores e por outras partes interessadas na resposta e na mitigação de efeitos dos desastres, para cumprimento do objetivo 4.

[1] O Script pode ser definido como um texto que contém os procedimentos a serem executados sequencialmente, para indicar as operações que o computador deve realizar. A sequência e os comandos, ao serem registrados no arquivo texto, serão sempre executados da mesma forma. Assim, os procedimentos gravados podem ser compartilhados e replicados em outros computadores.
(Perlin, M. S. Análise de Dados Financeiros com o R. Terceira Edição, Porto Alegre: Marcelo S. Perlin (publicação independente), 2021. Disponível em: https://www.msperlin.com/padfeR/index.html.

1.2 Procedimentos metodológicos, conteúdo dos artigos e organização da tese

O conteúdo dos artigos da tese está resumido no fluxograma abaixo (Figura 1). Os artigos da tese: Artigo 1 –" *Social Vulnerability to Environmental Disasters in the Paraopeba River Basin, Minas Gerais, Brazil*"; Artigo 2 – *"Assessing the resilience of communities affected by the collapse of the Córrego do Feijão tailings dam in the Paraopeba Basin, Minas Gerais, Brazil"*; Artigo 3 – *"Relationship between the Resilience Capacity and Social Vulnerability Indexes associated with environmental disasters: a case study of the socio-environmental disaster in the Paraopeba Basin, Brazil"; e* Artigo 4 – *"Mapping social vulnerability for the development of environmental disaster preparedness and mitigation strategies"* cumprem integralmente os procedimentos.

Figura 1: Conteúdo dos artigos da tese.



Nota: As variáveis apresentadas na Figura 1 foram adaptadas dos seguintes estudos: Bergstrand et al. (2014), Brasil (2020), Costa e Matguti (2015), Cutter et al. (2000), Cutter et al. (2003),Cutter, Finch e Burton (2008), Fundação Renova (2018), Godschalk (2003), Guoa e Kapucu (2020), Hewitt (2014), Holand e Lujal (2011), King e MacGregor (2000), Morrow (2008), Murphy (2007), Norris et al. (2008), Perry e Lindelle Tierney (2001), Sherrieb et al. (2010), Singh et al. (2014) e Taubenbock et al. (2008).

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2. Artigos científicos

2.1 Social Vulnerability to Environmental Disasters in the Paraopeba River Basin, Minas Gerais, Brazil

Manuscript submitted

Article 1

Social Vulnerability to Environmental Disasters in the Paraopeba River Basin, Minas Gerais, Brazil

Abstract

The increase in the number of environmental disasters, in recent years, has led to a reorientation of research and programs. Important studies have focused mainly on its physical aspects, however, the degree of vulnerability of populations is not only dependent on the proximity of the source of the threat, neither the physical nature of the disaster since social factors also play a key role in determining vulnerability. To improve natural disaster, it is important to recognize how social disparities influence the vulnerability populations to develop strategies based on the specific characteristics. This study proposes a set of 16 theoretically significant variables to measure and map vulnerability in Brazil. They were grouped into three indicators, social, economic, and infrastructure aspects of the population, obtained from the Brazilian census database. The Córrego do Feijão tailings dam, in Brumadinho, and the Casa de Pedra tailings dam, in Congonhas were taken as case studies. The vulnerability of 48 municipalities and 3,732 census sectors from the Paraopeba River Basin were explored from two different perspectives: where the disaster has already happened and where it could happen. The index and indicators used were developed in an open-source software and the maps in a geographic information system (SIG). The results show considerable variability. The most vulnerable municipalities are in the lower part of the basin while the high part of the basin vulnerable. This paper presents methodological and empirical contributions of the social dimensions of vulnerability the preparation, response, and recovery of affected communities to environmental disasters.

Keywords Social Vulnerability, Environmental Disasters, Census Sector level, Paraopeba River Basin

1 Introduction

Impacts related to natural hazards are increasing and threatening globally. Tailings dam failures used to be considered rare events (Thompson et al., 2020). However, in the last 20 years, the number of disassters has practically doubled around the world (Flanagan et al., 2011; Thompson et al., 2020). In the last six years, Brazil had two major environmental disasters caused by the collapse of dams (Armstrong et al., 2019; Filho and Dias, 2019; Thompson et al., 2020). The impacts caused by the collapse of the Córrego do Feijão tailings dam in Brumadinho in 2019 demonstrate that although the areas affected by these disasters, or susceptible to them, are the center of actions and strategies that minimize their impacts, preparation, response, and mitigation efforts must also involve, at different stages, the local communities (Juntunen, 2004; Flanagan et al., 2011; Hummell, 2017).

The Brumadinho disaster highlighted that not only the environmental impacts are important, but also the socioeconomic inequality of populations is a determining factor. Therefore, including the social dimension in environmental disasters studies should be considered as an important step in the development of strategies based on a socially fair approach for different stakeholders, enabling to achieve more comprehensive and lasting results (Zandt et al., 2012; Hummell, 2013; 2017; Bergstrand et al., 2015; Chakraborty et al., 2020).

Social vulnerability research emerges as a central issue to describe, through pre-existing conditions of the populations involved, the inherent capacity of systems to prepare, absorb, and respond to impacts caused by extreme events (Flanagan et al., 2011; Chakraborty et al., 2020; Adger et al., 2020; Cutter; Finch; Burton, 2008; Ran, Jing et al., 2020). The different degrees of vulnerability are associated both with the proximity and impact level of the events and the previous forms of social and economic organization of the communities, which are expressed by a set of assets, resources, and structures in which its access or insufficiency indicate a situation of socioeconomic inequality of the population involved (Morrow, 2008; Fundação Renova, 2018).

Further, socioeconomic inequality is reflected in the capacity or incapacity of communities to predict and respond to these events as well as to overcome the impacts on the environment, infrastructure, economy, and sociability. Understanding the factors that drive social vulnerability, caused by different levels of inequality, is essential in studies of disaster management programs, projects, and actions, as it demonstrates different capacities for involvement and participation of affected communities, by providing a more comprehensive and integrated portrait of its reality world (Flanagan et al., 2011; Bergstrand et al., 2015; Fundação Renova, 2018; Ran, Jing et al., 2020).

There is a relevant conceptual debate on the physical, and social components of disaster (Alexander, 1993) and about the use and development of indexes to measure social vulnerability (Cutter, 1996; Morrow, 1999; Cutter et al., 2003; Cutter et al., 2006; Boruff & Cutter, 2007; Cutter; Finch; Burton, 2008; Box et al., 2011; Zeng et al., 2012; Eric, 2013; Zebardast, 2013; Lixin et al., 2014; Rufat et al., 2014; Bergstrand et al., 2015; Fundação Renova, 2018; BRASIL, 2020; Ran, Jing et al., 2020; Costa and Marguti, 2021) that leads to questions about the best way to, empirically, approach these concepts (Rygel; O'sullivan; Yarnal, 2006; Schmidtlein et al., 2008; Lixin et al., 2014; Bergstrand et al., 2015; Ran, Jing et al., 2020).

In Brazil, research is still at an early stage (Fundação Renova, 2018; Costa & Marguti, 2021). As in the United States, the use of social vulnerability indexes has been recently replicated and adapted to different regions, mainly in studies at the census sector level (BRASIL, 2020), rather than at the municipality level, such Social Vulnerability Index (SoVI), developed by (Cutter et al., 2003; Hummell, 2013; Costa and Marguti, 2021), and in studies carried out to assess the greatest environmental disaster in the country, at the Rio Doce Basin, in Mariana (Fundação Renova, 2018). However, empirical studies are still lacking and major challenges permeate the development of vulnerability indexes (Morrow, 1999; Cutter et al., 2003; Guo & Kapucu, 2020). Some challenges are: to recognize the importance of measuring social aspects in disaster management (Cutter et al., 2003) to attribute weights (Opricovic & Tzeng, 2004) and to form a consensus in the development of variables in scales that allow the knowledge of the specificities of the populations involved since the available methods tend to map at scales that are not relevant for implementation.

Thus, given the lack of social indicators in disaster management, the main goal of this article is to fill this gap by proposing the construction of an index at the census sector level in Brazil. This article also shows the use of a set of internationally validated and acknowledged variables that were adapted to our context and scale of study. The index proposed here is more robust, as it incorporates, in addition to variables already approved in the literature and freely available for the entire country, some methodological adjustments, such as weights attributed by method of paired comparison by various experts, and census tract level scales, designed to provide more detail than municipal levels.

This study aims to outline a set of metrics nationally and internationally validated to assess social vulnerability in environmental disasters to repair, mitigate, and prevent responses in municipalities exposed or susceptible to them. For this purpose, two study areas are evaluated, one where the disaster has already happened and another where it could happen. The first is a major environmental disaster in Brazil, also considered one of the biggest in the world: the collapse of the Córrego do Feijão tailings dam in Brumadinho in 2019 (De Lima et al., 2020). The second is the Casa de Pedra tailings dam in Congonhas, currently considered the largest open-pit mine in urban areas in Latin America (CSN, 2021). The unit of analysis will be formed by the census sectors inserted in the basin of the Paraopeba River in Brazil (CPRM, 2015) (Fig. 1).

The paper is organized as follows: this Introduction; Section 2 reviews the literature on the concept and index of social vulnerability; Section 3 details the case studies, the choice of the database and set of variables, the weights, and methods for building the index and indicators; Section 4 explains the empirical results; Finally, we discuss and conclude in sections 5 and 6, respectively.

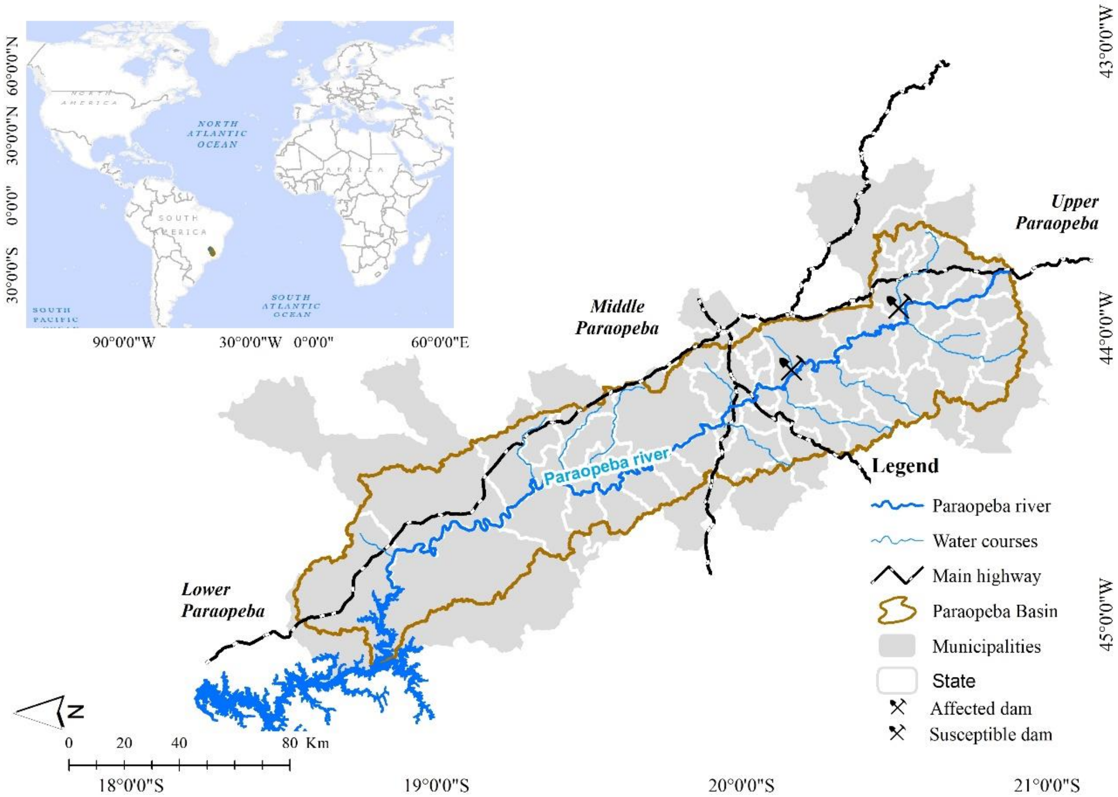

Figure 1 Geographic location of the Paraopeba River Basin, detail area affected by the collapse of the Feijão tailings dam in the municipality of Brumadinho and susceptible area, Casa de Pedra tailings dam in the municipality of Congonhas.

2 Social Vulnerability

Vulnerability can be understood as conditions determined by physical, environmental, social, and economic factors or processes that increase the susceptibility of a community or system to extreme events drivers (UNDRR, 2004; Singh et al., 2010; Lixin, et al., 2014). The United Nations Development Program (UNDP) (2013), completes this definition by emphasizing that vulnerability is a condition or a process of human nature resulting from physical, environmental, social, and economic factors that determine the scale of damage from the impacts of these events, whether of natural or anthropogenic origin (Singh et al., 2010). Hence, vulnerability can be defined as the susceptibility of social groups to potential losses due to damage caused by extreme events (Blaikie et al., 1994) considering that the existing differences in the living conditions of individuals influence their capacity to anticipate and deal with these events (Wisner et al., 2004). Chen et al. (2013) complement the definitions by Wisner and Uitto (2009) stating that social vulnerability influences people's capacity to prepare themselves before a disaster and recover from it, due to pre-existing conditions. Cutter et al. (2006) understood social vulnerability as a product of social inequalities (Kuhlicke et al., 2011; Lixin et al., 2014). Different authors have deeply discussed other important conceptual aspects of social vulnerability; for more details see Adger et al. (2005), Birkman et al. (2012), Turner et al. (2003), Wisner et al. (2004), and Schmidtlein et al. (2008).

Although multiple definitions of vulnerability have been proposed (Cutter et al., 2003), here we understand it as pre-existing conditions among different groups of people in a community that tends to increase and/or reduce the susceptibility to losses as a result of a real or potential risk event, as well as it capacity to recover from these events (Schmidtlein et al., 2008; Birkmann; Bach; Vollmer, 2012). It is important to highlight that not all communities that live close to a disaster are under the same risk. Socially vulnerable communities will have more difficulty dealing with the impacts of that event. Thus, social vulnerability provides a broader view of pre-existing conditions that influence the different experiences of disasters. Social factors are related to different exposure and impact and slow or insufficient recovery (Morrow, 2008; Flanagan et al., 2011; Zandt et al., 2012).

Social vulnerability is influenced by many factors that, are associated (Blaikie et al., 1994; Cutter; Finch; Burton, 2008; Morrow, 2008; Singh et al., 2010). Variables such as employment, and diversification of income (Bolin; Stanford; Shelter, 1991; Cutter et al., 2003; utter; Finch; Burton, 2008; Morrow, 2008); quality of housing and access to treated water, electricity, garbage collection, adequate sanitation (Fundação Renova, 2018), and essential services such as schools and health facilities (Bolin; Stanford; Shelter, 1991; Cutter et al., 2003); family structure (Morrow, 1999; 2008; Cutter et al., 2003); and social structures, such as racial minorities and ethnic groups, are factors whose access or absence result in different levels of social inequality and are directly or indirectly linked to historical patterns that act as obstacles to change, to combat, and to recover from disaster contexts (Cutter et al., 2003; 2008; De Lima et al., 2020; Singh et al., 2010; Burton, 2014).

3 Methodology

3.1 Case studies in the Paraopeba Basin, Brazil

The Paraopeba River Basin is a sub-basin of the São Francisco River with an area of 13,618 km² that corresponds to 5.14% of the territory of the main driver basin. The vegetation is a transition between the Cerrado and the Atlantic Forest biomes, both considered focal points for the conservation of global biodiversity (Roque; Neto; Faria, 2022). It covers 48 municipalities and 3,732 census sectors. Its population density is 93.24 hab/ km² and a total of 1.3 million inhabitants (CPRM, 2015; CBHSF, 2020). To deal with changes in vulnerability in this driver basin, we operate at the census sector level in two distinct perspectives: where the disaster has already happened and where it could happen (Fig. 1).

The first perspective refers to a major environmental disaster in Brazil, also considered as one of the largest in the world, the collapse of the Córrego do Feijão tailings dam, which collapsed on January 25th, 2019. About 12 million cubic meters of tailings and mud were released from the dam and traveled 8.5 km to the Paraopeba River, extending for more than 300 km along the river towards the

São Francisco River (De Lima et al., 2020, CBHSF, 2020; Thompson et al., 2020). The event resulted in the death of 262 people and the disappearance of another 8. Besides the environmental impacts, social problems are still in their beginning, as families, jobs, housing, among other factors were affected, resulting in many challenges for the society, the environment, and the mining company (CBHSF, 2020; Ramos et al., 2020).

The second perspective refers to the Casa de Pedra tailings dam. Created in 1946, in the municipality of Congonhas, it is the oldest operating mining area in Brazil and also the largest open-pit mine in urban areas in Latin America (Gomes, 2009; CSN, 2020), hence, justifying its notoriety and the importance of studies, plans, and action policies to increase the preparation to deal with extreme events in susceptible areas.

The Córrego do Feijão tailings dam and the Casa de Pedra tailings dam are in the Quadrilátero Ferrífero, in the state of Minas Gerais, Southeastern Brazil. Quadrilátero Ferrífero is one of the largest mineral provinces in the world (CPRM, 2015).

The failure of dams usually causes serious accidents (Du et al., 2020). According to the National Mining Agency (ANM) and the Minas Gerais Institute for Water Management (IGAM), 108 Brazilian dams have a medium to high risk of failure (Filho and Dias, 2019; BRASIL, 2020); from these, 65 have a high potential for associated damage. Currently, 264 dams fall into the high damage potential category (BRASIL, 2020). The Dam Safety Report classified the dams under study, including the one collpsed, as having a low risk of failure and a high potential for pollution, that is, high potential for human and ecosystem life loss, in addition to other impacts of social and environmental origin (De Lima et al., 2020).

3.2 Database and variable selection

The statistical data for the indicators and indexes used in this study were obtained directly from the Brazilian Demographic Census (IBGE, 2019), available on the website of the Brazilian Institute of Geography and Statistics (IBGE). This data is the only official data source in the country that best represents the specificities of the territory, due to its scale of action.

Tasnuva et al. (2021), when portraying social vulnerability in Bangladesh, also used data from the 2011 census as they are the most recent. All data are available in the form of electronic spreadsheets at the census sector level and covered the year of 2010. The data referring to the layers of the census sectors were obtained from IBGE, and those referring to the hydrographic limit, rivers, and watercourses were obtained from the National Agency of Water and Basic Sanitation (ANA) in shapefile format (Tasnuva et al. 2021; ANA, 2019).

To ensure that the indicators and the index were empirically valid and not redundant measures of the concepts, a review was made on important and validated variables that operationalize the indicators in the contexts in which they were studied. Subsequently, at the level of census sectors, the variables that are commonly used and endorsed in the national and international literature were selected. Besides the variables, our methodology was also different in terms of the weights to obtain the index by considering the understanding and analysis of specialists and the specificities in the 3,732 census sectors that make up the Paraopeba River Basin.

Subsequently, based on the studies of Sherrieb et al. (2010) and Burton (2014), these variables were transformed into comparable forms using percentage per capita and/or density functions, depending on how the variable was described in the literature. After this initial stage of selecting indicators and variables that took into account the methodologies of Cutter et al. (2003), Cutter, Finch, and Burton

(2008), Morrow (2008), Sherrieb et al. (2010), and Costa and Marguti (2015), the next steps were based on the methodologies developed by Cutter et al. (2003), Sherrieb et al. (2010), Bergstrand et al. (2015), Qin et al. (2017), Fundação Renova (2018), and Brasil (2020). An overview of the description of the chosen variables and the literature that validated them in different geographic contexts is shown in Table 1.

Table 1 Description of the variables chosen in the literature and criteria for preparing SVI.

Concept	Variables Description	Author and year
Social Indicator	(IS01) Literate child: V023 to V049 Total of people between 5 and 15 years old; V002 to V011 Literate people between 5 and 15 years old.	Morrow (2008); Norris et al. (2008); Fundação Renova (2018); Brazil, (2020)
	(IS02) Children: V001 Residents; V023 to V049 People below 15 years of age.	Cutter et al. (2003; 2010); Cutter, Finch, Burton (2008); Fundação Renova (2018); Brazil, (2020); Guoa, Kapucu (2020)
	(IS03) Elderly: V001 Residents; V099 to V134 People over 65 years of age	Guoa, Kapucu (2020)
	(IS04) Literate female heads of household: V001 Females head of household; V093 Literate females head of household	Sherrieb et al. (2010); Bergstrand et al. (2014); Singh et al. (2014); Fundação Renova (2018); Brazil, (2020)
	(IS05) Literate adults: V049 to V134 Total of people aged 16 and over; V012 to V077 Literate people aged 16 and over.	Morrow (2008); Norris et al. (2008)
	(IS06) Non-white people: V003 to V006 Resident people by color or race	Sherrieb et al. (2010); Bergstrand et al. (2014); Singh et al. (2014); Fundação Renova (2018); Brazil, (2020)
Economic Indicator	(IE01) Population income below the poverty line: V044 to V134 People aged 10 and over; V001 to V002 People aged 10 or over with income of up to 1 salary	Perry Lindell e Tierney (2001); Cutter et al. (2010); Hewitt (2014); Cutter et al. (2000); King and MacGregor (2000)
	(IE02) Heads of household without income: V001 Heads of household; V010 Heads of household without nominal monthly income	Fundação Renova (2018); Brazil, (2020)
	(IE03) People without income: V044 to V134 People aged 10 or over; V010 People aged 10 years and over with no nominal monthly income.	Fundação Renova (2018); Brazil, (2020)
	(IE04) Families dependent on the elderly: V001 Heads of household; V057 to V092 People over 65 years of age.	Morrow (2008); Bergstrand et al. (2014); Fundação Renova (2018); Brazil, (2020)
	(IE05) Property not owned: V002 Permanent houses; V008 to V011 Not owned houses.	Cutter et al. (2000); Fundação private Renova (2018)
Infrastructure Indicator	(II01) Housing location (rural or urban): V001 Sector situation. A value from 1 to 5 was assigned and variable he was normalized using a rescaling process, to produce a set of indicators in the same range.	Fundação Renova (2018); Brazil, (2020)

(II02) Houses with inadequate sewage disposal: V002 Permanent private houses; V019 to V023 Houses with sanitary sewage via a general sewage or rainwater network or septic tank.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
(II03) Houses without access to mains water supply network: V002 Permanent private houses; V012 Houses with mains water supply.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
(II04) Houses without access to mains electricity: V002 Permanent private houses; V045 and V046 Private houses without access to mains electricity.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
(II05) Houses with inadequate conditions: V002 Permanent private houses; V204 and V207 Houses in inadequate situation.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020) Cutter et al. (2010); Hewitt (2014);

3.3 Criteria and weights for the construction of social vulnerability index and indicators

The weights were assigned to each variable using Analytical Hierarchy Process (AHP), according to studies by Saaty (1990) and Pant et al. (2022). The AHP was used to calculate the score of each variable (Hummell, 2014), for more details see Saaty (1990) and Boroushaki, Malczewski (2008). The weights of the 16 variables collected from the 3,732 census sectors were calculated into the following indicators: social: consisting of six variables; economic and infrastructure with five variables, each, to create combined variables (equation I), which were calculated to produce the Social Vulnerability Index (SVI) (equation II) (Sherrieb et al., 2010; Bergstrand et al., 12015; Fundação Renova, 2018).

$$IVi = \sum_{i=1}^{n} x_i p_i \qquad \text{(I)}$$

in which SVI = IVi of indicator i; i = 1, 2, 3 (social vulnerability variables); xi = variable i; e pi = importance of variable i.

$$SVI = (VS1 + VS2 + VS3) / 3 \qquad \text{(II)}$$

in which SVI i = SVI per census sector; VS1 = vulnerability social indicator; VS2 = vulnerability economic indicator 2; VS3 = vulnerability infrastructure indicator.

We used the statistical environment R (version 3.6.1) (https://cran.r-project.org/bin/windows/base/old/3.6.1/) to select all variables, enter the weights and carry out the calculations. The ArcGis® 10.5.1 (ESRI, 2017) was used to spatialize and fill the result of sectors without information.

4 Results

4.1 Variables and criteria and weights for obtaining indicators

Table 2 shows the distribution of the weights of each variable to obtain the social, economic, and infrastructure indicators. We used AHP to assign the weights of the indicators considering a scale from 0 to 1. The criterion weights were assessed from data obtained from important literature on the subject, the analysis of experts, and the specificities of the communities involved.

Table 2 Variables and weights for SVI

Variables (%)		Weight
1 - Socials Indicators of SVI		
IS01	Illiterate children	0.06
IS02	Children	0.20
IS03	Elderly	0.20
IS04	Illiterate female heads of households	0.08
IS05	Illiterate adults	0.11
IS06	Non-white people	0.35
2 - Economics Indicators of SVI		
IE01	Property not owned	0.21
IE02	Population income below the poverty line	0.27
IE03	Heads of households without income	0.21
IE04	People without income	0.10
IE05	Elderly dependent families	0.21
3 – Infrastructure Indicators of SVI		
II01	Housing location	0.16
II02	Houses with inadequate sewage disposal	0.21
II03	Houses without access to mains water supply network	0.21
II04	Houses with inadequate conditions	0.21
II05	House without access to mains electricity	0.21

Note: Weights were assigned to the variables to obtain the indicators. To calculate SVI, no justification from the specialists or literature that could increase and/or decrease the importance of one indicator over another was found.

4.2 Variables, calculation of indicators, and social vulnerability index

The results are grouped by the equal intervals method and color-coded to show the different vulnerability classes: very low (dark blue), low (light blue), medium (beige), high (orange), and very high (red). The analyzes, at the census sector level, are discussed considering the two case studies: the susceptible dam, Casa de Pedra tailings dam; the one affected by the rupture, Córrego do Feijão tailings dam; and the municipality divisions (48 municipalities) and regional divisions of the basin (High, Low, and Middle Paraopeba).

In Table 2, we have an overview of the description of the chosen variables and the literature that validated them in different geographic contexts. The variables are positively related to social vulnerability, so the higher the values of the variables, the higher the social vulnerability. For variable II01 this method was not applied.

Fig. 3 shows the social, economic, and infrastructure indicators used to calculate the SVI across the basin. The first indicator, social, ranged from 0 to 1 with an average of 0.49 and a standard deviation of 0.12 (Fig. 3A). The second, the economic indicator, ranged from 0 to 1 with an average of 0.35 and a standard deviation of 0.17 (Fig. 3B). The third indicator, infrastructure, ranged from 0 to 0.1 with an average of 0.20 and a standard deviation of 0.19 (Fig. 3C). In the Paraopeba Basin, the SVI ranged from 0.00 to 0.78 with an average of 0.34 and a standard deviation of 0.12 (Fig. 4). Fig. 5 detail the social, economic, infrastructure indicators and o SVI of area affected by the collapse and susceptible area the basin.

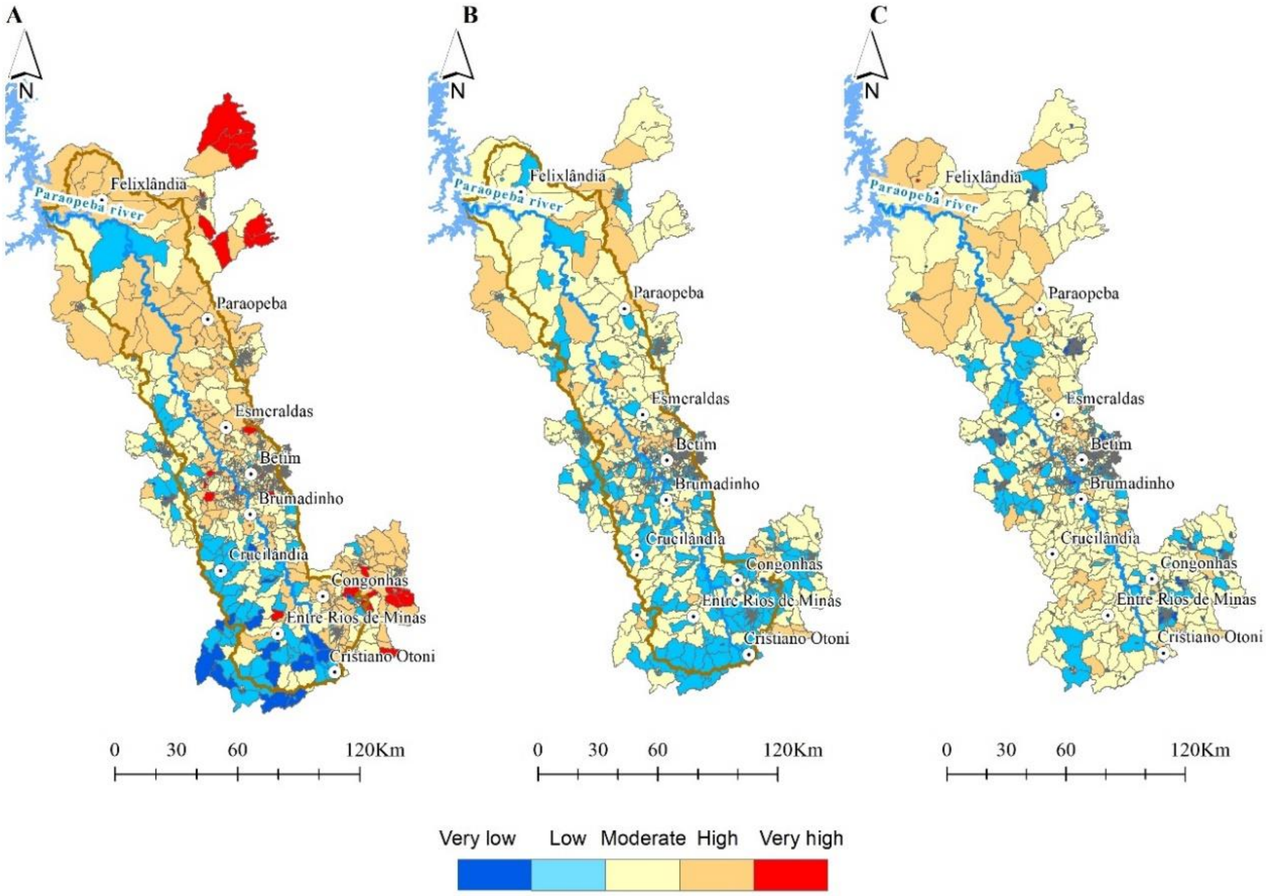

Figure 3 Spatial distribution of indicators in the Paraopeba Basin at the census sector level. (A) social indicator, (B) economic indicator, and (C) infrastructure indicator.

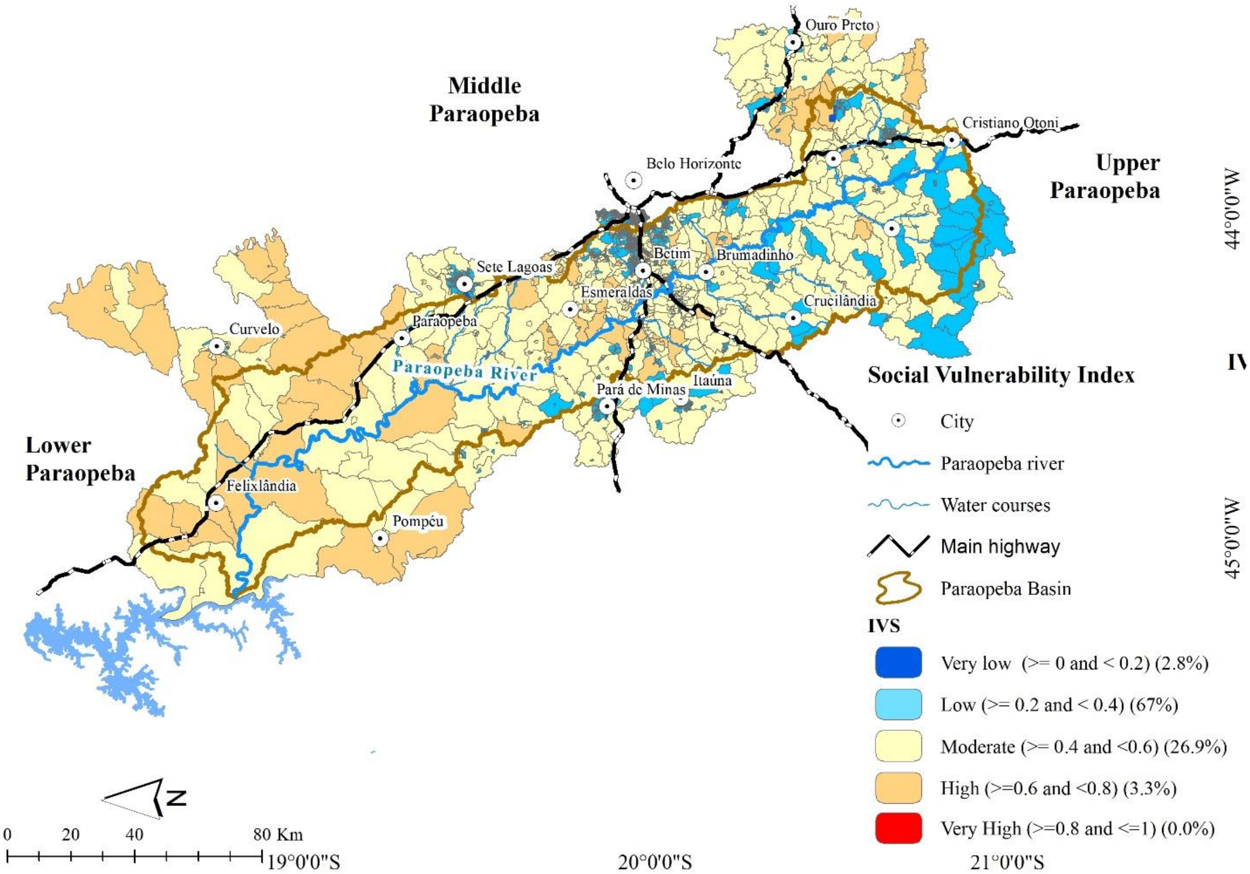

Figure 4 Social vulnerability index of Paraopeba Basin.

The results show considerable variability across the Basin. In rural areas, it ranged from 0 to 0.74, and in urban areas from 0 to 0.78. It was noted that about 69.8% of the sectors are classified with very low and/or low vulnerability. About 26.9% of them are classified with medium variability and 3.3% as high and/or very high. Among the main, the municipalities with the greatest quantity of the most vulnerable sectors in the basin are Curvelo and Felixlândia, and the least vulnerable ones are Betim, Contagem, Pará de Minas, and Sete Lagoas.

We found that 47.1% of the sectors to municipality Brumadinho, the municipality affected by the disaster, are classified with very low and low vulnerability and around 47.2% with medium, and 5.7% with high. In the susceptible area (Casa de Pedra), the results indicated the inexistence of very low vulnerability. It was found that 63.6, 30.3, 6.1% of the sectors are classified with low, medium, and high vulnerability, respectively (Fig. 5).

In Fig. 4, we noted that the SVI medium and high vulnerability classes are more present in the Lower Paraopeba and less in the high Paraopeba. In the High Paraopeba region, there were municipalities with highly vulnerable clusters (for example, Ouro Preto, and Congonhas). It was found that 3.9, 65.6, 28.0, 2.5% of the sectors from the High Paraopeba are classified with very low, low, medium, and high vulnerability, respectively; In the Middle, they correspond to 4.3, 73.4, 20.9, 1.3%; and in the Lower, at 1.6, 78.5, 46.4, 7.9%, respectively.

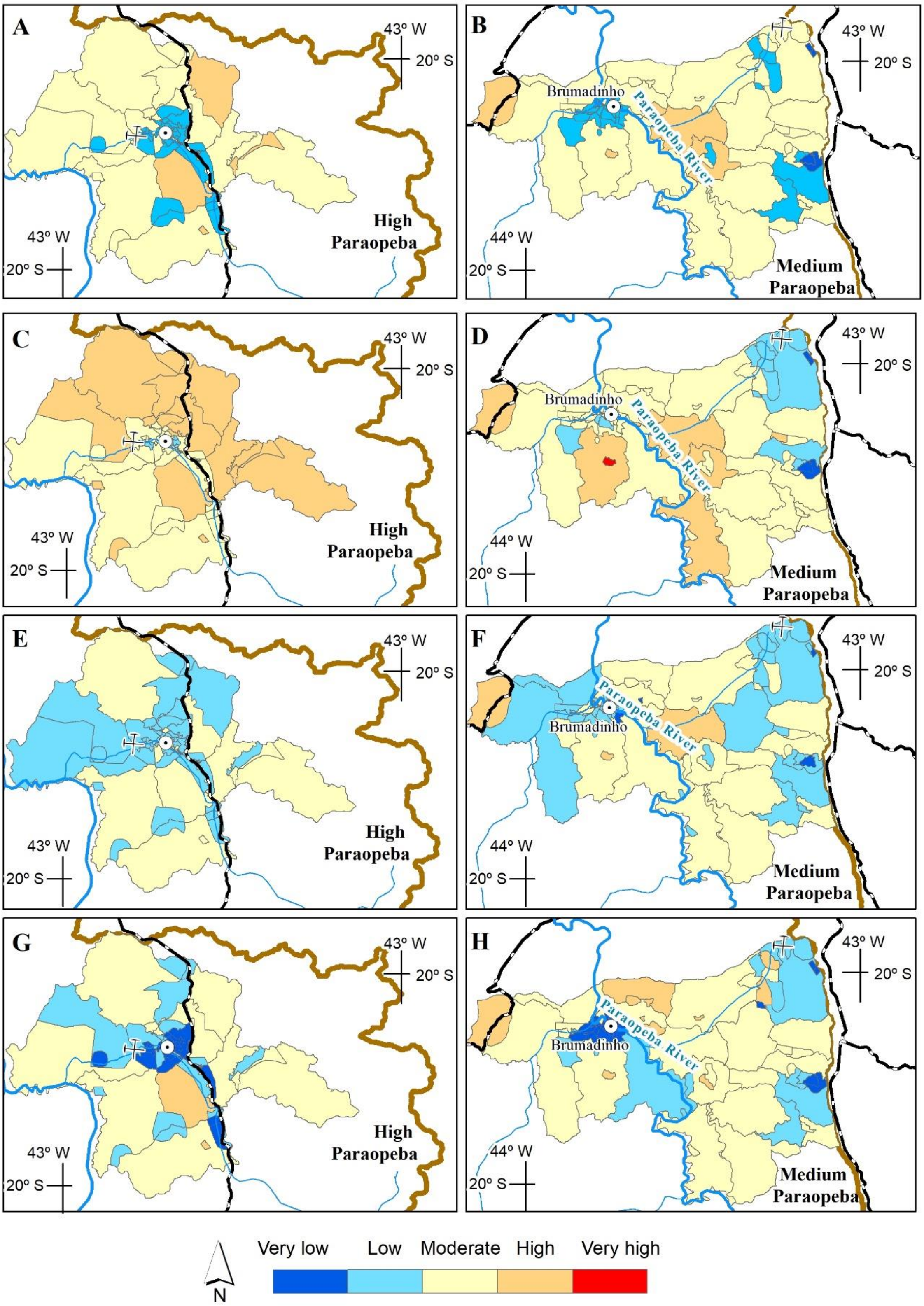

Figure 5 Social vulnerability index, (A) area affected by the collapse of the Feijão tailings dam in the municipality of Brumadinho and (B) susceptible area, Casa de Pedra tailings dam in the municipality of Congonhas. Spatial distribution of indicators area affected and susceptible, (C) and (D) social indicator; (E) and (F) economic indicator; and (G) and (H) infrastructure indicator, respectively.

5 Discussion

Although the discussions and results suggest that social factors can shape and influence populations to prepare, respond, and/or recover from disasters, the inclusion of these factors in research, planning, management, and mitigation is still scarce (Zandt et al., 2012). The vulnerability mapping in the Paraopeba Basin at a detailed scale offered a unique opportunity to identify characteristics in these communities that can interfere, positively and/or negatively, in the possible impacts from a disaster, whether in the context of preparation and response in areas susceptible to disasters or the correction, and mitigation in areas affected by the collapse of the tailings dam in the Basin under study.

Our results corroborate the findings by Kuhlicke et al. (2011) who stated that, so far, there is no consensus on the indicators of social vulnerability. In this study, special attention was given to the selection of variables. To explain the characteristics of the community from the basin, we reviewed a series of social vulnerability indicators and indexes; for more details see Refs. (Cutter et al., 2003; Bergstrand et al., 2015; Cutter; Finch; Burton, 2008; Morrow, 2008; Finch; Emrich; Cutter, 2010; Fundação Renova, 2018; Costa and Marguti, 2015; BRASIL, 2020; Qin et al., 2017).

Variables such as illiterate children and adults (IS01 and IS05, respectively) (Cutter; Finch; Burton, 2008; Norris et al., 2008; BRASI, 2020; Fundação Renova, 2018), population age (IS02 and IS03) (Cutter; Finch; Burton, 2008; Fundação Renova, 2018; Finch; Emrich; Cutter, 2010; Singh et al., 2010; BRASIL, 2020), family structure headed by illiterate women (IS04) (Morrow, 2008; Sherrieb et al., 2010; Fundação Renova, 2018; Finch; Emrich; Cutter, 2010; Singh et al., 2010; Bergstrand et al., 2015; BRASIL, 2020), and non-white population (IS06) (Singh et al., 2010; Sherrieb et al., 2010; Bergstrand et al., 2015; Fundação Renova, 2018; BRASIL, 2020) were used to measure the social indicator.

The variables income of the population below the poverty line (IE02) (Cutter; Mitchell; Scott, 2000; Tierney et al., 2001; Finch; Emrich; Cutter, 2010), people without income, heads of household without income, status of housing and families dependent on elderly people (IE04, IE03, IE01 and IE05, respectively) (Morrow, 2008; Bergstrand et al., 2015; Fundação Renova, 2018, BRASIL, 2020) were chosen to measure the economic indicator.

The infrastructure indicator was be measured based on the variables: access to treated water (II03), electricity (IIF5), adequate sanitary sewage (II02) (Costa and Marguti, 2015; Fundação Renova, 2018; BRASIL, 2020), location of communities based on high and low population density (II01), condition of housing (II04) (Bergstrand et al., 2015; Costa and Marguti, 2015; BRASIL, 2020; Finch; Emrich; Cutter, 2010; Cutter; Mitchell; Scott, 2000).

Another important issue that is different from other indexes and makes SVI an adjustable index for other contexts is the weight, which was assigned to each variable using process AHP, what is method of paired comparison by experts. The weights 0.06, 0.20, and 0.08 assigned to the variables IS01, IS02, and IS04 were based the greatest importance it IS02 have about other variables (IS01 and IS04). So on the historical characteristics of the basin population, which tend to act as obstacles to change, and the literature which shows that communities with a higher percentage of children, elderly, and female heads of households are more prospect to have low purchasing power and access to basic resources and assets, in addition to needing more care and assistance (Frigerio et al., 2016; Morrow, 2008).

The greater importance attributed to IS06 is based on the studies by Finch et al. (2010), and Singh et al. (2010), who emphasize that racial minorities are geographically located in areas further away from the centers with less access to resources and infrastructure or with low-skilled jobs. Consequently, salaries and stability are low. The authors emphasize that these racial minorities tend to be more vulnerable at all stages of the disaster (Singh et al., 2010; Finch; Emrich; Cutter, 2010).

Were estimated as equally important to variables IE01, IE03, and IE05, resulting in the attribution of equal weight. Based in on the fact that the effects of vulnerability to income were felt at all stages of the disaster. Furthermore, there is no scientific basis in the literature that justifies different weight attribution. When economically disadvantaged populations are exposed to negative externalities from extreme events, it is impossible to expect them to be able to anticipate and respond effectively to external changes and threats without assistance. These families, mainly, reside in regions with precarious housing without infrastructure and without resources to help them in times of crisis (Morrow, 2008). Although IE05 is not directly linked to inequalities like others used here, this variable is added by the age factor (65 or more). Several scientific studies have shown that the elderly tend to need more specific care at different stages due to mobility difficulties, health status, among other factors (Cutter; Finch; Burton, 2008; Finch; Emrich; Cutter, 2010; Tierney et al., 2001; Cutter; Mitchell; Scott, 2000).

The equal weight to variables II02, II03, II04, and II05 is based on the fact that we did not find any justification that could increase and/or decrease the importance of one factor over another. As the studies developed by the Fundação Renova (2018) suggest, access to basic sanitation, infrastructure, and housing services such as treated water, collection via mains sewage or rainwater network, or even septic tank, and garbage collection should, in principle, to be available to everyone, as they are first necessity. Their deprivation generates significant effects on the well-being of individuals, especially when this unequal access is enhanced by the impacts resulting from disasters (Fundação Renova, 2018).

The choice of the variable II01 was based on important literature (Finch; Emrich; Cutter, 2010; Tierney et al., 2001; Cutter; Mitchell; Scott, 2000; Ainuddin & Routray, 2012), since although communities in central areas have more access to resources, health, and infrastructure, they tend to have a higher population density. In the event of a disaster, they may have more difficulties in getting around than, for example, peripheral housing. Hence, the more peripheral the communities, the smaller the possibilities of access to infrastructure, schools, among other services (Finch; Emrich; Cutter, 2010; Tierney et al., 2001; Cutter; Mitchell; Scott, 2000).

Our results are consistent with recent research (Zandt et al., 2010; Chakraborty et al., 2020) that indicate that the social, economic, and infrastructure characteristics of a population differentiate the situation of geographic locations in terms of the level of social vulnerability (Chakraborty et al., 2020). As expected, we found that social vulnerability is inequitably distributed across the basin with some places more vulnerable than others.

The Middle Paraopeba portion, where the Metropolitan Region of the capital of Minas Gerais is located, presented a large discrepancy in the vulnerability levels. The population from Lower Paraopeba, on the other hand, has higher levels of infrastructure vulnerability than the one from the Middle and Upper portions. This inequitable pattern in the basin was also verified within the municipalities (Fig. 5G and 5H). The studies by Hummell et al. (2017), for Brazil, contribute to our research by suggesting that social differences between groups within the same municipality are partly reflected in housing standards, access to basic infrastructure services, education, among other factors.

Thus, the unit of analysis of the study, the census sector, made it possible to map in detail the variability of vulnerability in the Paraopeba Basin. Based on the work by Hummell et al. (2017), Zandta et al. (2012), and Chakraborty et al. (2020), it is recommended that research, programs, and/or action plans for disaster preparation and recovery should not be based on a single strategy for the entire affected and/or susceptible territory, as there are significant differences in social inequalities between regions and also within the same municipality.

The greater presence of sectors classified with medium and high vulnerability close to the disaster-prone area reinforces their need to receive high priority assistance. On the other hand, the lower variability and lower vulnerability of the sectors close to the affected area reinforce the argument that proximity to the disaster cannot be the only factor to be considered. This is an important result, as it shows that greater proximity to the disaster is not always spatially related to the most vulnerable populations (Zandt et al., 2010; Chakraborty et al., 2020). Vulnerability in the susceptible area is driven by social e indicators, however, economic and social indicators have a significant impact on improving the vulnerability of areas affected by the collapse of the Córrego do Feijão tailings dam.

The vulnerabilities in the area affected by the collapse cannot be associated with the collapse of the Córrego do Feijão tailings dam in the municipality of Brumadinho since the local population already had a history of great social inequality caused by the region's development process (Hummell, 2017). Although the data used in this research are from before the disaster, they can help us understand where the impacts will be more or less severe and what are the main vulnerabilities in each reality.

Our results are designed to allow governments, researchers, and a wide range of stakeholders to manage measures and resources more effectively, to respond and mitigate the effects of disasters and eventual disasters more assertively and targeted to local characteristics. As in the studies by Thompson et al. (2020), which portrayed the environmental aspects, our study shows that the impacts caused by the rupture were added to the impacts that already existed in the basin.

Sete Lagoas, Contagem, Pará de Minas, and even Brumadinho are among the municipalities with the highest number of less vulnerable sectors. Besides high population density and good quality of life, these municipalities have a developed economy with better literacy levels (IS01), for example. Curvelo, and Felixlândia, are the most vulnerable municipalities. The results obtained in this research suggest that these municipalities have higher concentrations of racial minorities (IS06), elderly, and children (IS03, IS02, respectively).

Thus, communities in the Lower Paraopeba Basin have less access to resources to prepare and/or rebuild after disasters. Additionally, the study showed that the highest levels of illiterate people are found in the lower part of the basin. Therefore, the SVI and the indicators and their components, added to the studies by Cutter et al. (2003), Morrow, (1999), Bolin et al. (1991), and Ainuddin and Routray (2012), indicate the importance of higher levels of education (IS01), as low levels of education can create barriers during all phases of the disaster, for example, to understand the measures and procedures to be adopted and even in the resolution of bureaucracies.

Ethnicity or racial minority can also affect vulnerability, however, its effects rarely occur on their own. The literature points out that this variable must be carefully analyzed and correlated with other variables, as race or ethnicity may not always be related to areas that are more or less vulnerable (Morrow, 2008). The results of this study indicate a greater proportion of racial minorities in the Lower Paraopeba part, however, in the Upper part, close to the municipalities of Congonhas and Ouro Preto, there is also a large concentration of these minorities. Similarly, the lower part has the highest percentage of mothers with low levels of education, which tends to be associated with informal jobs with low salaries (Morrow, 1999; Cutter et al., 2003). Thus, our results reflect other studies that emphasized regional differences in economic and social indicators with the conclusion that many of the highest levels of vulnerability, in this study, are located in the lower and some parts of the Middle Paraopeba, while the high remains particularly less vulnerable to threats.

This fact shows that, instead of following random spatial standards, the SVI pointed to the existence of regions with vulnerabilities ranging from low to high risk with significant implications for emergency planners and for the authorities responsible for identifying and directing resources to areas in need (Bergstrand et al., 2015).

Given the scenarios described, the results of this study emphasize how the socioeconomic differences of a population must be integrated into physical/environmental strategies for the prevention and mitigation of environmental disasters. The SVI showed high spatial heterogeneity throughout the basin with significant clusters that evidenced the different vulnerability characteristics of the local communities.

The social analysis of vulnerability is necessary, as it addresses the issue of how individuals and social groups predict, resist, and deal with a real threat as well as how to recover from them (Kuhlicke et al., 2011; Frigerio et al., 2016). Thus, the knowledge of previous forms of social, demographic, and economic organization of these communities, expressed by a set of assets, resources, and structures, can be considered an important factor to increase the opportunities to expand the possibilities of emergency management, correction, and mitigation to obtain more satisfactory results (Frigerio et al., 2016; Deria; Ghannad; Lee, 2020).

6 Conclusion

In this paper, a model for social vulnerability assessment was proposed and applied at the census sector level for the entire Paraopeba Basin. Based on national and international literature and AHP criteria, we determined the weight of each variable and calculated the social, economic, and infrastructure indicators as well as the social vulnerability index.

This study represented the first approach to obtain and spatially assess social vulnerability to disasters at the census sector level in the Paraopeba Basin and Brazil. After facing one of the biggest environmental disasters of the world, the results showed the location of the communities most susceptible to negative impacts due to their socioeconomic and demographic characteristics. Our results can help us understand where the consequences will be more or less severe if a disaster happens since vulnerabilities are an inherent condition of society and the impacts of the disaster add to the existing ones.

Analyzing the basin from two different angles: where the disaster has already happened (Brumadinho) and where it could happen (Congonhas), our findings indicate that the areas closest to the disaster will not always overlap spatially with the most vulnerable ones. Furthermore, the data showed the existence of more vulnerable areas in the Lower part of the basin while in the Middle and Upper Paraopeba the results showed high variability and less vulnerability, respectively. In the Upper part, more vulnerable clusters close to the susceptible area were evidenced.

This research can serve as a basis for different stakeholders to expand their strategies based on a more socially equitable approach for preparing, correcting, and mitigating the consequences of impacts from extreme events to achieve more inclusive and permanent results.

This social vulnerability assessment model showed the advantages of the proposed method since this type of study is still scarce in the Brazil as well as its applicability in the assessment of social vulnerability where the disaster has already occurred and where it may occur.

The use of a census data source for the elaboration of the index and indicators aims to allow the higher level of detail replication of the proposed methodology throughout the national territory, as these are official data available for the entire country and freely accessible. It is noteworthy that the lack of recent to the set of factors is a limitation of the study which, on the other hand, allowed a greater level of detail and recognition of the specificities within inside the municipality. So far, the existence of empirical studies on disaster social vulnerability in the Paraopeba Basin is unknown.

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Data availability The datasets generated and/or analysed as part of the current study are available from the corresponding author upon reasonable request.

Declaration of competing interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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2.2 Resilience of communities affected by the collapse of the Córrego do Feijão tailings dam in the Paraopeba Basin, Minas Gerais, Brazil

Manuscript submitted

Article ***2***

Resilience of communities affected by the collapse of the Córrego do Feijão tailings dam in the Paraopeba Basin, Minas Gerais, Brazil

Abstract

The assessment of resilience to disasters, including environmental ones, is paramount as the damage caused by disasters is increasing worldwide. Hence, the need for methods to quantify resilience in communities in different geographical contexts has also increased. However, existing metrics for measuring resilience have significant conceptual and empirical challenges. This work proposes a set of metrics, validated in the national and international literature, and adapted to the Brazilian context. The Resilience Capacity Index (RCI) was built, it is composed of three dimensions (institutional, community, and ecological). The index was applied to the Paraopeba Basin, which was recently the scene of one of the biggest socio-environmental disasters in the world. Key drivers of resilience were identified and analyzed. The results were obtained using an open-source software and a geographic information system (GIS). Scores were assigned using the Analytical Hierarchical Process (AHP). This study evidenced significant differences in community resilience in the Paraopeba Basin, Brazil. It was found that the (RCI) of the Upper and Middle Paraopeba was higher than that of the Lower Paraopeba. The study provided a robust and replicable metric to identify more and less disaster-resilient areas in the Paraopeba Basin to assess disaster readiness, response, recovery, and mitigation capabilities.

Keywords: Resilience Capacity, Social and Environmental Disasters, Paraopeba Basin, Brazil.

1 Introduction

The impacts associated with natural disasters are increasing worldwide and becoming more and more threatening (Masozera et al., 2007; GAR, 2015; UNISDR, 2015). In the last 30 years, the number of people affected by these events has increased significantly. Therefore, a new relationship between nature and society and an understanding of the factors associated with the impacts and losses caused by natural disasters is required (Orencio, 2013; Yoon; Kang; Pescaroli, 2018; Vazquez-Gonzalez et al., 2019). The Global Assessment Report on Disaster Risk Reduction (GAR) found that developing countries, which represent 97% of the communities affected worldwide, are the ones to suffer the greatest impacts and losses (UNISDR, 2015; SIWI, 2005; Ainuddin: Routray, 2012; Orencio, 2013; UNISDR, 2019).

In disaster management, preparation, response, recovery, and successful adaptation to present and future conditions must be understood not only as environmental processes, but also social ones. Hence, disaster management solutions range from physical-environmental technical solutions to the understanding of a myriad of threats to human aspects in the occurrence of disasters (Blaikie et al., 1994; Cannon, 1994; Orencio, 2013). This includes applying systems to increase security through resilience. Therefore, knowing the factors that mitigate the adverse effects of disasters is essential to improve the resilience of communities in the different phases of the disaster (Orencio, 2013; Cutter et al., 2020).

Resilience has been a very present topic in national and international discussions (Mavhura et al., 2021), and is currently part of the Sendai Framework for Disaster Risk Reduction (SFDRR), of the Sustainable Development Goals (SDGs), of United Nations' Agenda 2030, and the Paris Agreement (Mavhura et al., 2021). Its concept has gained worldwide attention as a way to improve the ability to deal with changes and disturbances (Klein et al., 2003; Berkes, 2007; Plummer; Armitage, 2007; Bohle, 2008; Zhou et al., 2010). However, there is little consensus when it comes to conceptualizing and/or measuring resilience (Cutter, 2016).

Several authors have investigated the theoretical framework of resilience (Berkes et al., 2003; Cutter et al., 2008, 2010; Perz et al., 2010; Wilson, 2010). Some have established different methods to quantify conditions that help communities to resist and reorganize themselves after disturbances (Campanella, 2006; Alessa et al., 2008; Ernstson et al., 2010; Sherrieb et al., 2010; Smith et al., 2011; Ainuddin; Routray, 2012; Ledger et al., 2012; Coaffee, 2013; Mason; Pulvirenti, 2013; Sadiq; Noonan, 2015; Ai et al., 2016). A review of the literature on resilience showed several studies related to natural disasters such as floods, hurricanes, tsunamis (Ainuddin; Routray 2012; Wilson, 2013; Sadiq; Noonan, 2015; Burton, 2015; Znati; Comfort 2016), water crises, and climate change (Brock et al., 2003; Alessa et al., 2008; Saavedra; Budd, 2009; Ledger et al., 2012).

Thus, resilience is increasingly seen as a key step towards reducing the effects of disasters (UNISDR, 2005; Yoon; Kang; Asadzadeh et al., 2017), and the ability to measure it is widely spread. However, its conceptualization and quantification are marked by different approaches, tools, and methods that are rarely geographically comparable (Cutter, 2019; Ostadtaghizadeh et al., 2015; Beccari, 2016; Sharif, 2016; Asadzadeh et al., 2017). Most research on empirical measurements of resilience is based on unofficial primary data and complex methodologies that are difficult to understand and reproduce (Asadzadeh et al., 2017; Cutter, 2020), being of little use. Furthermore, despite being useful references, existing resilience indices for developing countries are not fully applicable to Brazil. The analysis of resilience capacity adapted to developing nations, particularly to the Brazilian context, is an urgent need. Developing a tool capable of quantifying resilience based on good quality official data, easy to use ad replicable over time and space to be used as a reference for research, remains a challenge.

Environmental disasters happen frequently in Brazil, with serious consequences and increasing social and environmental damage (De Lima et al., 2020). However, so far, no studies conducted to reveal the country's resilience to disasters are known. Thus, based on the case of the Paraopeba River Basin, which in 2019 suffered one of the biggest socio-environmental disasters recorded to date caused by the collapse of B1 Tailing Dam in Córrego do Feijão, in Brumadinho (De Lima et al., 2020), this study comprised three main parts: (1) the proposal a set of metrics, which were validated in the national and international literature, and their adaptation to the national context; (2) the construction of an index, replicable in time and geographically adaptable, to measure the resilience of the community in the Paraopeba Basin (Fig.1) and used as a reference in future studies; and (3) the analyses of the main drivers of overall resilience in the communities of the basin.

The rest of the article is structured as follows. Section 2 discusses how resilience is defined in recent and important research on socio-environmental disasters, as well as its advantages and drawbacks. In Section 3, all stages of the development of the Resilience Capacity Index are methodologically evaluated. In Section 4, it is presented the results and a discussion of the results. In Section 5 are the conclusions and implications for different stakeholders.

Figure **1** Location of the Paraopeba Basin, MG, in a global context.

2 Theoretical Framework

2.1. Resilience

The concept of resilience was first used in "Resilience and Stability of Ecological Systems" by Holling (1973). The author defined resilience as the capacity to absorb changes and disturbances and still keep the same relationships that control the behavior of a system (Folke, 2006; Mayunga, 2007; Fleischhauer, 2008; Finch; Emrich; Cutter, 2010). A decade later, Timmerman (1986) brought the term to research on natural hazards and described resilience as the capacity of a system to absorb or recover itself from an extreme event. Later, David Alexander (2013) also highlighted the origins of resilience, with special emphasis on the social context and environmental disaster risk reduction (Cutter, 2016).

In Ecology, resilience can be defined from two perspectives: engineering resilience and ecosystem resilience. The first emphasizes control, consistency, efficiency, and predictability. The second focuses on persistence, adaptability, variability, and unpredictability (Mavhura et al., 2021). Based on the second definition, and because this research proposal applies to societies affected by or susceptible to environmental disasters, resilience is defined here as the capacity of social systems to absorb changes or disturbances effectively to deal with potential impacts from extreme events. Resilience is what causes communities to reorganize themselves, change and learn in response to an event. This expansion of the concept with the inclusion of the social component brought, besides the physical component, the role of institutions and community capacities (Adger et al., 2005; Kates et al., 2006; Finch; Emrich; Cutter, 2010; Morrow, 2008; Ainuddin; Routray, 2012; Burton, 2014).

Some authors have established different methods to quantify the conditions that help communities to resist and reorganize themselves after disturbances. The indices proposed by Cutter and Finch (2008), Cutter et al. (2010), and Sherrieb et al. (2010) are based on the disaster resilience of place model (DROP). They are the most widespread and followed models, as they list a parsimonious set of variables and tools to measure them. While Sherrieb et al. (2010) based their work on two indicators: economic development and social capital, Cutter et al. (2010) developed five indicators: social, economic, institutional, infrastructure, and community capacity (Alshehri; Rezgui; Li, 2015). Recent research relies on other models, such as the one proposed by Burton (2014), who developed six indicators: social, economic, infrastructure, institution, community, and environment. Qin et al. (2017) proposed the index based on four dimensions: institution, infrastructure, economic and social. Norris et al. (2008) considered that community resilience is a process that links a network of adaptive capabilities, including four dimensions: economic development, social capital, information and communication, and community competence (Qin et al., 2017; Mavhura et al., 202). Our methodology differed from that of the cited literatures including we considered three indicators: institutional, community, and ecological.

Although the DROP model presented a resilience metric that is theoretically effective and amenable to empirical applications (Finch; Emrich; Cutter, 2010; Cutter, 2016), some studies point out that determining a common arrangement for each indicator in resilience is a challenge. Some studies attribute to the lack of a standard method for measuring and conceptualizing resilience, the difficulty of assessing and weighing the access or absence of a set of assets, resources, and structures, due to the complex nature of a community's disaster resilience (Buckle, 2006; Finch; Emrich; Cutter, 2010; Alshehri; Rezgui; Li, 2015).

3 Methodology

3.1. Study area

In the southeast Brazil, the Paraopeba River Basin extends for approximately 280 km, with an area of 13,618 km^2, covering 48 municipalities and 3,732 census sectors (Fig. 1). Its population density is 93.24 inhab./km² and the total population is 1.3 million inhabitants; of these, 5.82% live in rural areas (CBHSF, 2020).

According to the Köppen classification, the main climate in the region is Aw (tropical with dry winter) near the basin's river mouth, Cwa (humid subtropical with dry winter and hot summer) in the north-central portion, and Cwb (humid subtropical with dry winter and temperate summer) in the south-central region (Alvares et al., 2014). Total precipitation is around 1,700 mm year-1 in the headwater regions and 1,150 mm year-1 in the region close to the mouth of the basin (CBHSF, 2020; Silva et al., 2022).

The vegetation is a transition between the Cerrado and the Atlantic Forest biomes, both considered focal points for the conservation of global biodiversity (Myers et al., 2000). According to the São Francisco Basin Committee, the Paraopeba Basin is divided into three parts: Upper, Middle, and Lower Paraopeba. Lower Paraopeba is in the northern portion whereas Upper Paraopeba is in the southern portion The Serra Azul mountain range, that cuts through the center of the basin, was one of the areas with the lowest RCI in the three dimensions (institutional, community, and ecological). The Serra Azul mountain range, cuts through the center of the basin (CBHSF, 2020).

3.2. Data source

The dataset used to build the Resilience Capacity Index were obtained mainly from the Brazilian Institute of Geography and Statistics (IBGE, 2019) and the Department of Health (2019). It was also used data from Mapbiomas (2019-2020), the National Mining Agency (ANM, 2020), the National Institute of Educational Studies and Research (INEP, 2020), and the State Foundation for the Environment (FEAM 2010). Data are available at the municipal level, census sector, and on 1:100.000 scale, from 2019 to 2020, except for the Soil map that dates from 2010 (Tab. 1). The variables were gathered based on three equally important criteria: first, justified in the disaster resilience literature; second, present in the official database; and third, with a frequency that allows monitoring. ArcGis® 10.5.1 was used to select and calculate all variables and spatialize their results. A detailed description of the methodological procedures used to construct the variables and the literature consulted are described in table 1.

Table **1** Description of the variables used to calculate the Resilience Capacity Index and its indicators

	Variables	Description	Measure	Data Source	Reference
Institucional dimension of RCI	Rate of health facilities	The number of health facilities in the municipality (psychosocial care center-caps, health center/basic health unit, general hospital, health post, and general emergency), by the estimate of the total population of the municipality).	Per thousand	DATASUS	Heinz Center (2002); Cutter et al. (2010)
	Inpatient bed rate	The number of hospital beds in the municipality, by on the estimate of the total population of the municipality.	Per thousand	DATASUS	Heinz Center (2002); Cutter et al. (2010)
	Density of dams protected by safety plans	Risk category and associated potential harm.	Kernel density/ zonal statistics, area by census sector/municipality	ANM	--
	Population density	The number of inhabitants divided sector area.	Inhab./km^2	IBGE	Singh et al. (2014)
Community dimension of RCI	Rate of higher education institutions	The number of higher education institutions (federal, state, and private).	Kernel density/ zonal statistics, area by census sector/municipality	INEP	Morrow (2008)
	Percentage of preschools	Number of public and private preschools, by on the estimate of the total population of the municipality	Per thousand	INEP	Cutter et al. (2003; 2010); Cutter, Finch, Burton (2008)
	Participation of civil society and associated stakeholders	The number of departments, unions, governments, and councils, by the estimate of the total population of the municipality.	Per thousand	--	Murphy (2007); Morrow (2008); Cutter; Burton; Emrich (2010)
	Civic organizations	The number of cultural and community organizations, by the estimate of the total population of the municipality.	Per thousand	--	Murphy (2007); Morrow (2008);

					Cutter; Burton; Emrich (2010)
	Economic diversity	The number of economic sectors in the municipality.		--	Cutter et al. (2020)
Ecological dimension of the RCI	Land use and land cover	The following Land use and land cover classes were considered: forest, rock outcrop, natural non-forest formation, pasture, agriculture, forestry, agriculture and pasture mosaic, urban areas, and mining. The values assigned were: 1, 1, 2, 3, 4, 4, 4, 5, and 5, respectively.	--	MAPBIOMAS	--
	Soil	For the soil variable, classification was performed to determine capacity as a function of soil. The following soil classes were considered: Rocky outcrop, dystrophic and strophic Leptsols, Haplic Cambisols, dystrophic Yellow Latosol, dystrophic Red-Yellow Latosol, dystrophic and strophic Red Latosol. The soil types were grouped according to Lepsch et al. (2015). Later, to portray the soil variable, a classification was performed to determine Land use and land cover capacity that ranged from I to VIII, with class I being the least restrictive class and VIII the most restrictive one, for each group (class) a value from 1 to 5 was assigned. The values assigned were: 5, 4, 4, 3, 2, 2, 2, and 1, for the class I, II, III, IV, V, VI, VII, and VIII, respectively.	--	FEAM	Lepsch et al. (2015); Rio Grande do Sul (1979); Vale (unpublished)
	Distance from highways	Paved and non-paved highways/roads	Euclidean distance	DNIT	Singh et al. (2014)

3.3. Resistant variables choice

3.3.1. Institucional dimension

Institutional variables examine capacities related to disaster planning and mitigation and portray the fundamental conditions of access to basic health services that, in essence, should be present in society and that substantially influence the possible impacts arising from environmental disasters. For instance, the greater the number of health services, the lower the risk and potential damage of a dam. Also, the lower the population density around dam sites, the greater resilience of the communities (Norris et al., 2008; Cutter et al., 2010).

Some studies have shown that planning and mitigation are important to reduce losses and achieve more comprehensive and lasting results. The greater resilience of a system is due to institutions enabling quick and effective responses to possible challenges from environmental disasters. They do so by providing tools for social cooperation and the participation of local communities in mitigation measures (Adger, 2000; Norris et al., 2008; Cutter et al., 2010; Aigica; Tarko, 2014; Burton, 2014). Health services, such as hospitals and clinics that are close to or capable of providing care for the injured, are also paramount in the community response and recovery phases (Ainuddin; Routray, 2012; Lixin et al., 2014; Qin et al., 2017). Previous research stated that population density is highly correlated with exposure to disasters, as the higher the population density, the greater the demand during periods of environmental disturbance (Yuan; Gao; Qi et al., 2019; Sung; Liaw, 2021).

3.3.2. Community dimension

The sense of community is directly related to the existing bond among its members. It is characterized by a great concern for community issues. It is a sense of connection present in society to deal with possible impacts arising from environmental disasters. Communities with greater public awareness at the local level, participation in civil society and civic organizations, characterized by having associations, organizations, educational institutions, and research centers based on knowledge, science, engineering, arts, design, and media, as well as having preschools and diversified economy, tend to develop higher levels of resilience (Florida, 2002; Finch; Emrich; Cutter, 2010; Norris et al., 2008). The literature also emphasizes the importance of the variable number of governments and/or representatives. In the Brazilian context, this information was measured with the participation of civil society and stakeholders.

Studies state the importance of networks and trust for community resilience during and after disasters. Individuals with a greater sense of community will tend to have more engaged members. Clubs, entities, and other community organizations provide connections that can be requested, whether to facilitate future employment opportunities, make recommendations, guide, or provide resources. Thus, the lack of networks makes individuals more isolated and, therefore, impairs the capacity for resilience, especially when dealing with adversities (Perkins; Hughey; Speer, 2002; Morrow, 2008; Cutter et al., 2010; Ainuddin; Routray, 2012). In this sense, political engagement, which is social participation, has a positive relationship with the capacity for resilience (Scherzera; Lujalab; Røda, 2019; Sung; Liaw, 2021).

Previous research suggests that if daycare centers and schools were affected by the effects of a disaster, their lack, especially for children's early years, would let families incapable of becoming more resilient (Cutter et al., 2003; 2010; Finch; Emrich; Cutter, 2010). The literature also highlights that the level of education is significantly related to the ability to understand information (Guoa; Kapucu, 2020; Sung; Liaw, 2021). Hence, the percentage of preschools and the percentage of higher education schools were used as variables.

3.3.3. Ecological dimension

The ecological dimension provides an assessment of environmental patterns and distance from highways/roads. Variables such as distance, soil type, and Land use and land cover can contribute to uneven patterns of resilience. The effects of these variables on resilience are more complex and depend on the combination of several factors (Ainuddin; Routray, 2012).

Research confirms that different resilience classes may be related to soil characteristics and their potential for human, industrial, and/or agricultural activities. Therefore, understanding the different levels of resilience based on Land use and land cover is extremely important for environmental disaster management processes. Some studies have shown that the variable distance from roads is crucial at different stages of the disaster. It provides means for pre-disaster evacuation and acts as an access route to vital supplies during and after the disaster (Singh et al. (2014). Peripheral communities, when access is only possible through bridges and/or rural roads, for instance, may be less resilient than communities with more access to roads, as there is a risk of being isolated and dependent on air transport or supply boats, until alternative and/or definitive action is taken (Cutter et al., 2003; 2010).

3.4. Multicriteria analysis

In this study, the Analytical Hierarchical Process (AHP) was used to calculate the score of each variable. This method assumes that decision-making for complex problems can be handled through a simple and understandable hierarchical structure (Li et al., 2009; Vale (unpublished).

The relative importance of each variable was assessed by the method of paired comparison by experts, using a scale from 1 to 9 (Tab. 2) (Li; Huang, 2009). The Coefficient of Consistency (CR) was applied to verify the consistency of the experts' judgments. A CR value greater than 0.10 indicates that the scores were assigned adequately (Eastman, 2003; Wang et al., 2009; Vale (unpublished).

Table **2** Scale for expert paired comparison.

Intensity of importance	Verbal judgment of the expert
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between adjacent scale values

Note: Adapted from Saaty (1980) and Boroushaki, Malczewski (2008).

3.5. The development of the Resilience Capacity Index and its dimensions

The variables were normalized using a rescaling process, to produce a set of indicators in the same range. This rescaling process is a way of decomposing each variable in the same range between 0 and 1. Thus, regions of high resilience obtained normalized values close to 1, and less resilient regions obtained normalized values close to 0.

The importance (score), defined through the Hierarchical Analytical Process for each of the 12 produced variables, was multiplied to obtain the weighted average of the indicators: institutional, with four variables; community, with five variables; and ecological, with three variables, in the R environment. Each of the indicators was again multiplied in a GIS environment to obtain the Resilience Capacity Index (RCI) map.

The calculations to obtain the three indicators and the RCI were performed using the R statistical environment (Version 3.6). The maps, which are the results of the processing, were reclassified into five classes (very low, low, moderate, high, and very high), using the Equal Interval method of the ArcGis® 10.5.1 reclassify tool. Fig. 2 shows the flowchart with the methodological description.

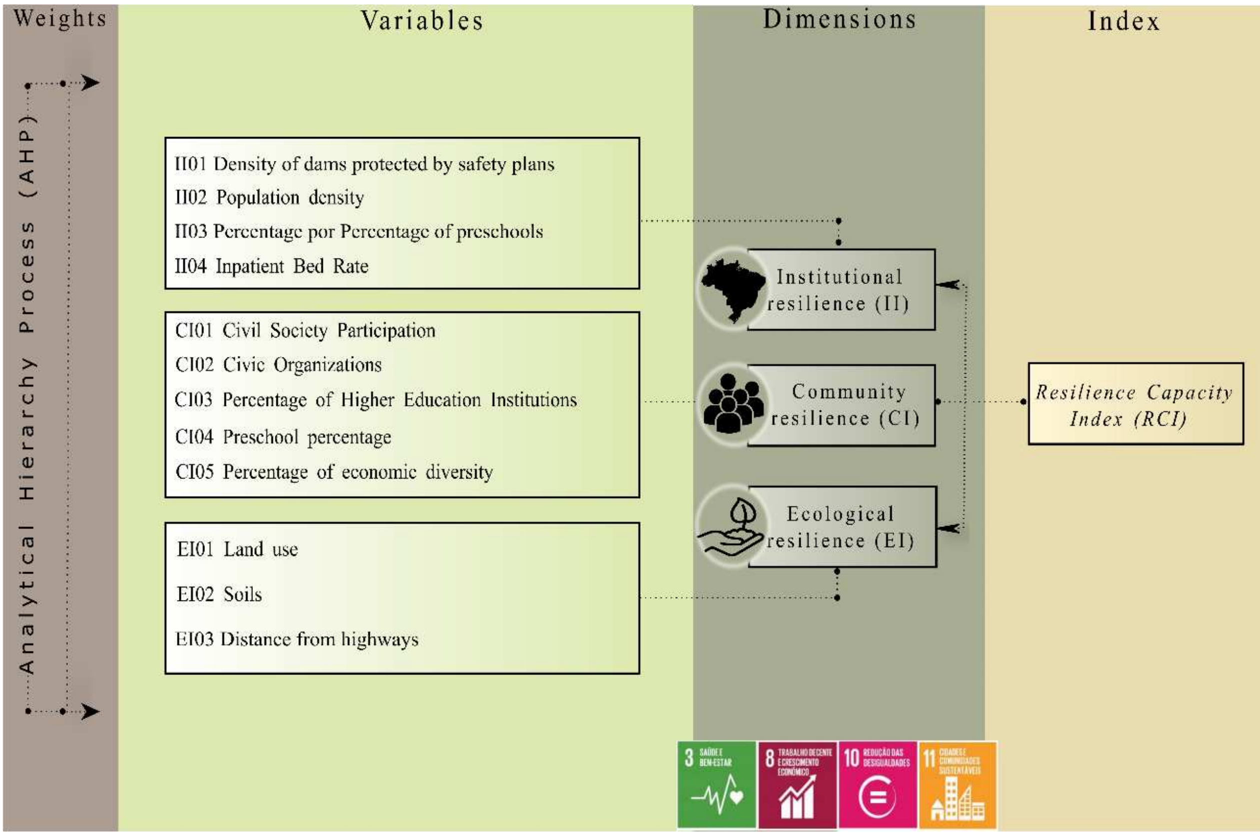

Figure **2** Flowchart of the methodological description.

4 Results and discussion

4.1. Scores assigned to the variables and indicators

The RCI was developed and applied as part of this study to assess the resilience to disasters in the Paraopeba Basin. It was identified which municipalities are more or less resilient to environmental disasters than others, and which factors weaken or boost resilience. The 12 variables used, validated in national and international literature and adapted to the national context, covered the subdomains of institutional, community, and ecological resilience.

The RCI applied to the Paraopeba Basin becomes the starting point for the temporal monitoring of the resilience levels of the municipalities in the basin. The database consists of official data annually available for the entire national territory, making it comparable and allowing its application in other areas of the country.

In this study, special attention was given to the selection of variables. To explain the characteristics of the basin's community, several resilience capacity indicators were reviewed; for more details check the references (Cutter et al., 2003; 2010; Norris et al., 2008; Burton, 2014; Qin et al., 2017; Mavhura et al., 2021). The results found support important studies that used variables of similar dimensions to quantify community resilience in Korea (Yoon et al., 2016), Zimbabwe (Mavhura et al., 2021), and the United States (Bergstrand et al., 2015).

Scores were assigned by AHP (Saaty, 1980; Boroushaki, Jacek Malczewski1, 2008; Cutter et al., 2010; Qin et al., 2017), the 12 variables were grouped and multiplied in a GIS environment to obtain the institutional, community, and ecological dimensions. The CR value was greater than 0.10

for the three dimensions (0.9, 0.6, and 0.3, respectively). This indicates that the scores were adequately assigned according to the studies by Eastman (2003) and Wang et al. (2009). Institutional, community, and ecological indicators were considered equally important, so their scores were the same (Tab. 2).

The institutional indicator is measured by four variables: density of dams protected by safety plans (II01), population density (II02), rate of health facilities (II03), and inpatient bed rate (II04). The factor density of dams protected by safety plans was considered extremely more important than the other variables. Health facilities and inpatient bed rates, in turn, were estimated as equally important, and moderately more important than population density. The scores assigned were 0.44, 0.08, 0.24, and 0.24, respectively.

The community indicator is measured by five variables: participation of civil society and associated stakeholders (CI01), number of civic organizations (CI02), number of higher education institutions (CI03), number of preschools (CI04), and economic diversity (CI05). The variable number of higher education institutions was estimated to be twice as important as the participation of civil society and associated stakeholders and the number of civic organizations. The variable number of preschools was estimated to be moderately more important than CI01 and CI02. Economic diversity was considered strongly more important than CI01 and CI02, and moderately more important than CI04. The scores given were 0.13, 0.13, 0.30, 0.20, and 0.24, respectively.

The ecological indicator is measured in terms of three variables: Land use and land cover (EI01), soil (EI02), and distance from highways (EI03). Variables EI01 and EI02 were estimated to be twice as important as the distance from highways, with scores of 0.4, 0.4, and 0.2 assigned, respectively. Tab. 3 shows the scores calculated for the three indicators.

Table **3** Scores given to the Resilience Capacity Index and subindices at the Paraopeba basin.

Dimension	Variables	Score
	Institucional Dimension	
	Density of dams protected by safety plans	0.44
	Population density	0.08
Institutional	Rate of health facilities	0.24
	Inpatient bed rate	0.24
	Total score	**1.0**
	Community dimension	
	Participation of civil society and associated stakeholders	0.13
	Civic organizations	0.13
Community	Percentage of higher education institutions	0.30
	Percentage of preschools	0.20
	Economic diversity	0.24
	Total score	**1.0**
	Ecological dimension	
	Land use and land cover	0.40
Ecological	Soil	0.40

Distance from highways	0.20
Total score	**1.0**

4.2. Resilience Capacity Index Spatialization

The results are grouped by color to show the different resilience classes: very low (red), low (orange), moderate (beige), high (light green), and very high (dark green). The analyzes are discussed considering the case study: rupture of the Córrego do Feijão dam, in the municipality of Brumadinho; the municipal divisions (48 municipalities); the regional divisions (Upper, Lower, and Middle Paraopeba); the northern and southern portions of the basin.

Fig. 3 shows the spatialization of the RCI in the Paraopeba Basin. It was found that the high and very high RCI classes were smaller than the low and very low RCI classes. About 41.7% of the sector fell into the very low to low resilience categories, 31.2% in the moderate category, while only 27.1% have high and very high resilience. The RCI was better in the southern and central regions of the basin, and the resilience capacity was lower at the basin's mouth (Fig. 3).

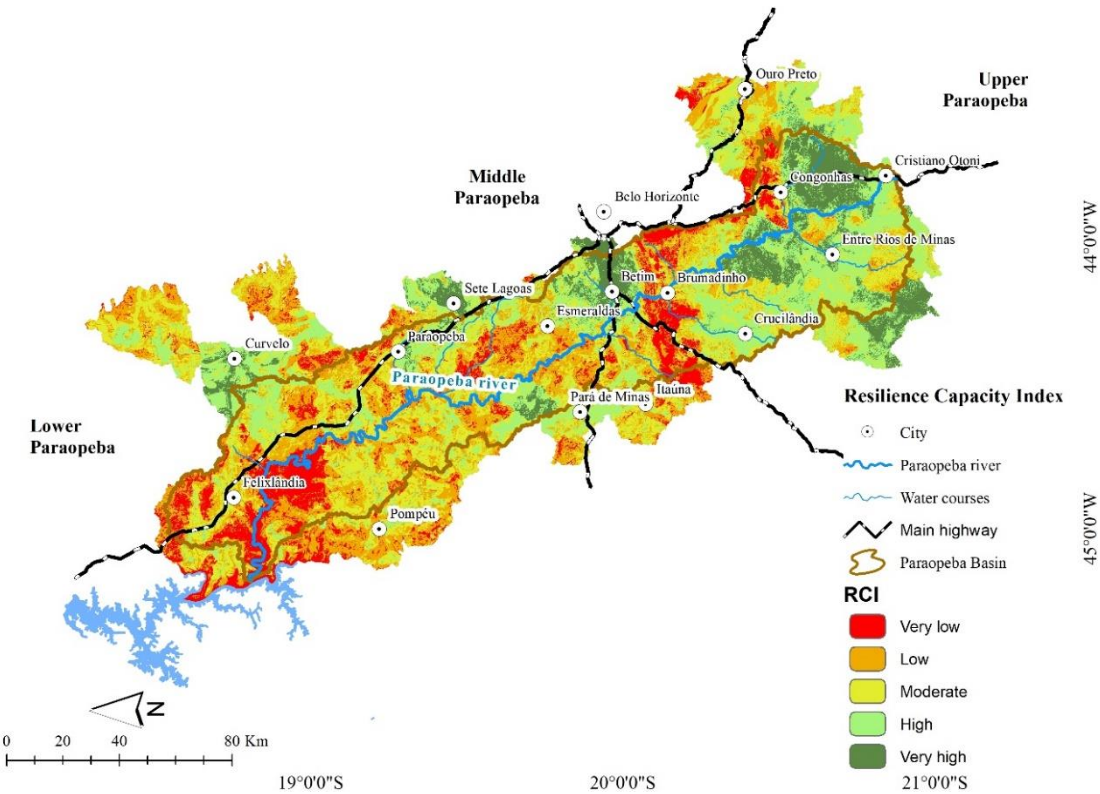

Figure **3** Resilience Capacity Index for the Paraopeba Basin, MG.

Fig. 4 shows, in descending order, the RCI for the Paraopeba Basin. The least resilient municipalities are mainly in the Lower Paraopeba, except for Moeda, São Brás do Suaçuí and Ouro Preto (Middle Paraopeba) (Fig. 5). The most resilient municipalities (Conselheiro Lafaiete and Betim) are the ones with the highest population densities, best access to basic health and education services and are in the central region of the basin, in Middle Paraopeba.

Fig. 5 shows the institutional, community, and ecological indicators used to calculate the RCI across the basin. The first indicator (institutional) ranged from 0 to 0.84, with a mean of 0.48 and a standard deviation of 0.13 (Fig. 5A). The second indicator (community) ranged from 0 to 0.73, with a mean of 0.25 and a standard deviation of 0.14 (Fig. 5B). The third indicator (ecological) ranged from 0 to 1, with a mean of 0.60 and a standard deviation of 0.16 (Fig. 5C). In the southern portion of the basin, the RCI was better for the ecological dimension than for the community dimension. At the basin's river mouth, near Felixlândia, the RCI was the lowest in all dimensions. (Fig. 5).

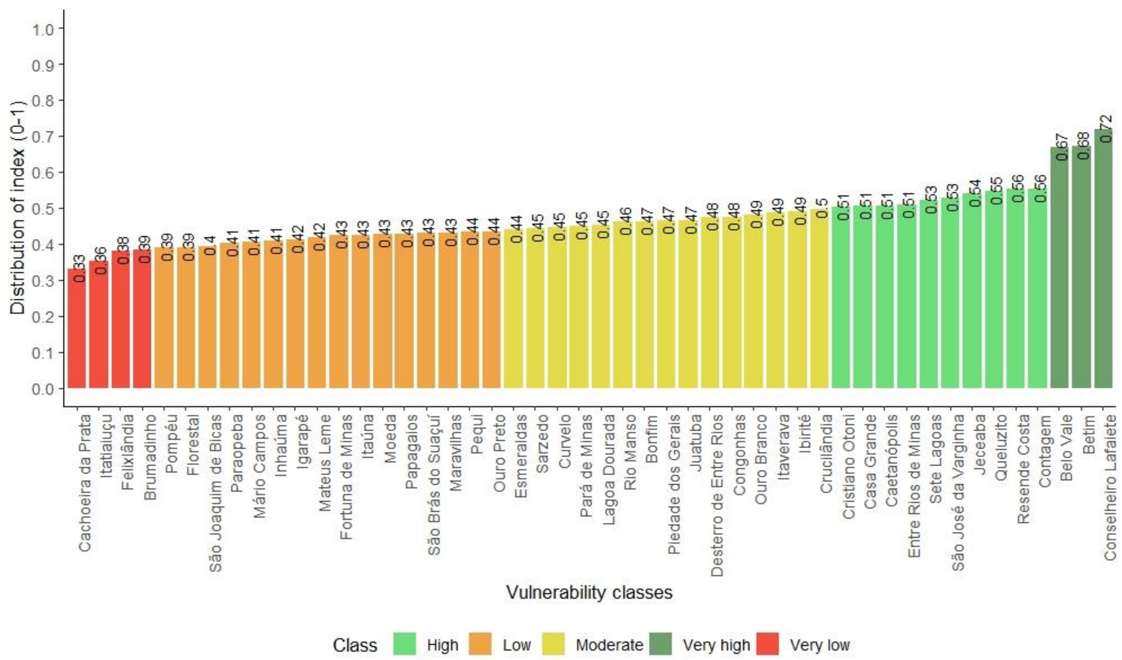

Figure **4** – RCI results in the municipalities of the Paraopeba Basin, MG, in descending order.

Sarzedo, São Joaquim de Bicas, Mario Campos, and Igarapé are among the least resilient municipalities in terms of the institutional dimension, while Resende Costa, Belo Vale, Conselheiro Lafaiete and Curvelo are among the most resilient (Fig. 5). As for the community dimension, Felixlândia, Pompéu, Papagaios, and Paraopeba are among the least resilient municipalities, while Ibirité, Sarzedo, Contagem, Betim, and Conselheiro Lafaiete are among the most resilient. In the ecological dimension, Cachoeira da Prata, Fortuna de Minas, Itatiaiuçu, Mario Campos, and Felixlândia are among the municipalities with low and/or very low resilience capacity. Contagem, Betim, Piedade do Gerais and Conselheiro Lafaiete are the ones with the greatest resilience.

In the basin, 79% of the municipalities have very low to moderate resilience in the institutional factor. About 21% are categorized as having high and very high resilience. The institutional dimension was better in the southern portion, close to Queluzito, and in the northern portion, close to the municipality of Curvelo (Fig. 5).

Health facilities and hospital beds are concentrated, notably, in urban areas and/or in cities with greater population density. Less populated and very remote districts have the worst access to basic health facilities. About 14% of the municipalities do not have hospitals, emergency rooms, or other types of health facilities, namely: Maravilhas, Piedade dos Gerais and Jeceaba. Among those who have a hospital, around 56% do not have hospital beds. Therefore, many families, not only from rural areas but also from less populated municipalities, need to travel to other cities to access basic services. Mavhura et al. (2021) emphasize that access to healthcare is critical when a community suffers physical and emotional damage caused by disasters, epidemics, pandemics, and other extreme events. Global frameworks such as the Sendai Framework for Disaster Risk Reduction (SFDRR) and the Sustainable Development Goals (SDGs) emphasize the importance of access to health as a way of building disaster resilience (Maini et al., 2017; Mavhura et al., 2021).

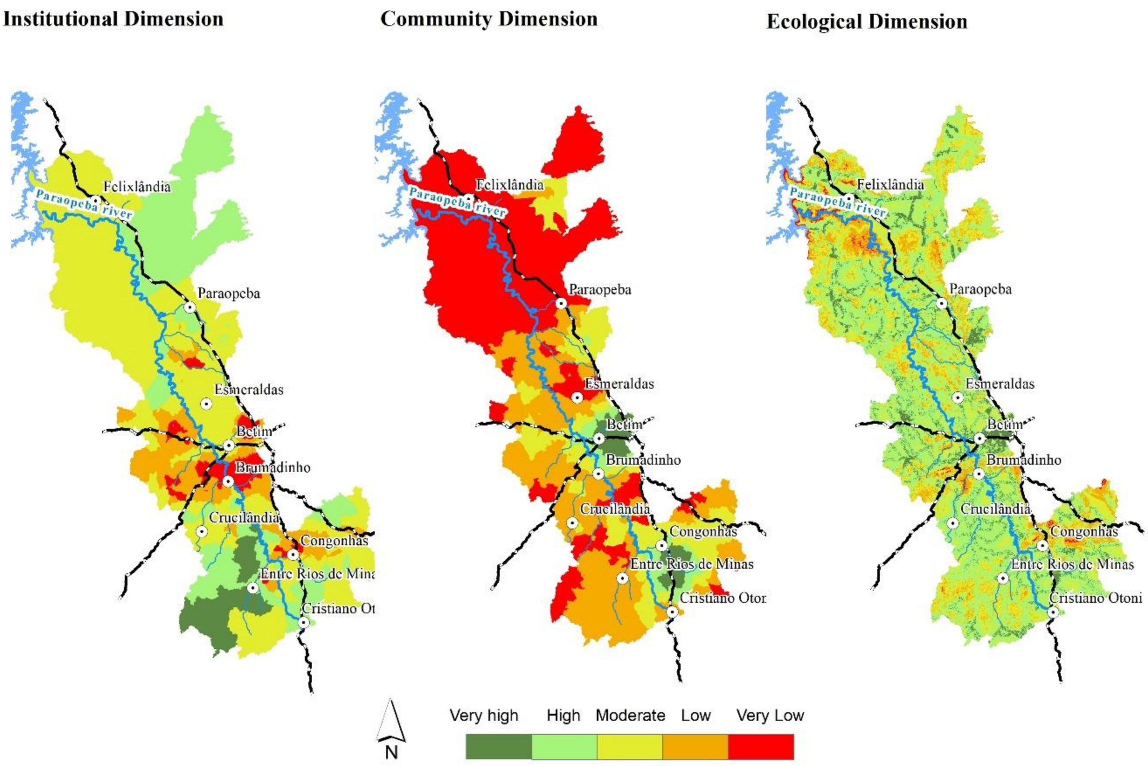

Figure **5** – Institutional, community, and ecological dimensions in the Paraopeba basin, MG.

The institutional dimension also included the variable density of dams protected by safety plans. This variable shows the increase and/or decrease of the risks and potential damages associated with possible dam ruptures. In the Upper and Middle Paraopeba region, activities related to mining, especially iron ore, are expressive. Most of these areas are in the Quadrilátero Ferrífero region, considered one of the largest mining regions in the country, more specifically in Serra de Itatiaiuçu and Serra Azul, between the municipalities of Ouro Preto and Congonhas, in Upper Paraopeba, and Brumadinho and Itatiaiuçu, in the Middle. The dams with the greatest risk and potential for damage associated with loss of human life and socioeconomic and environmental impacts resulting from the dam failure are mainly in the limits of Belo Vale, Ouro Preto, Congonhas, Brumadinho, and Itatiaiuçu.

Regarding the community dimension, the results showed that resilience is low in the northern portion of the basin, near the basin's outlet, in the municipalities of Felixlândia and Pompéu, whereas it is high in the municipalities in the central region. Areas of very low, low, moderate, high, and very high resilience account for 16.7, 41.7, 18.8, 12.5, and 10.4%, respectively.

Large-scale disasters, such as the collapse of the B1 Dam in Brumadinho, are examples of the impacts whose ramifications are broad and long-lasting (Lima et al., 2020). Our results corroborate those found in recent research (Pescaroli; Alexander. 2018), indicating that municipalities with little economic diversification tend to be less resilient in the long term. Concerning the results of the community dimension, Brumadinho, Itatiaiuçu, and Belo Vale are among the least economically resilient municipalities, while Contagem, Betim, and Conselheiro Lafaiete are among the most resilient.

In addition to the economic factor, the community dimension included variables on the participation of civil society and the number of civic organizations. The studies by Cutter et al. (2008) and Morrow (2008) contributed to this research by showing that impacts tend to be reduced through social and community factors, with greater community participation. The results suggest that the factors that influence more or less social interaction and community engagement are concentrated in the peri-urban areas of municipalities with the highest population density. Therefore, cities with smaller populations such as Crucilândia, Paraopeba, and Esmeraldas tend to have a less active role in the disaster recovery process and have lower levels of resilience.

The third indicator to compose the Resilience Capacity Index for the Paraopeba Basin is the ecological one. In the basin, 44% of the municipalities fell into the categories of very low to low resilience capacity. About 33% are categorized as having moderate resilience, and 23% as high and very high. The RCI of the ecological dimension was better in the southern portion, and its resilience capacity was lower in the basin's close to the mouth of the basin (Fig. 5).

In this dimension, the least resilient municipalities are also the ones with soils with the greatest limitations for agricultural activity. The municipalities with the lowest ecological resilience include Itatiaiuçu, Ouro Preto, Mario Campos, Felixlândia, Pompéu, Sarzedo, Brumadinho, and Congonhas. The municipalities of Contagem, Betim, Piedade do Gerais, Conselheiro Lafaiete, Pará de Minas, and Queluzito have moderate to high ecological RCI. These results corroborate the findings of Frischen (2020), who stated that agriculture is a key variable, as it has a direct influence on disaster resilience.

Measuring resilience in absolute terms is not easy. There is no universal set of pre-established and available metrics (Alessa et al., 2008; Cutter et al., 2010). However, this study was based on important literature (Fleischhauer, 2008; Cutter et al., 2008; Cutter et al., 2010) that allowed the building of a set of metrics validated in the national and international literature and adapted to the Brazilian context.

To manage an area affected by natural disasters, it is essential to assess its resilience. The results obtained in this study can provide important information for policymakers to prioritize areas of low resilience to make them more resilient. Hence, it was presented and analyzed the main drivers of resilience in the basin. So far, the existence of empirical studies on disaster resilience in the Paraopeba Basin is unknown.

5 Conclusion

This study was the first approach taken to obtain and spatially assess the resilience capacity for disaster in the Paraopeba Basin, after facing one of the biggest socio-environmental disasters in the world. The result of the resilience index and sub-indices (institutional, community, and ecological) provided sufficient knowledge to identify the municipalities and assess the main factors responsible for the different levels of resistance in the basin.

This study evidenced significant differences in community resilience in the Paraopeba Basin, Brazil. The RCI of Upper and Middle Paraopeba was higher than that of the Lower part. The municipalities of Betim and Contagem, in the central and southern region of the basin, are areas of high RCI, especially in the vicinity of Conselheiro Lafaiete, Queluzito, Rezende Costa, and Belo Vale. The northern portion, in Lower Paraopeba, near the basin's river mouth, is an area of low RCI, including the municipalities of Felixlândia and Pompéu.

The Serra Azul mountain range, that cuts through the center of the basin, was one of the areas with the lowest RCI in the three dimensions (institutional, community, and ecological). The municipalities in the northern region have a high RCI in the institutional dimension but lower in the other dimensions. In the municipalities of the southern portion, in High Paraopeba, close to the river's spring in Cristiano Otoni, the results indicate a low RCI in the community dimension but an ascending RCI for the institutional and ecological dimensions.

The study provided an effective tool to identify areas that are more and less resilient to disasters and to assess readiness, response, recovery, and mitigation capacities. It is noteworthy that the scale applied to the set of factors was designed to provide professionals and decision-makers with an easy-to-understand, robust, replicable, and monitorable metric.

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2.3 Relationship between the Resilience Capacity and Social Vulnerability Indexes associated with environmental disasters: a case study of the socio-environmental disaster in the Paraopeba Basin, Brazil

Manuscript submitted

*Article **3***

Relationship between the Resilience Capacity and Social Vulnerability Indexes associated with environmental disasters in the Brazil

Abstract

Environmental disasters are more and more frequent, especially in developing countries. Countries such as Brazil lack measuring systems to quantity vulnerability and resilience for disasters risk evaluation. The goal of this work was to identify and analyze the relationship between social vulnerability and resilience to environmental disasters in the Paraopeba River Basin in Brazil. The basin is in a global biodiversity hotspot and, recently, was the scenario of one of the biggest socio-environmental disasters in the world: the rupture of the Córrego do Feijão tailings dam, in Brumadinho (MG). Thus, understanding the different levels of social vulnerability and resilience of the communities involved is very important to neutralize their negative impacts. The potential impacts of the disaster were assessed by calculating the Resilience Capacity (RCI) and Social Vulnerability (SVI) Indexes and spatially correlating them. Pearson and Moran's I correlation analyzes were used to assess the spatial autocorrelation between indices. The results indicate regional differences in levels of vulnerability and resilience. The south of the basin showed low levels of susceptibility to damage caused by disasters, while the north of the Paraopeba basin showed a lower ability to recover from impacts. Through the data obtained by spatial correlation, it was found that 50% of the most vulnerable municipalities tend to be the least resilient ones. Our fndings contribute to the mitigation strategies designed for the communities involved of one of the biggest socio-environmental disasters in global.

Keywords: Socio-environmental disaster, Resilience, Social Vulnerability, Paraopeba Basin, Dam collapse, Spatial autocorrelation analysis

1 Introduction

Vulnerability and resilience research is becoming more and more important in a world of increasing technological and extreme weather disasters (Bergstrand et al., 2014). Vulnerability and resilience to extreme events are, respectively, the potential loss in the face of threats and the ability to prepare, respond and recover in case of disasters. Both are caused by exposure and proximity to stressors related to the environment and social structures (Adger, 2006; Sung; Liaw, 2021). To support communities in disaster planning and recovery, it is important to understand how the damage extends across different sectors of the community and what resources and strategies the communities can use to recover themselves (Bergstrand et al., 2014).

The concepts of vulnerability and resilience to natural disasters have been applied in the field of disaster management (PNUD, 2014; Cutter et al., 2016; Sung; Liaw, 2021). Vulnerability is the social conditions previous to an event, such as a disaster, that determine risk exposure. This pre-existing condition influences whether the community can prepare and mitigate damage caused by environmental disturbances. Resilience is a condition that helps social systems absorb and respond to risks and adapt to the impact of disasters (Cutter et al., 2008; Kuhlicke et al., 2011; Eidsvig et al., 2014; Zhou et al., 2014; Bergstrand et al., 2014; Sung; Liaw, 2021). Previous research had a different view of the link between resilience and vulnerability. They consider the concepts to be distinct but related components (Cutter; Ash; Emrich, 2014; Sung; Liaw, 2021).

Efforts to quantify vulnerability and resilience through indices have been made (Cutter et al., 2010). Several models and metrics have been developed and applied to study vulnerability and resilience to natural hazards (Cutter et al., 2008; Myers; Slack, 2008; Eidsvig et al., 2014; Cutter, 2016; Frigério et al., 2016). Recent research focuses on quantifying vulnerability and resilience as a way of assessing the socioeconomic and biophysical conditions of the environment (Turner et al., 2003; Birkmann, 2007; Cutter et al., 2008; Rose, 2007; Frazier et al., 2013). Important literature advocates the quantification and identification of vulnerable and resilient areas to prepare for and mitigate extreme events in high-risk areas (Morrow 1999, Bergstrand et al., 2014). This is because understanding the most susceptible areas can help implement programs to prepare communities and mitigate damage before disasters, as well as to better direct aid and resources to areas in difficulty after disasters (Morrow 1999, Cutter, 2016; Bergstrand et al., 2014; Sung; Liaw, 2021).

To contribute to the existing gaps in studies on vulnerability and resilience to environmental disasters, this article involved the compilation of two indices composed of a robust set of internationally validated variables, which were adapted to the Developing countries of the Southern Hemisphere context and scale of study. The goal was to explore spatial patterns and differences between vulnerability and resilience to disasters in the Paraopeba Basin in southeastern Brazil. Thus, the Social Vulnerability Index (SVI) and the Resilience Capacity Index (RCI) were calculated, both at the municipal level. Pearson's, Spearman correlation analysis and Moran's I of spatial autocorrelation were applied to detect the spatial distribution patterns of the two indices (Sung; Liaw, 2021).

Furthermore, the paper has three more sections. Section 2 details the study case and describes the methodology. Section 3 shows the empirical results and discusses them. Finally, section 4 concludes the paper.

2 Material and Methods

2.1. Study area

The Paraopeba Basin, in southeastern Brazil, covers 48 municipalities in the state of Minas Gerais. Located in the metropolitan region of the state, close to the capital Belo Horizonte, the basin is part of the Quadrilátero Ferrífero region, considered one of the largest mining regions in the country with socioeconomic importance for the entire Brazilian territory. The area of the basin is 12,054.25 km² (Fig. 1). Taking into account the total extension of the 48 municipalities and the 3,732 census sectors that comprise the basin, 21,806.32 km² are examined. More than 1.3 million people live in this region. From this total, about 94% live in urban areas and 6% in rural areas (CBHSF, 2020).

The basin is in a transition region between two highly threatened biomes: Cerrado and Atlantic Forest (Roque; Neto; Faria, 2022). In January 2019, one of the biggest socio-environmental disasters happened in Brazil. It was caused by the rupture of the B1 dam in Córrego Feijão, in the Southeast Region of the country, in the city of Brumadinho (MG), between the coordinates 20° 7' 6″ S and 44 ° 12' 4″ W. The dam had an average elevation of 881m and average annual rainfall of about 1,267 mm (De Lima et al., 2020). Existing social and environmental problems enhanced the effects of this disaster, affecting families, jobs, housing, and even loss of human life (CPRM, 2019; De Lima et al., 2020; Ramos et al., 2020).

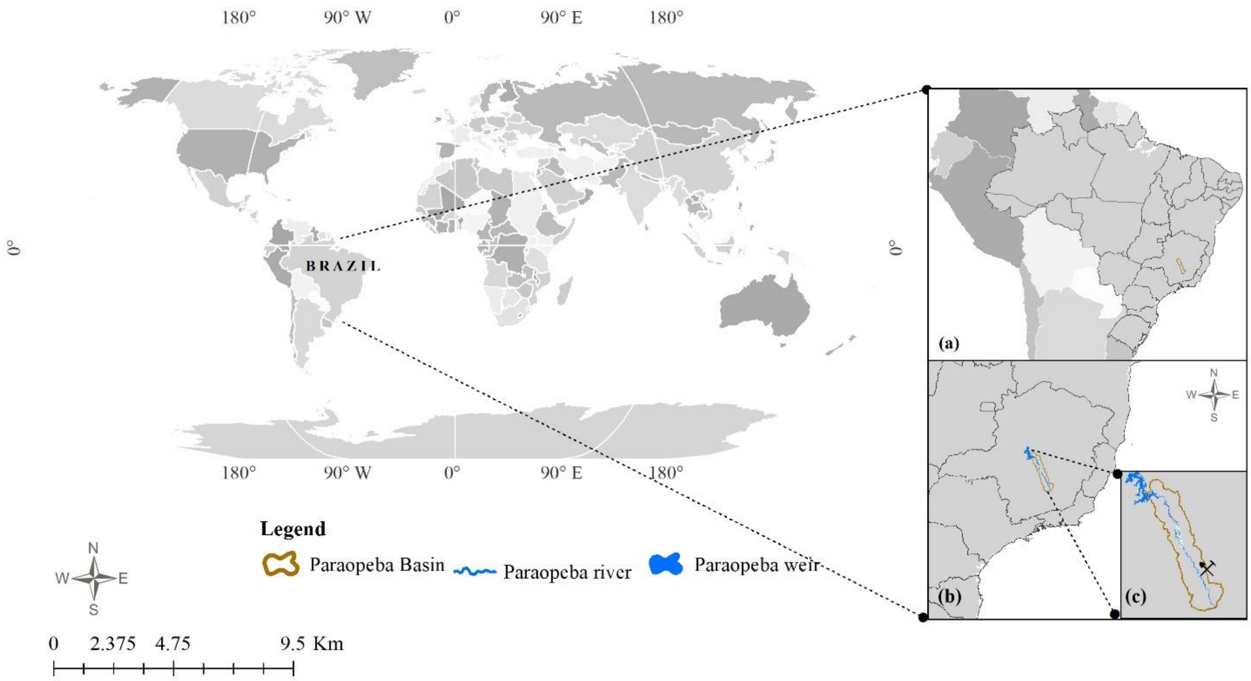

Figure 1: Location of the Paraopeba Basin in a global context.

2.2. Social Vulnerability Index

The statistical data used to calculate the indices in this study were gathered directly from the Brazilian Demographic Census (IBGE, 2010). They are available on the website of the Brazilian Institute of Geography and Statistics (IBGE). These data are the only official data in the country that best represent the specificities of the territory, due to its scale of action. All data are available in electronic spreadsheets at the census sector level from 2010. Data referring to the layers of census sectors and municipalities were obtained in shapefile format (IBGE, 2019; Tasnuva et al., 2021). The variables were segmented into three dimensions. The indicators and variables were based on the methodologies of Cutter et al. (2003), Cutter, Finch, and Burton (2008), Morrow (2008), Sherrieb et al. (2010), Costa and Marguti (2015), Bergstrand et al. 2015, Qin et al. (2017), Fundação Renova (2018) and Brazil (2020). Table 1 lists the variables used to build the SVI, their methodological descriptions, and the literature on which they are based.

Table 1: SVI variables, their methodological descriptions, and their base literature.

	Variables	Variables Description	Reference
Social Indicator			
	Illiterate child	V023 to V049 Total of people between 5 and 15 years old; V002 to V011 Literate people between 5 and 15 years old.	Morrow (2008); Norris et al. (2008); Fundação Renova (2018); Brazil, (2020)
	Children	V001 Residents; V023 to V049 People below 15 years of age.	Cutter et al. (2003; 2010); Cutter, Finch, Burton (2008); Fundação Renova (2018); Brazil, (2020); Guoa, Kapucu (2020)

	Elderly	V001 Residents; V099 to V134 People over 65 years of age	Guoa, Kapucu (2020)
	Illiterate female heads of household	V001 Females head of household; V093 Literate females head of household	Sherrieb et al. (2010); Bergstrand et al. (2014); Singh et al. (2014); Fundação Renova (2018); Brazil, (2020)
	Illiterate adults	V049 to V134 Total of people aged 16 and over; V012 to V077 Literate people aged 16 and over.	Morrow (2008); Norris et al. (2008)
	Non-white people	V003 to V006 Resident people by color or race	Sherrieb et al. (2010); Bergstrand et al. (2014); Singh et al. (2014); Fundação Renova (2018); Brazil, (2020)
Economic Indicator	Population income below the poverty line	V044 to V134 People aged 10 and over; V001 to V002 People aged 10 or over with income of up to 1 salary	Perry Lindell e Tierney (2001); Cutter et al. (2010); Hewitt (2014); Cutter et al. (2000); King and MacGregor (2000)
	Heads of household without income	V001 Heads of household; V010 Heads of household without nominal monthly income	Fundação Renova (2018); Brazil, (2020)
	People without income	V044 to V134 People aged 10 or over; V010 People aged 10 years and over with no nominal monthly income.	Fundação Renova (2018); Brazil, (2020)
	Families dependent on the elderly	V001 Heads of household; V057 to V092 People over 65 years of age.	Morrow (2008); Bergstrand et al. (2014); Fundação Renova (2018); Brazil, (2020)
Infrastructure Indicator	Housing location (rural or urban)	V001 Sector situation. A value from 1 to 5 was assigned to the variable that was later normalized using a rescaling process, to produce a set of indicators in the same range.	Fundação Renova (2018); Brazil, (2020)
	Houses with inadequate sewage disposal	V002 Permanent private houses; V019 to V023 Houses with sanitary sewage via a general sewage or rainwater network or septic tank.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
	Houses without access to mains water supply network	V002 Permanent private houses; V012 Houses with mains water supply	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
	Houses without access to mains electricity	V002 Permanent private houses; V045 and V046 Private houses without access to mains electricity.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
	Houses with inadequate conditions	V002 Permanent private houses; V204 and V207 Houses in an inadequate situation.	Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)
	Property not owned	V002 Permanent private houses; V008 to V011 Not owned houses.	Cutter et al. (2010); Hewitt (2014); Cutter et al. (2000); Costa and Marguti (2015); Fundação Renova (2018); Brazil (2020)

2.3. Resiliency Capacity Index

The dataset used to build the Resilience Capacity Index were gathered mainly from IBGE (2019) and the Health Department (2019). It was also used data from Mapbiomas (2019-2020), the National Mining Agency (ANM, 2020), the National Institute of Educational Studies and Research (INEP, 2020), and the State Environmental Foundation (FEAM, 2010). The data are available at municipal, census sector, and pixel levels. The variables were segmented into three dimensions according to Cutter, Heinz Center (2002), Cutter et al. (2010), Sherrieb et al. (2010), Singh et al. (2014), Bergstrand et al. (2015), and Qin et al. (2017): Institutional, Community and Ecological.The variables used to build the RCI, their methodological descriptions, and the literature on which they are based are listed in Table 2.

Table 2: RCI variables, their methodological descriptions, and their base literature.

	Variables	Variables Description	Reference
Institutional Indicator	Rate of health facilities	The number of health facilities in the municipality (psychosocial care center-caps, health center/basic health unit, general hospital, health post, and general emergency), by the estimate of the total population of the municipality).	Heinz Center (2002); Cutter et al. (2010)
	Inpatient bed rate	The number of hospital beds in the municipality, by on the estimate of the total population of the municipality.	Heinz Center (2002); Cutter et al. (2010)
	Density of dams protected by safety plans	Risk category and associated potential harm. Was performed Kernel density/ zonal statistics, area by census sector/municipality	--
	Population density	The number of inhabitants divided by sector area (Inhab./km2).	Holand; Lujala; Rod, (2011); Singh et al. (2014)
Community Indicator	Proportion of higher education institutions	The number of higher education institutions (federal, state, and private). Was performed Kernel density/ zonal statistics, area by census sector/municipality	Morrow (2008)
	Proportion of preschools	Number of public and private preschools, by on the estimate of the total population of the municipality	Cutter et al. (2003; 2010); Cutter, Finch, Burton (2008)
	Participation of civil society and associated stakeholders	The number of departments, unions, governments, and councils, by the estimate of the total population of the municipality.	Murphy (2007); Morrow (2008); Cutter; Burton; Emrich (2010)
	Civic organizations	The number of cultural and community organizations, by the estimate of the total population of the municipality.	Murphy (2007); Morrow (2008); Cutter; Burton; Emrich (2010)
	Economic diversity	The number of economic sectors in the municipality by the estimate of the total population of the municipality.	Cutter et al. (2020)
Ecological Indicator	Land use and land cover	The following Land use and land cover classes were considered: forest, rock outcrop, natural non-forest formation, pasture, agriculture, forestry, agriculture and pasture mosaic, urban areas, and mining. The values assigned were: 1, 1, 2, 3, 4, 4, 4, 5, and 5, respectively.	--
	Soil	For the soil variable, classification was performed to determine capacity as a function of soil. The following soil classes were considered: Water bodies, rocky outcrop, urban area, dystrophic and strophic Leptsols, Haplic Cambisols, dystrophic Yellow Latosol, dystrophic Red-Yellow Latosol, dystrophic and strophic Red Latosol. The soil types were grouped according to Lepsch et al. (2015). Later, to portray the soil variable, a classification was performed to determine land use and land cover capacity that ranged from I to VIII, with class I being the least restrictive class and VIII the most restrictive one, for each group (class) a value from 1 to 5 was assigned. The values assigned were: 5, 4, 4, 3, 2, 2, 2, and 1, for the class I, II, III, IV, V, VI, VII, and VIII, respectively.	Lepsch et al. (2015); Rio Grande do Sul (1979); Vale (unpublished)

	Distance from highways	Paved and non-paved highways/roads. Was obtained the Euclidean distance.	Singh et al. (2014)

2.4. Building the indices

Specialists from different scientific areas evaluated the relative importance of each variable for the two indices, using the Analytical Hierarchical Process (AHP) for paired comparison, for more details check (Li and Huang, 2009). The consistency coefficient (CR) was used to verify the consistency of the experts' judgment (Li and Huang, 2009).

The scores defined by the AHP for each of the 12 variables of the RCI were multiplied to obtain the weighted average of the indicator. The 12 variables are comprised of three indicators: institutional, with four variables; community, with five variables; and ecological, with three variables. Each of the indicators was multiplied again in a GIS environment to obtain the Resilience Capacity Index (RCI) map. As for the SVI, the 16 variables were multiplied to obtain the weighted average of the indicators. The 16 variables are comprised of three indicators: social, with six variables; economical, with four variables; and infrastructure, with six variables. Each of the indicators was multiplied again in a GIS environment to obtain the Social Vulnerability Index (SVI) map. The indices and indicators resulting from the processing were reclassified into three categories (low, moderate, and high), using the Equal Interval method of the ArcGis® 10.5.1 reclassify tool.

2.5. Spatial analyses of the Social Vulnerability and Resilience Capacity

In this study, the generated maps of social vulnerability and resilience capacity for the Paraopeba Basin were evaluated simultaneously to verify similar and contrasting areas. The SVI and RCI indices were summarized at the municipality level by the tool Zonal Statistics as table, on ArcGis® 10.5.1. The indices were normalized using Eq. 1 (Cutter et al., 2016; Sherrieb et al., 2010; Burton, 2014; Qin et al., 2017). With the normalized data, Moran's I index (Eq. 2) was performed to assess the spatial autocorrelation between areas of high and low social vulnerability and resilience. The bivariate method verifies the degree of connection between the values of the observed variable in a given location and the values assumed by the other variable in nearby locations (Aguiar et al. 2020; Campos et al., 2021; Pires et al., 2021). The Queen Contiguity Neighborhood Matrix was used to calculate the I of Moran and its statistical significance was tested through 999 randomizations, according to the studies by Campos et al. (2021). Moran's I analyzes were performed using GeoDa software (version 1.18.0), for more details check Anselin et al. (2002) and Campos et al. (2021). The Pearson and Spearman correlation coefficients were calculated for the Social Vulnerability and

Resilience Indices. These analyzes were performed with the free software R 3.6.1, we used the packages corrplot (Wei et al., 2021), PerformanceAnalytics (Peterson et al., 2020) and ggplot2 (Wickham, 2016) for the analyzes and spatialization of the correlation analyses.

$$X_p = \frac{x_1 - mean\,(x)}{sd\,(x)} \quad (1)$$

In which mean (x) is the average of x values; $sd\,(x)$ is the standard deviation (SD).

$$I = \frac{N}{\Sigma_i\, \Sigma_j\, wij}\, \frac{\Sigma_i\, \Sigma_j\; wij\,(X_i - \bar{X})\,(Y_j - \bar{Y})}{\Sigma_i\; (Y_i - \bar{Y})^2} \quad (2)$$

In which N is the total number of areas, X_i and Y_j are the height values of areas i and j, respectively. $\bar{X}$ and $\bar{Y}$ is the height average of areas i and j and w_{ij} is the matrix of weights.

The association map between the two indices was colored to highlight the different groupings. Thus, high resilience and vulnerability are shown in red; low resilience and vulnerability in orange; high resilience and low vulnerability in blue; low resilience and high vulnerability in light blue. Areas with no correlation are in gray. ArcGis® 10.5.1 (Esri, Redlands, CA, USA) was used to spatialize the results.

3 Results and discussion

Regarding the Social Vulnerability Index (SVI), the first indicator (social) is composed of illiterate children and adults, the population's age, illiterate female heads of household, and the non-white population. The second indicator (economic) includes the income of the population below the poverty line, without income, heads of households without income, and households dependent on the elderly. The third indicator (infrastructure) includes access to treated water, electricity, sewage services, community location based on high and low population densities, housing conditions, and properties not owned (Table 1).

Fig. 2 shows the Social Vulnerability Index and its indicators (2b, 2c, and 2d). The SVI ranged from 0 to 1, with a mean of 0.48 and a standard deviation of 0.22 (Fig. 3a). Moran's I index was greater than zero and the p-value lower than 0.05 (Table 1), which indicated significant spatial clustering for the SVI (Frazier et al., 2013). The northern and the metropolitan region of the Middle Paraopeba are the most vulnerable. In Upper Paraopeba, small portions were identified with moderate and high vulnerabilities. We found that 31.3% of the municipalities have low vulnerability. About 37.4% moderate and 31.3% high (Fig. 2a). This result reveals that the municipalities inserted in the portion of the Lower Paraopeba have greater socioeconomic and infrastructure vulnerability.

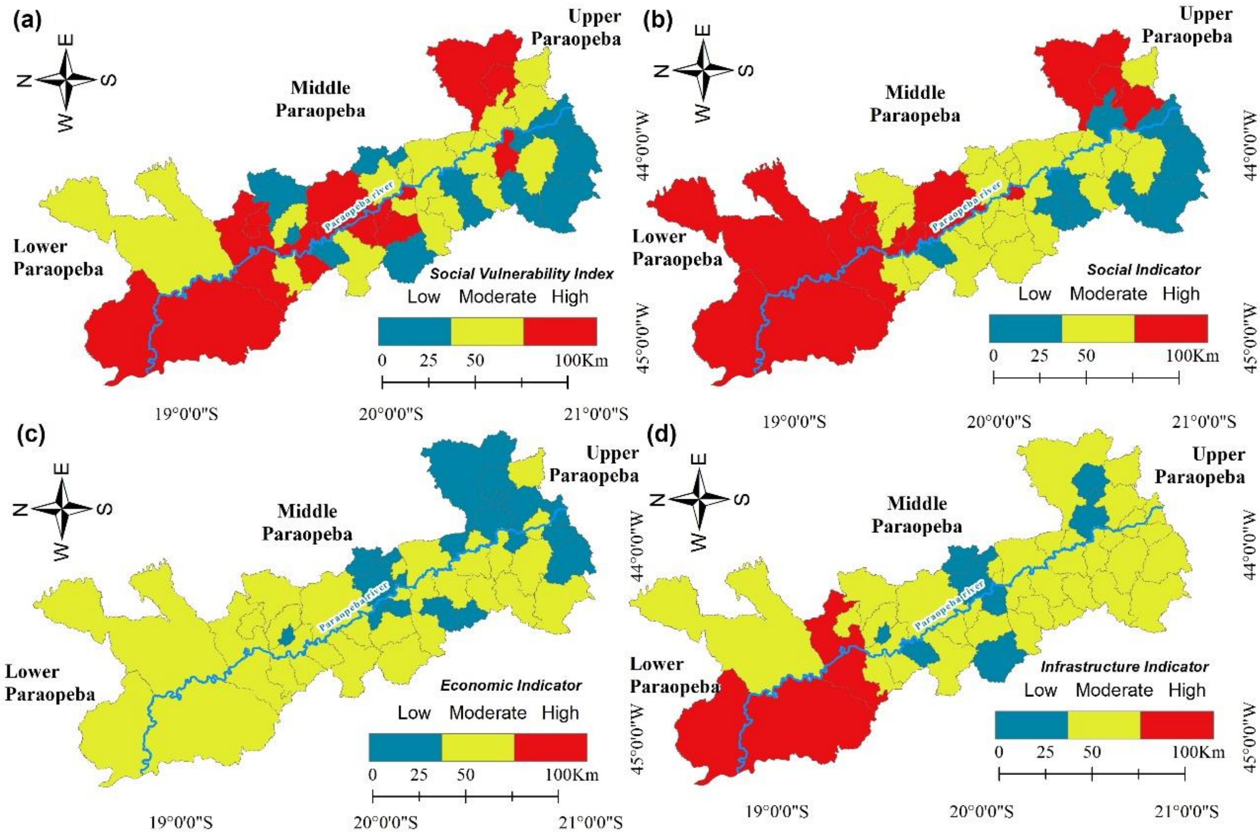

Figure 2: (a) Social Vulnerability Index in the Paraopeba Basin, Minas Gerais, Brazil. Indicators of social (b), economic, and (c) infrastructure (d) indicators.

For the Resilience Capacity Index (RCI), the first indicator (institutional) consists of the variables, rate of health facilities, inpatient bed rate, the density of dams protected by safety plans, and population density. The community dimension (second indicator) brings together the percentage of higher education institutions and preschools, participation of civil society and associated stakeholders, civic organizations, and economic diversity. The third (ecological) indicator covers land use and land cover, soil types, and distance from highways (Table 1).

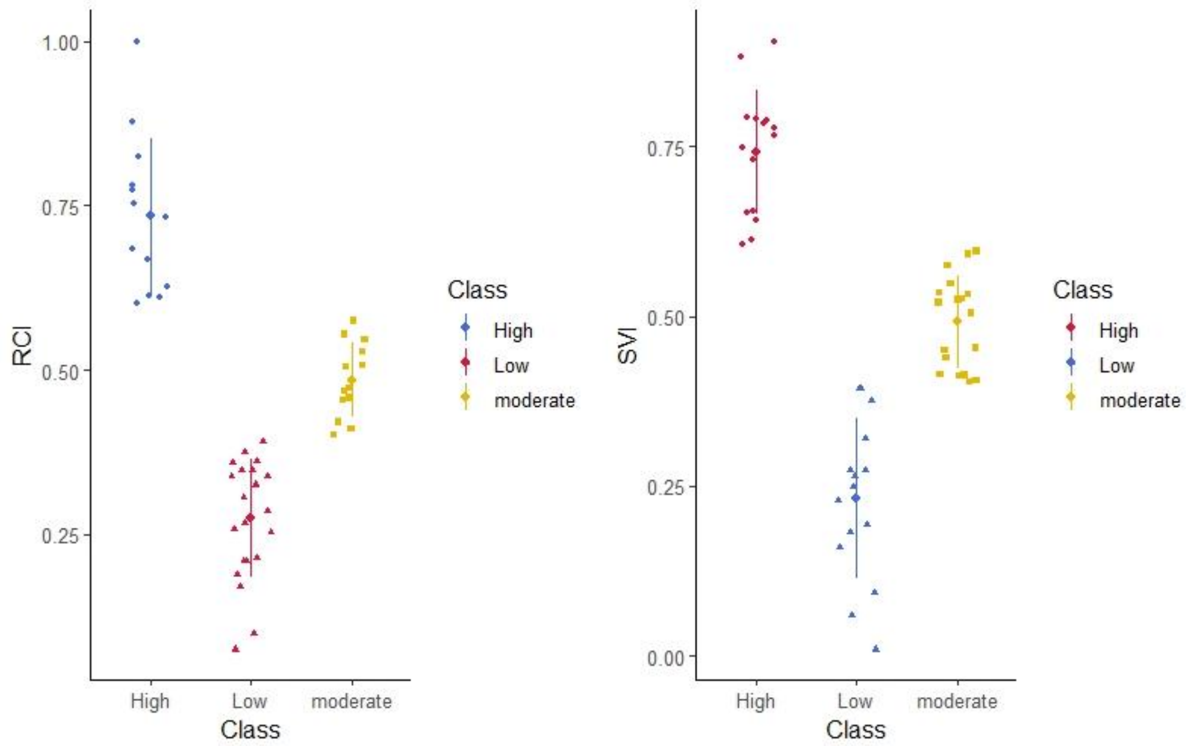

Figure 3: Class distribution of (a) Social Vulnerability Index and b) Resilience Capacity Index in the Paraopeba Basin, Minas Gerais, Brazil.

Fig. 4 shows the Resilience Capacity Index and its indicators (4b, 4c, and 4d). The RCI ranged from 0 to 1, with a mean of 0.45 and a standard deviation of 0.20 (Fig. 3b). Moran's I index was greater than zero and close to one and the p-value lower than 0.05 (Table 2), which indicated significant spatial clustering, however, with a clustered most distribution, with similar most values data for the RCI than for SVI (Frazier et al., 2013; Campos et al., 2021). About 45.8% of the sectors are in the low resilience categories, 27.1% in the moderate category, and 27.1% have high resilience. The RCI was better in the southern portion (Upper Paraopeba) and the Middle region of the basin. The resilience capacity was lower in the basin’s river mouth in the northern part of Paraopeba (Fig. 3a).

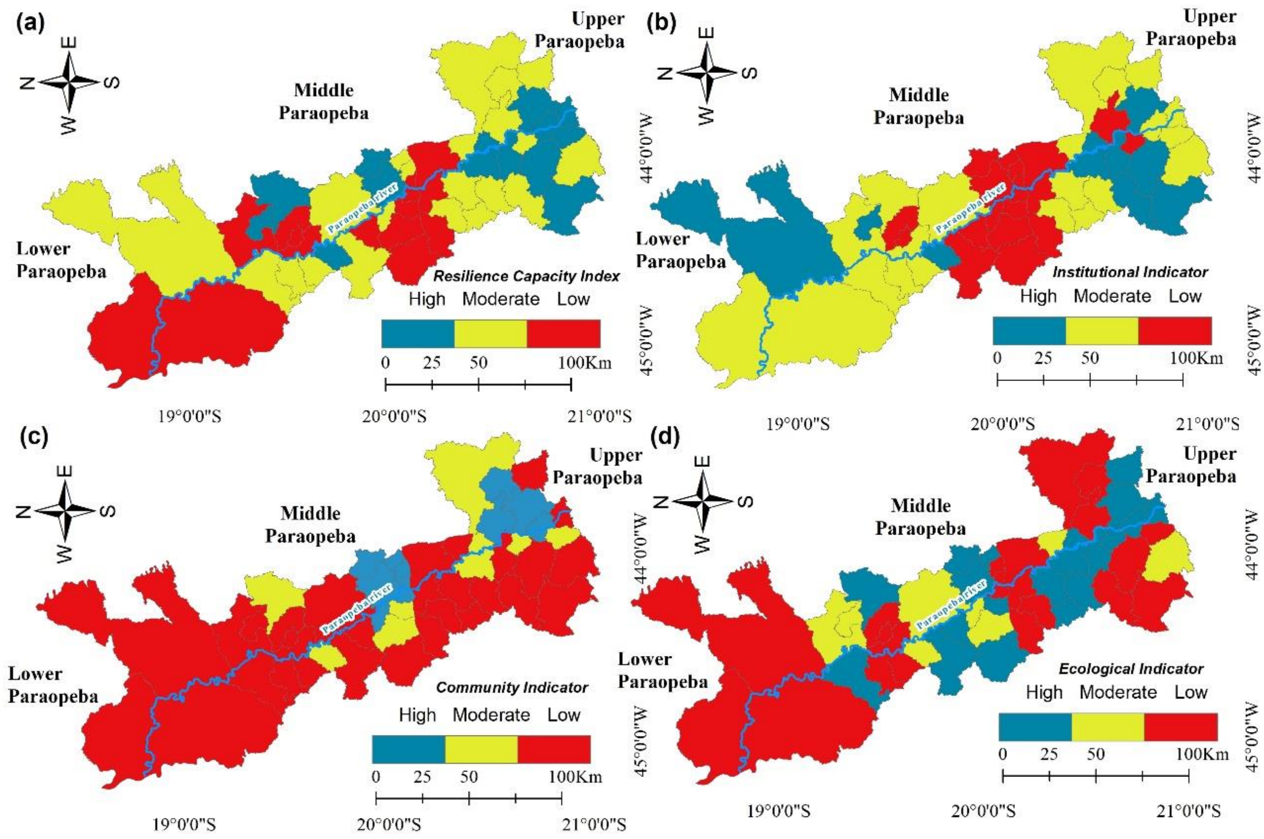

Figure 4: (a) Resilience Capacity Index in the Paraopeba Basin, Minas Gerais, Brazil. Indicators of institutional (b), community (c), and ecological (d) indicators.

In Fig. 5 we have the associative map of SVI and RCI that shows the distribution of vulnerability and resilience in the two indices. Pearson's correlation was -0.42 (p-value 0.002), and Spearman's correlation was -0.46 (p-value 0.001) (Fig. 6). In other words considering the relationship between the two indicators, as vulnerability increases, resilience decreases along the basin. By evaluating this associative map between the vulnerability and resilience indices, it is possible to identify that approximately 80% of the basin area is in the classes of low vulnerability with high resilience and high vulnerability with low resilience. Lower Paraopeba has the largest number of the most vulnerable and less resilient municipalities, covering more than half of the basin area (60%). While Upper Paraopeba has moderate vulnerability and resiliency. The Middle part brings together the most vulnerable and less resilient, with a percentage of around 50% of the whole basin.

This evaluation made it possible to recognize the specificities throughout the extension of the basin under study. Above all, it emphasizes the regions that suffer most in the process of repairing and mitigating the impacts of extreme events. The results point to two different outcomes. First, in a larger portion of the basin, there are areas of high vulnerability and low resilience (50%), and areas of low vulnerability and high resilience were found (29.2%). In the background, in smaller numbers, there are cases of high vulnerability and high resilience (8.3%) and low vulnerability and low resilience (12.5%). These results agree with important literature (Bergstrand et al., 2014; Sung; Liaw, 2021) on the application of vulnerability and resilience indices in different contexts and countries.

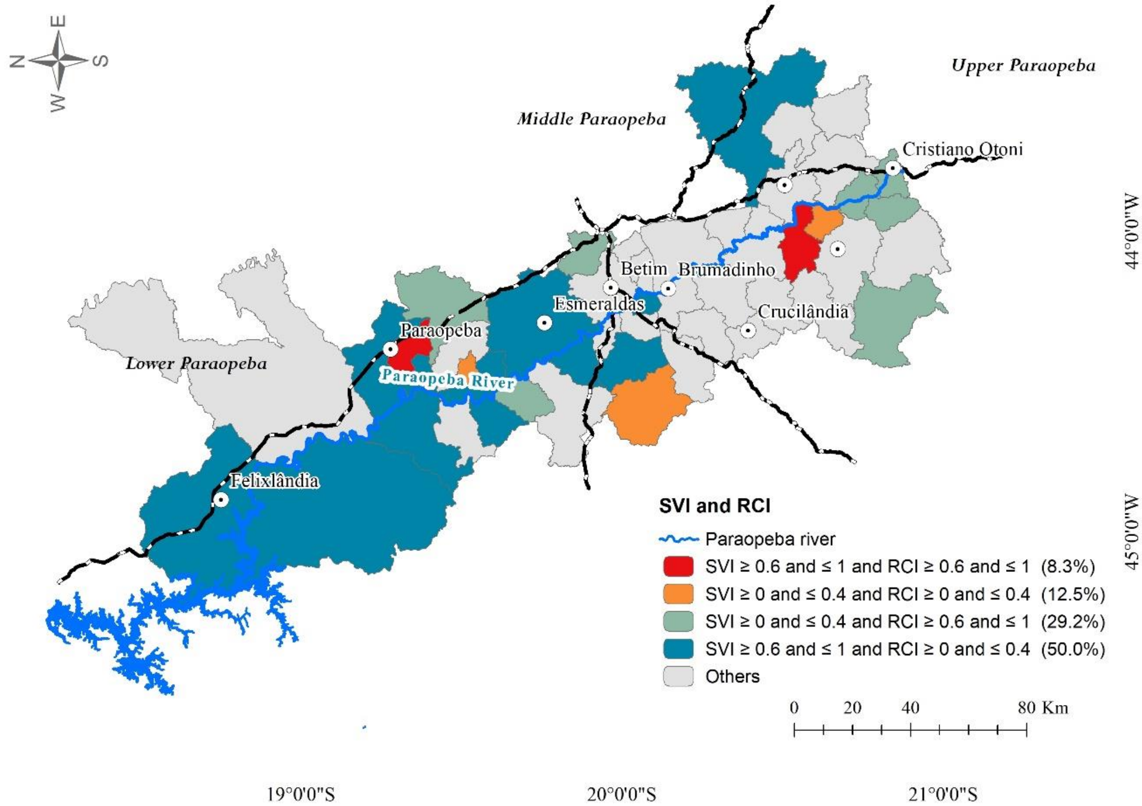

Figure 5: Map of the association between the Resilience Capacity Index and the Social Vulnerability Index in the Paraopeba Basin, Minas Gerais, Brazil

Note: The "other" class was excluded from the statistics.

To verify whether areas of high vulnerability and low resilience tend to cluster together, the spatial autocorrelation measure known as Moran's I was calculated (Bergstrand et al., 2015). By evaluating the Moran index, the results show that the multivariate analysis of vulnerability and resilience have negative and significant autocorrelation (-0.360 and p-value 0.001). As in the studies by Campos et al. (2021), the results found in this paper indicated that the data are not random and spatially independent, thus, demonstrating the identification of spatial patterns (Kumari et al. 2019; Campos et al., 2021).

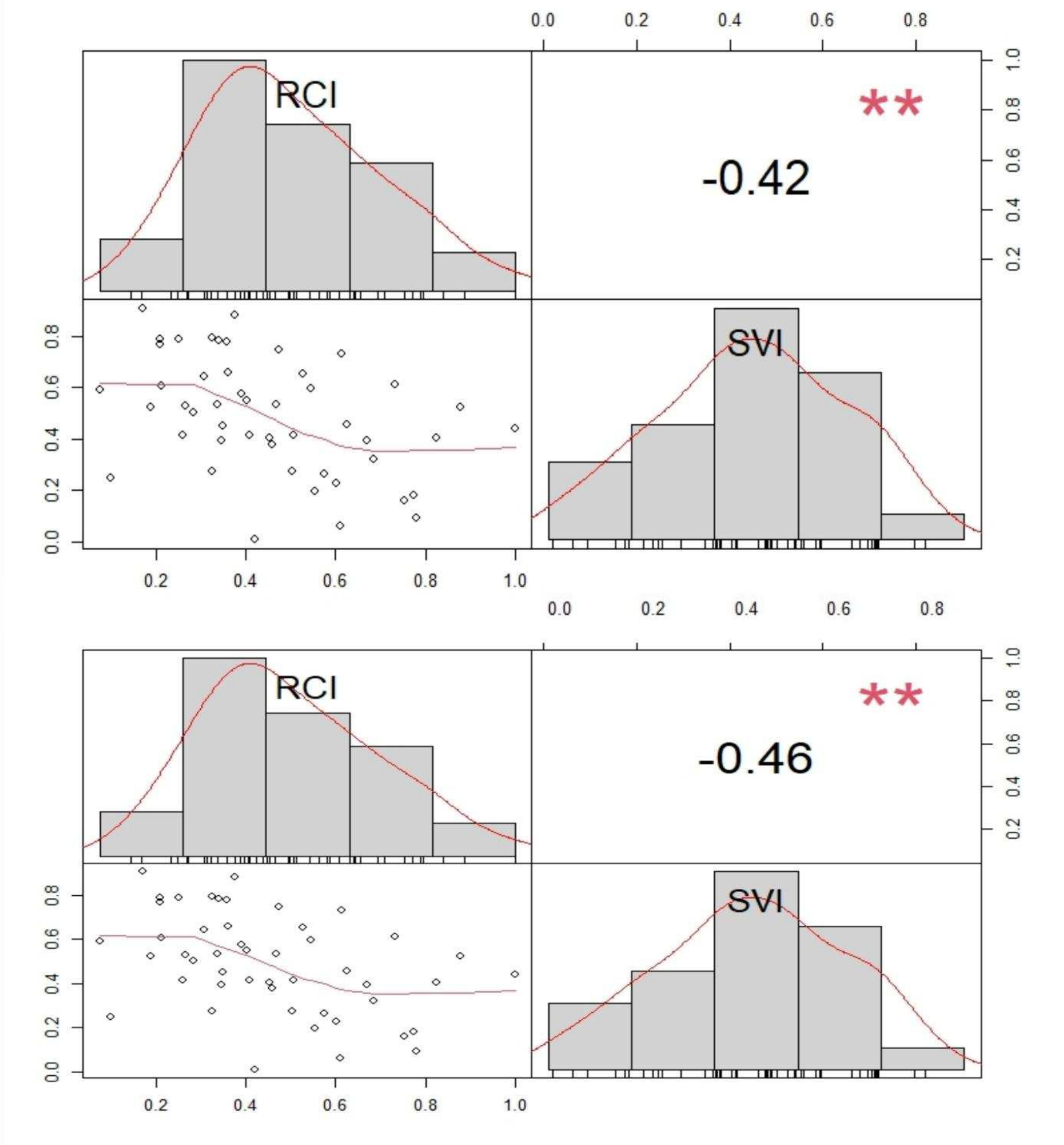

Figure 6. Pair-wise scatter plot with Pearson correlation coefficient and Spearman.

The results indicate a correlation between the least vulnerable and most resilient areas, suggesting that the least vulnerable municipalities tend to be the most resilient (29.2%). The municipalities with the highest number of less vulnerable and more resilient sectors are in the southern part of the basin, whereas the municipalities in the central region of the basin are the least resilient and most vulnerable ones, corresponding to 50.0% of the basin. The results agree with the study carried out by Bergstrand et al. (2014), who also found that vulnerability and resilience are often inversely correlated and that the most vulnerable municipalities also lack the means to effectively recover, while the least vulnerable municipalities tend to have more resources that ease recovery.

Table 2. Moran's I Univariate and Bivariate Analysis

Index	***Univariate Moran's I***	***p-value***
Social Vulnerability Index	0.653	0.001
Resiliency Capacity Index	0.953	0.001
Relation	***Local bivariate Moran's I***	
Social Vulnerability and Resiliency Capacity Index	-0.360	0.001

Note: Scores were assigned by the Queen Contiguity Neighborhood Matrix, the significance test for 999 randomizations.

Sectors of high vulnerability and resilience (8.3%) and sectors of low vulnerability and resilience were also identified (12.5%), notably in the central and southern regions of Paraopeba. Some of these areas have diversified economic sectors that enable the people who were affected by the negative impacts in one sector of the economy to find work in another. However, this option is less viable for smaller municipalities in terms of population density and whose economy is sometimes dependent on a single economic sector. This work's evidence corroborates the study, who described the link between social vulnerability and resilience in North American counties by showing a tendency for counties with high social vulnerability and high community resilience to be close to large counties (Cutter et al., 2010; 2016; Bergstrand et al., 2014).

Overall, the results provide a comprehensive view of the existing vulnerabilities and the resilience of the communities involved in the biggest socio-environmental disaster in the Paraopeba Basin. The approach and methodology used in this study are compatible with the limitations associated with the inability to obtain data with more recent temporal scales and more detailed spatial scales.

Finally, future research is needed. While it is important to understand where vulnerability and resilience occur simultaneously to identify areas that need help at different stages of a disaster, it is also important to understand whether these areas are actually receiving the help and support they really need when at risk. It is expected that in the future there are data to check whether the areas that need assistance are the ones that receive the most support since the most vulnerable and least resilient communities are the ones that most need the state's effort to overcome the impact caused by disasters.

4 Conclusion

The results indicate a correlation between high vulnerability and low resilience and low vulnerability and high resilience, suggesting that the most vulnerable municipalities, indeed, tend to be the least resilient and the least vulnerable more resilient. This relationship was found in 79.2% of the census sectors of the Paraopeba Basin. Regional differences in vulnerability and resilience were found, with Upper Paraopeba showing low levels of susceptibility to damage caused by disasters, while Lower Paraopeba showed less ability to recover from the impact. The findings also suggest that the most vulnerable areas are not always the least resilient. Exceptions were found in several regions of the basin. That is areas with low levels of social vulnerability and resilience (12.5%) as well as areas with high social vulnerability and high resilience (8.3%).

Socioeconomic and biophysical factors contribute to vulnerability and resilience levels in different ways. Therefore, understanding the specificities of the communities involved is important to prepare and later mitigate the impacts caused by disasters. By understanding where the most vulnerable areas are and what factors account for that vulnerability and affect resilience, policymakers and planners can better target mitigation strategies and resources to areas of greatest need.

Ethics statement. Tis study did not receive nor require ethics approval, as it does not involve human and animal participants.

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Data availability The datasets generated and/or analyzed as part of the current study are available from the corresponding author upon reasonable request.

Declaration of competing interest The authors declare that they do not know about competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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

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Article ***4***

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

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 socioenvironmental 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: Índice de Vulnerabilidade Social, Brumadinho, desastre socioambiental, 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; Fundação Renova, 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 (SVI). 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 SVI 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), Fundação Renova (2018) and Brazil (2020).

2.2. Construction of the SVI

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; Fundação Renova, 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 SVI. 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 SVI 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).

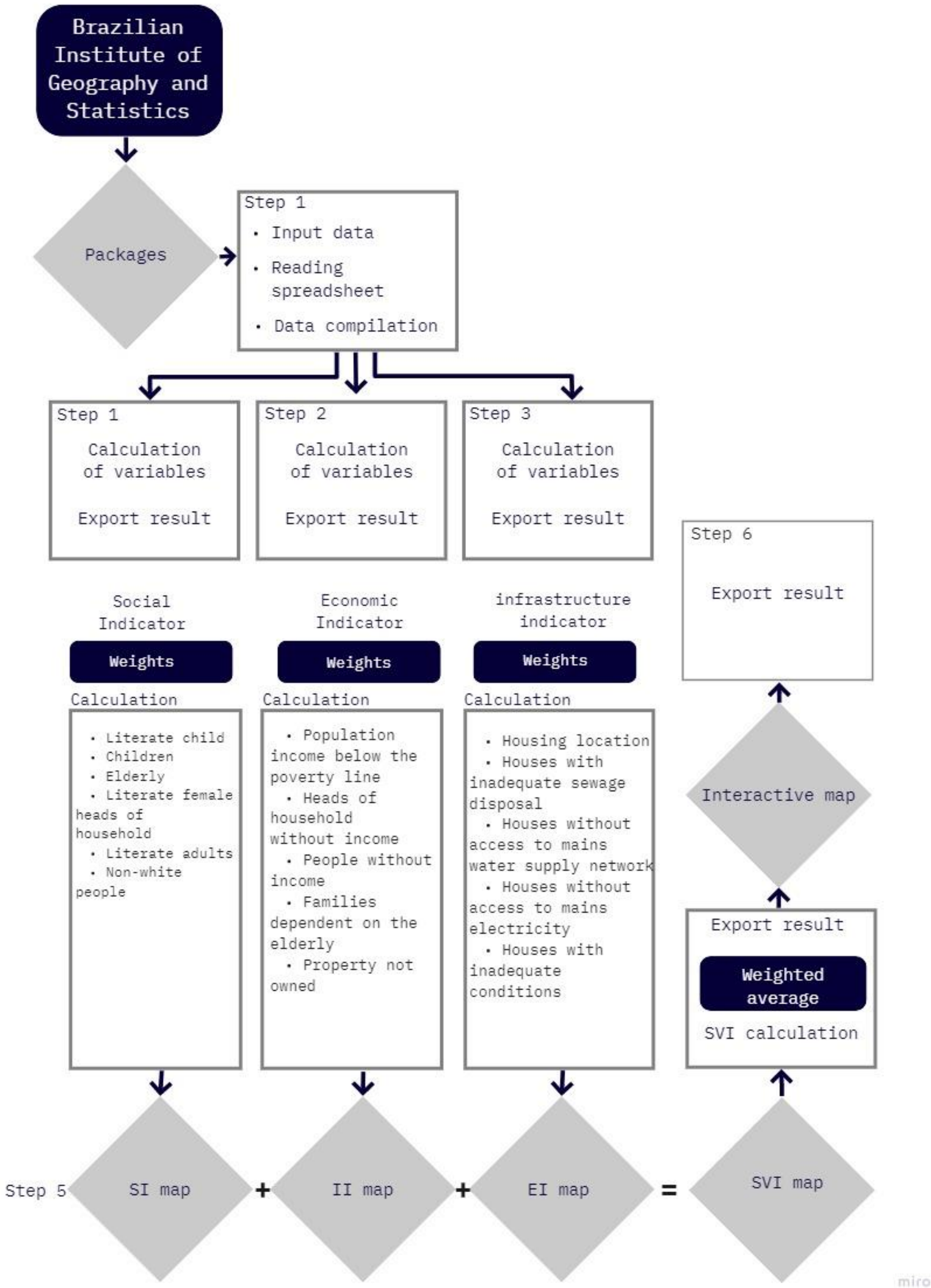

Figure **1**: Methodological structure of the script.
Note: The structure created for the R script and presented in the figure above is based on a study by Lapworth and Kinniburgh, 2009.

2.3. 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 SVI.

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).

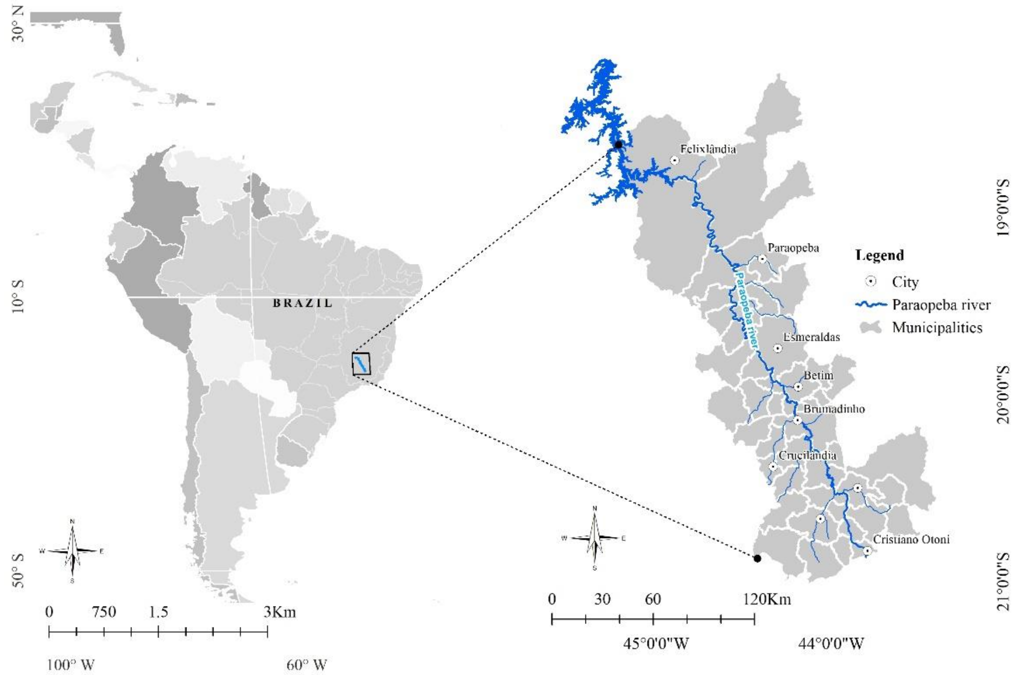

Figure **3**: Location of the Paraopeba River Basin, Minas Gerais, Brazil

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 SVI

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 SVI, 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 SVI, see https://github.com/MarianeRoque/indicedevulnerabilidadesocial.

The generated vulnerability index interactive map can be opened on a computer, with a browser operation 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 SVI to the Paraopeba Basin

First we present a tool for the elaboration of the SVI. 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 SVI 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 SVI 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
SVI 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 SVI 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 SVI 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 the Social Vulnerability Index (SVI), Social Indicator (SI), Economic Indicator (EI) e Infrastructure Indicator (II) by vulnerability classes.

Description	Too low	Low	Medium	High	Too High
IS Social Indicator	2.6	18.3	48.6	29.0	1.5
IE Economic Indicator	3.9	60.0	33.6	2.4	0.1
II Infrastructure Indicator	66.9	10.4	17.6	4.8	0.4
SVI Social Vulnerability Index	2.8	67.4	26.8	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 SVI 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.

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.

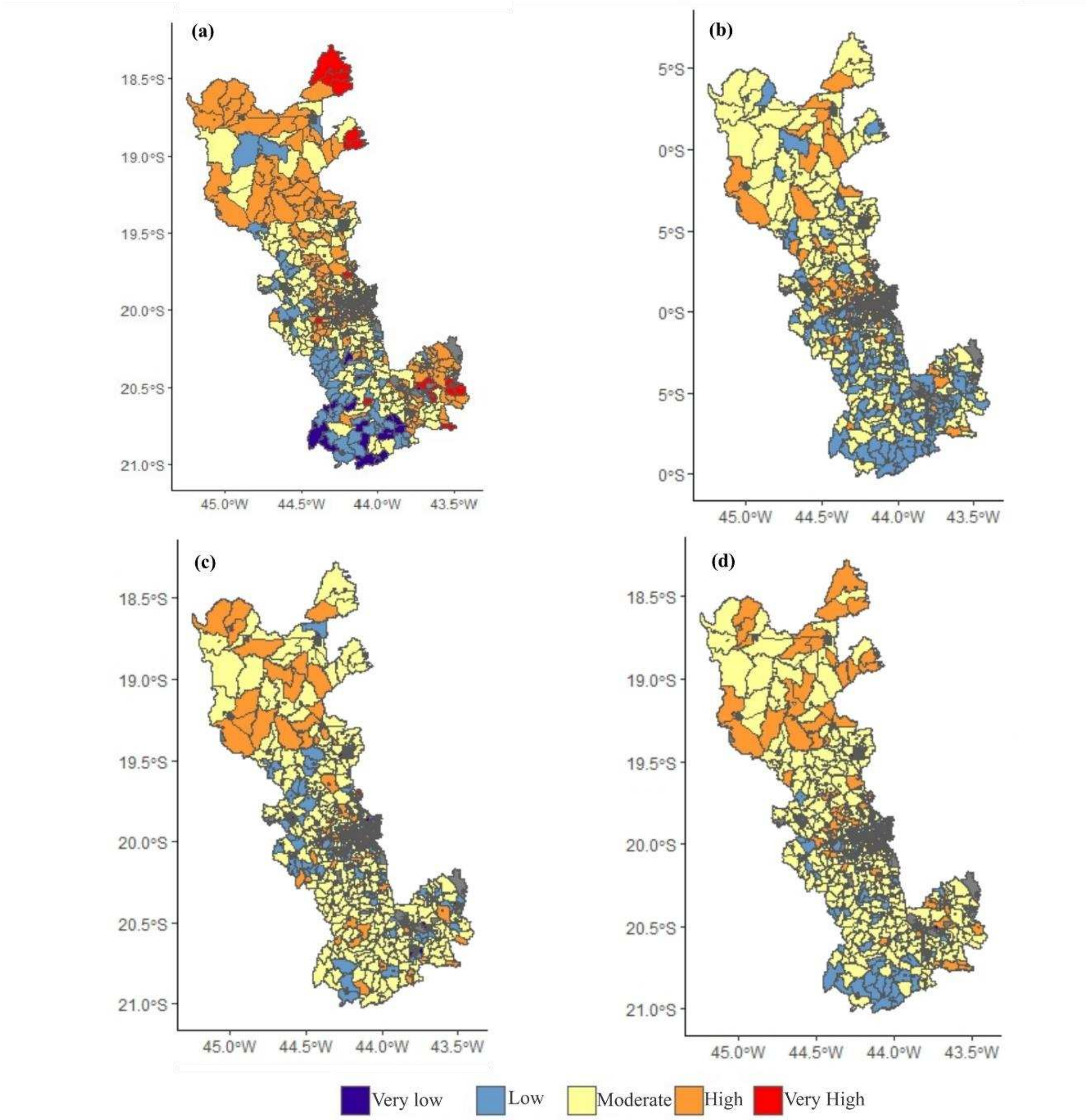

Figure **4**: Mapping social vulnerability to the Social Indicator (a), Economic Indicator (b) and Infrastructure Indicator (c) and the Social Vulnerability Index (d) in the Paraopeba River Basin, Brazil.

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 SVI 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

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

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3. Conclusão

Os enormes desafios associados ao aumento de desastres em todo o mundo, na última década, e a escala dos impactos indicam a necessidade de ir além do componente físico e ambiental. No Brasil, estudos ambientais com base em abordagens sociais ainda estão emergindo no debate sobre desastres ambientais.

Este estudo avaliou as contribuições dos componentes sociais categorizados por Índices de Vulnerabilidade Social e Capacidade de Resiliência nos municípios expostos a desastres ambientais ou suscetíveis a eles. O estudo de caso se deu na Bacia do Rio Paraopeba, que viveu um dos maiores desastres socioambientais do mundo. Além dos danos ambientais à biodiversidade e aos recursos hídricos, o desastre acarretou perdas humanas e graves danos socioeconômicos, diretos e indiretos.

Esta pesquisa foi a primeira abordagem realizada para obter e avaliar espacialmente a vulnerabilidade e a capacidade de resiliência a desastres na bacia em estudo. O SVI e ICR foram desenvolvidos e avaliados para toda a bacia. Os resultados desencadearam diferentes desdobramentos, com existência de aglomerados com variados níveis de susceptibilidade ao longo da bacia: áreas de alto SVI no Baixo, ao norte da bacia, enquanto no Médio e Alto Paraopeba, ao sul, os resultados mostraram alta variabilidade e menor vulnerabilidade, respectivamente. Os municípios da região central e ao sul da bacia são áreas de alto ICR. Por outro lado, a região ao norte evidenciou o maior quantitativo de municípios de menor resiliência.

Adicionalmente, os resultados apontaram uma relação inversamente proporcional entre os dois índices. Assim, foram identificadas, em maior quantidade, áreas de alta vulnerabilidade e baixa resiliência e áreas de baixa vulnerabilidade e alta resiliência, o que indica que os municípios mais vulneráveis tendem a ser os menos resilientes, e os menos vulneráveis, os mais resilientes. Exceções foram encontradas em algumas regiões da bacia, ou seja, áreas com baixos níveis de vulnerabilidade e resiliência e áreas com altos níveis de vulnerabilidade e resiliência.

A ferramenta desenvolvida para elaboração do Índice de Vulnerabilidade compreendeu um expressivo banco de dados sociais do Censo brasileiro, disponíveis para todo o território nacional, o que permite uma ampla replicação da técnica em todo o País. O algoritmo desenvolvido, e consequentemente sua aplicação para a bacia, é uma alternativa que possibilita um maior alinhamento com a realidade, o que auxilia as partes interessadas entenderem as características dessas comunidades que podem interferir positiva e/ou negativamente nos possíveis impactos decorrentes do desastre.

Constatamos que os fatores socioeconômicos e biofísicos influenciam os níveis de vulnerabilidade e de resiliência de diferentes maneiras. Portanto, o entendimento das especificidades das comunidades envolvidas tende a ampliar as possibilidades de preparação de respostas e mitigação às externalidades decorrentes de desastres ambientais. Ao identificar as áreas mais vulneráveis e os fatores que respondem por essa vulnerabilidade e afetam a resiliência, os formuladores de políticas e os planejadores serão capazes de direcionar melhor as estratégias e os recursos para as áreas de maior necessidade.

Material Suplementar (Apêndice – Artigo 4)

scriptivs.R

```
#O Script realiza os procedimentos para o cálculo do Índice de #vulnerabili
dade
#Social e seus indicadores: indicador social, indicador de infraestrutura
#e indicador econômico.

#Cada etapa é acompanhada de uma breve explicação.

#Limpando o script---------------------------------------------------------
-----
rm(list = ls())
gc()

##          used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 452264 24.2     970358 51.9   643648 34.4
## Vcells 825341  6.3    8388608 64.0  1886902 14.4

#Carregando os pacotes-----------------------------------------------------
-----

require(tinytex)

require(readxl)

require(dplyr)

require(sf)

require(xlsx)

require(tmap)

require(tmaptools)

require(ggplot2)

library(FactoMineR)

library(devtools)

library(psych)

library(RColorBrewer)

library(shiny)

library(shinyjs)

getwd()

## [1] "C:/dadost"

#(Substituir) E necessário fazer essa alteração em todo o script----------
-----
```

```
#Listar todos arquivos dentro da pasta dados com padrao"xls"---------------
-----
arq = list.files("C:/dadost/dados_v/excel", pattern = "xls", full.names = T
RUE)
arqS = list.files("C:/dadost/dados_v/excel", pattern = "xls", full.names =
FALSE)
#arqS

arqS = gsub(patter = "MG.xls", "", arqS)
#print(arqS)
#Leitura das panilhas de interesse do Censo Demografico--------------------
-----

#1 Ler primeiro arquivo xls.
pla1 = read_excel(arq[10]) #arq[10] = Pessoa01_MG.xls

#Selecão das variaveis de interesse----------------------------------------
----
names(pla1)

pla1s = as.data.frame(select(pla1, Cod_setor, V001:V085))

#Renomear
names(pla1s) = c("Cod_setor",
                 paste(arqS[10],
                       names(pla1s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".---
#pla1s
pla1s[pla1s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla1s)){
  pla1s[,i] = as.numeric(as.character(pla1s[,i]))
}

#2 Ler segundo arquivo excel-----------------------------------------------
----

pla2 = read_excel(arq[12]) #arq[12] = Pessoa03_MG.xls
names(pla2)

#Selecionar variaveis de interesse-----------------------------------------
----
pla2s = as.data.frame(select(pla2, Cod_setor, V001:V251))

#renomear
names(pla2s) = c("Cod_setor",
                 paste(arqS[12],
                       names(pla2s)[-1],
                       sep = ""))

#pla2s
```

```
pla2s[pla2s == "X"] = NA #Converter dados com  "X" em NA-

#Transformar todas colunas para numerico
for (i in 1:ncol(pla2s)){
  pla2s[,i] = as.numeric(as.character(pla2s[,i]))
}

#3 Ler o terceiro arquivo.----------------------------------------------------
-----
pla3 = read_excel(arq[22]) #arq[22] = Pessoa13_MG.xls

#Selecionar variaveis de interesse
names(pla3)

pla3s = as.data.frame(select(pla3, Cod_setor, V001:V134))

#Renomear
names(pla3s) = c("Cod_setor",
                 paste(arqS[22],
                       names(pla3s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla3s
pla3s[pla3s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla3s)){
  pla3s[,i] = as.numeric(as.character(pla3s[,i]))
}

#4 Ler quarto arquivo xls.----------------------------------------------------
-----
pla4 = read_excel(arq[24]) #arq[24] = Responsavel01_MG.xls

#Selecionar variaveis de interesse
names(pla4)

pla4s = as.data.frame(select(pla4, Cod_setor, V001:V108))

#Renomear colunas
names(pla4s) = c("Cod_setor",
                 paste(arqS[24],
                       names(pla4s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla4s
pla4s[pla4s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla4s)){
  pla4s[,i] = as.numeric(as.character(pla4s[,i]))
}
```

```r
#5 Ler quinto arquivo xls.------------------------------------------------
-----
pla5 = read_excel(arq[25]) #arq[25] = Responsavel02_MG.xls

#Selecionar variaveis de interesse
names(pla5)

pla5s = as.data.frame(select(pla5, Cod_setor, V001:V216))

#Renomear colunas
names(pla5s) = c("Cod_setor",
                 paste(arqS[25],
                       names(pla5s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla5s
pla5s[pla5s == "X"] = NA#Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla5s)){
  pla5s[,i] = as.numeric(as.character(pla5s[,i]))
}

#6 Ler sexto arquivo xls.-------------------------------------------------
-----
pla6 = read_excel(arq[2]) #arq[2] = Domicilio01_MG.xls

#Selecionar variaveis de interesse
names(pla6)

pla6s = as.data.frame(select(pla6, Cod_setor, Situacao_setor, V001:V241))

#Renomear colunas
names(pla6s) = c("Cod_setor",
                 paste(arqS[2],
                       names(pla6s)[-1],
                       sep = ""))

#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla6s
pla6s[pla6s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla6s)){
  pla6s[,i] = as.numeric(as.character(pla6s[,i]))
}

#7 Ler setimo arquivo xls.------------------------------------------------
-----
pla7 = read_excel(arq[6]) #arq[6] = Entorno02_MG.xls

#Selecionar variaveis de interesse
names(pla7)
```

```
pla7s = as.data.frame(select(pla7, Cod_setor, V202:V421))

#Renomear colunas
names(pla7s) = c("Cod_setor",
                 paste(arqS[6],
                       names(pla7s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla7s
".
#pla7s
pla7s[pla7s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numÃ©rico
for (i in 1:ncol(pla7s)){
  pla7s[,i] = as.numeric(as.character(pla7s[,i]))
}

#8 Ler oitavo arquivo xls.-------------------------------------------------
-----
pla8 = read_excel(arq[23]) #arq[23] = PessoaRenda_MG.xls

#Selecionar variÃ¡veis de interesse
names(pla8)

pla8s = as.data.frame(select(pla8, Cod_setor, V001:V132))

#Renomear
names(pla8s) = c("Cod_setor",
                 paste(arqS[23],
                       names(pla8s)[-1],
                       sep = ""))
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla8s
pla8s[pla8s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla8s)){
  pla8s[,i] = as.numeric(as.character(pla8s[,i]))
}

#9 Ler nono arquivo xls
pla9 = read_excel(arq[26]) #arq[26] = ResponsavelRenda_MG.xls

#Selecionar variaveis de interesse
names(pla9)

pla9s = as.data.frame(select(pla9, Cod_setor, V001:V132))

#Renomear colunas
names(pla9s) = c("Cod_setor",
                 paste(arqS[26],
                       names(pla9s)[-1],
                       sep = ""))
```

```
#criar vetor com nome "Cod_setor" e nome das colunas selecionadas em "pla1s
".
#pla9s
pla9s[pla9s == "X"] = NA #Converter dados com  "X" em NA

#Transformar todas colunas para numerico
for (i in 1:ncol(pla9s)){
  pla9s[,i] = as.numeric(as.character(pla9s[,i]))
}

#Fazer isso para todos os arquivos de interesse para o IVS-----------------
-----

#Combinar todos arquivos em uma unica planilha com base no codigo do setor-
-----

dff1 = inner_join(pla1s, pla2s, by = "Cod_setor")
#names(dff1)
dff2 = inner_join(dff1, pla3s, by = "Cod_setor")
#names(dff2)
dff3 = inner_join(dff2, pla4s, by = "Cod_setor")
#names(dff3)
dff4 = inner_join(dff3, pla5s, by = "Cod_setor")
#names(dff4)
dff5 = inner_join(dff4, pla6s, by = "Cod_setor")
#names(dff5)
dff6 = inner_join(dff5, pla7s, by = "Cod_setor")
#names(dff6)
dff7 = inner_join(dff6, pla8s, by = "Cod_setor")
#names(dff7)
dff8 = inner_join(dff7, pla9s, by = "Cod_setor")
#names(dff8)
df = dff8
#gc() #limpar caso necessario

#Retirar os NoData---------------------------------------------------------
-----

df= na.omit(df)
sum(is.na(df))

## [1] 0

#df

# (Substituir para o arquivo shapefile de interesse) Carregar e combinar #a
rquivo
#shapefile dos setores-----------------------------------------------------
-----

setores = st_read("C:/dadost/dados_v/setores/limite_setores_compl2010_parao
p_SIRGAS_2000_UTM_Zone_23.shp")

## Reading layer `limite_setores_compl2010_paraop_SIRGAS_2000_UTM_Zone_23'
from data source
```

```
##   `C:\dadost\dados_v\setores\limite_setores_compl2010_paraop_SIRGAS_2000
_UTM_Zone_23.shp'
df = subset(df, Cod_setor %in% setores$CD_GEOCODI)

#Conferir se ainda há noData---------------------------------------------
-----

sum(is.na(df))

#df
#Cálculo das variáveis-----------------------------------------------------
-----
# Variável 1--------------------------------------------------------------
-----
# Pessoas não alfabetizadas entre 5 a 14 anos------------------------------
-----
#Variável 1.1: Pessoas de 5 a 15 anos de idade

x = select(df, Pessoa13_V039:Pessoa13_V049)
v11 = apply(x, MARGIN = 1, FUN = sum)

#Variavel 1.2: Pessoas alfabetizadas com 5 anos de idade

v12 = apply(select(df, Pessoa01_V002:Pessoa01_V012),
            MARGIN = 1,
            FUN = sum)

var1 = (v11-v12)/v11
#print(var1)

#Jogar variavel 1 para df

df$var1 = var1
df_v1 = as.data.frame(cbind(df$Cod_setor, var1))
names(df_v1) = c("Cod_setor", "v1")

#Ao final selecionar dados para exportar----------------------------------
-----

gc()

write.xlsx(df_v1, "C:/dadost/dados_v/resultados/v1.xlsx", row.names = FALS
E)#substituir nome do diretorio

#Variavel 2---------------------------------------------------------------
-----
# crianças (pessoas com até 15 anos)
#Variavel 2.1: Pessoas Residentes

v21 = select(df, Pessoa03_V001)
#print(v21)

#Variavel 2.2: Pessoas 0 a 15 anos

v22 = apply(select(df, Pessoa13_V023:Pessoa13_V049),
```

```
            MARGIN = 1,
            FUN = sum)
#print(v22)

var2 = v22/v21
#print(var2)

#Jogar variavel 2 para df

df$var2 = var2
df_v2 = as.data.frame(cbind(df$Cod_setor, var2))
names(df_v2) = c("Cod_setor", "v2")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v2, "C:/dadost/dados_v/resultados/v2.xlsx", row.names = FALS
E) #substituir nome do diretorio

#Variavel 3-------------------------------------------------------------
-----
# Idosos (pessoas com mais de 65 anos)
#Variavel 3.1: V001 Pessoas residentes

v31 = select(df, Pessoa03_V001)
#print(v31)

#Variavel 3.2: V001 Pessoas acima de 65 anos

v32 = apply(select(df, Pessoa13_V099:Pessoa13_V134),
            MARGIN = 1,
            FUN = sum)

var3 = v32/v31
#print(var3)

#Jogar variavel 3 para df

df$var3 = var3
df_v3 = as.data.frame(cbind(df$Cod_setor, var3))
names(df_v3) = c("Cod_setor", "v3")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v3, "C:/dadost/dados_v/resultados/v3.xlsx", row.names = FALS
E) #substituir nome do diretorio

#Variavel 4-------------------------------------------------------------
-----
#  Mulheres chefes de família não alfabetizadas
```

```
#Variavel 4.1: V001 Pessoas responsáveis, do sexo feminino

v41 = select(df, Responsavel01_V001)

#Variavel 4.2: V093 Pessoas alfabetizadas responsáveis, do sexo feminino

v42 = select(df, Responsavel01_V093)

var4 = (v41-v42)/v41
#print(var4)

#Jogar variavel 4 para df

df$var4 = var4
df_v4 = as.data.frame(cbind(df$Cod_setor, var4))
names(df_v4) = c("Cod_setor", "v4")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v4, "C:/dadost/dados_v/resultados/v4.xlsx", row.names = FALS
E) #substituir nome do diretorio

#Variavel 5----------------------------------------------------------------
-----
# Pessoas com 15 anos ou mais não alfabetizadas
#Variavel 5.1: Total de pessoas com 15 anos ou mais

x = select(df, Pessoa13_V049:Pessoa13_V134)
v51 = apply(x, MARGIN = 1, FUN = sum)

#Variavel 5.2: Pessoas com 15 anos ou mais alfabetizadas

v52 = apply(select(df, Pessoa01_V012:Pessoa01_V077),
            MARGIN = 1,
            FUN = sum)

var5 = (v51-v52)/v51
#print(var5)

#Jogar variavel 5 para df

df$var5 = var5
df_v5 = as.data.frame(cbind(df$Cod_setor, var5))
names(df_v5) = c("Cod_setor", "v5")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v5, "C:/dadost/dados_v/resultados/v5.xlsx", row.names = FALS
E)#substituir nome do diretorio
```

```
#Variavel 6-----------------------------------------------------------------
-----
# Pessoas nao brancas
#Variavel 6.1: Pessoas residentes

v61 = select(df, Pessoa03_V001)

#Variavel 6.2: Pessoas negras, pardas e indigenas

v62 = apply(select(df, Pessoa03_V003:Pessoa03_V006),
            MARGIN = 1,
            FUN = sum)

var6 = v62/v61
#print(var6)

#Jogar variavel 6 para df

df$var6 = var6
df_v6 = as.data.frame(cbind(df$Cod_setor, var6))
names(df_v6) = c("Cod_setor", "v6")

#Ao final selecionar dados para exportar

gc()

write.xlsx(df_v6, "C:/dadost/dados_v/resultados/v6.xlsx", row.names = FALS
E)#substituir nome do diretorio

# (Substituir os pesos) Indicador Social-----------------------------------
---------------------------
#v1-Pessoas não alfabetizadas entre 5 e 14 anos
#v2-Crianças
#v3-Idosos
#v4-Mulheres chefes de família não alfabetizadas
#v5-Pessoas com 15 anos ou mais não alfabetizadas
#v6-Pessoas não brancas
indsocial= (0.06*var1+0.20*var2+0.20*var3+0.08*var4+0.11*var5+0.35*var6) #p
esos
#print(indsocial)
indsocialn = (indsocial-min(indsocial))/(max(indsocial)-min(indsocial))
df_GA = as.data.frame(cbind(df$Cod_setor, indsocialn))
names(df_GA) = c("Cod_setor", "IVSSOCIAL")

#Ao final selecionar dados para exportar-----------------------------------
-----

write.xlsx(df_GA, "C:/dadost/dados_v/resultados/TIVSSOCIAL.xlsx", row.names
= FALSE)#substituir nome do diretorio
df_GA = read.xlsx("C:/dadost/dados_v/resultados/TIVSSOCIAL.xlsx", sheetInde
x = 1)#substituir nome do diretorio

#carregar shapefile
```

```
setores = st_read("C:/dadost/dados_v/setores/limite_setores_compl2010_parao
p_SIRGAS_2000_UTM_Zone_23.shp")

#criar coluna "Cod_setor" e transformar código em números

setores$Cod_setor = as.numeric(as.character(setores$CD_GEOCODI))

#adicionar dados de IVS em df_final no shapefile

ta = left_join(as.data.frame(setores), df_GA, by = "Cod_setor")

#adicionar IVS ao shapefile

setores$IVSSOCIAL = ta$IVSSOCIAL
#print(ta$IVSSOCIAL)

#classificar com intervalo fechado à direita e verificar se os dados foram
atualizados em setores

#print(setores$IVSSOCIAL)

# Histograma---------------------------------------------------------------
-----

IS = data.frame(y = setores$IVSSOCIAL)
hS <- ggplot(IS, aes(y)) + geom_histogram(alpha = .4) + theme_classic()+
  xlab("IS - Indicador Social") + ylab("frequência")
hS

# Mapa---------------------------------------------------------------------
-----

setores$IVSSOCIAL_classes = cut(setores$IVSSOCIAL,
                                breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1),
                                labels = c("Muito Baixo", "Baixo", "Médio",
"Alto", "Muito Alto"),
                                right = TRUE)

nc = length(unique(setores$IVSSOCIAL_classes))-1 #número de classes

display.brewer.pal(n = 5, name = 'Spectral') #paletas sem nodata

a = brewer.pal(n = 5, name = 'Spectral') #armazenar

getwd()

## [1] "C:/dadost"

ggplot(data = setores) + theme_classic()+
  geom_sf(aes(fill = IVSSOCIAL_classes), lwd = 0) +
  scale_fill_manual(values = c("Muito Baixo" = "#330099",
                               "Baixo" = "#6699CC",
                               "Medio" = "#FFFF99",
                               "Alto" = "#FF9933",
                               "Muito Alto" = "#FF0000"))
```

```
describe(indsocialn) #estatística do indicador social

#(Substituir os pesos) Variavel 7---------------------------------------
-----
#Localização da moradia (rural-urbana)
#Variavel 7.1:

v71 = select(df, Domicilio01_Situacao_setor)
#v71

#Variavel 7 final:

var7 = v71 #pesos
v71[v71==1]=0.5 #urbanas com alta densidade de edificações
v71[v71==2]=0.4 #urbanas baixa densidade de edificações
v71[v71==3]=0.1 #nucleo urbano
v71[v71==4]=0.1 #nucleo rural
v71[v71==5]=0.1 #povoado
v71[v71==6]=0.1 #lugarejo
v71[v71==7]=0.4 #zona rural
v71[v71==8]=0.5 #Zona rural
#print(v71)

#Jogar variavel 7 para df

df$var7 = v71
df_v7 = as.data.frame(cbind(df$Cod_setor, v71))
names(df_v7) = c("Cod_setor", "v7")

#Ao final selecionar dados para exportar---------------------------------
-----

gc()

write.xlsx(df_v7, "C:/dadost/dados_v/resultados/v7.xlsx", row.names = FALS
E)#substituir nome do diretorio

#Variavel 8--------------------------------------------------------------
-----
# Moradias com destinação inadequada do esgoto
#Variavel 8.1: Domicílios particulares permanentes

v81 = select(df, Domicilio01_V002)

#Variavel 8.2: Domicílios com esgotamento sanitário inadequado

v82 = apply(select(df, Domicilio01_V019:Domicilio01_V023),
            MARGIN = 1,
            FUN = sum)

var8 = v82/v81
#print(var8)

#Jogar variavel 8 para df
```

```
df$var8 = var8
df_v8 = as.data.frame(cbind(df$Cod_setor, var8))
names(df_v8) = c("Cod_setor", "v8")

##Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v8, "C:/dadost/dados_v/resultados/v8.xlsx", row.names = FALS
E)#substituir nome do diretorio

#Variavel 9------------------------------------------------------------------
-----
#Moradias sem acesso a rede geral de distribuição de água
#Variavel 9.1: Domicílios particulares permanentes

v91 = select(df, Domicilio01_V002)

#Variavel 9.2: Domicílios particulares permanentes com abastecimento de águ
a da rede geral

v92 = select(df, Domicilio01_V012)

var9 = (v91-v92)/v91

#Jogar variavel 9 para df

df$var9 = var9
#print(var9)
df_v9 = as.data.frame(cbind(df$Cod_setor, var9))
names(df_v9) = c("Cod_setor", "v9")

#Ao final selecionar dados para exportar------------------------------------
-----

write.xlsx(df_v9, "C:/dadost/dados_v/resultados/v9.xlsx", row.names = FALS
E)#substituir nome do diretorio

#Variavel 10-----------------------------------------------------------------
-----
#Condição de moradia inadequada
#Variavel 10.1: V002 Domicílios particulares permanentes

v101 = select(df, Domicilio01_V002)

#Variavel 10.2: Domicílios particulares permanentes com moradia semi-adequa
da ou inadequada

v102 = apply(select(df, Entorno02_V204:Entorno02_V207),
             MARGIN = 1,
             FUN = sum)

var10 = (v102/v101)
#print(var10)
```

```
#Jogar variavel 10 para df

df$var10 = var10
df_v10 = as.data.frame(cbind(df$Cod_setor, var10))
names(df_v10) = c("Cod_setor", "v10")

#Ao final selecionar dados para exportar-----------------------------------
-----

write.xlsx(df_v10, "C:/dadost/dados_v/resultados/v10.xlsx", row.names = FAL
SE)

#Variavel 11---------------------------------------------------------------
-----
# Domicílios sem acesso a rede geral de energia elétrica
#Variavel 11.1: Domicílios particulares permanentes

v111 = select(df, Domicilio01_V002)

#Variavel 11.2: Domicilios sem acesso a rede geral de distrubuicao energia

v112 = select(df, Domicilio01_V046)

var11 = v112/v111
#print(var11)

#Jogar variavel 11 para df

df$var11 = var11
df_v11 = as.data.frame(cbind(df$Cod_setor, var11))
names(df_v11) = c("Cod_setor", "v11")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v11, "C:/dadost/dados_v/resultados/v11.xlsx", row.names = FAL
SE)#substituir nome do diretorio

# (Substituir os pesos) Indicador Infraestrura-----------------------------
-----
#v7-Localizacao da moradia
#v8-Moradias com destinação inadequada do esgoto
#v9-Moradias sem acesso a rede geral de distribuição de água
#v10-Famílias com condição de moradia inadequada
#v11-Domicílios sem acesso a rede geral de energia elétrica

indinfra = (0.14*v71+0.21*var8+0.21*var9+0.21*var10+0.21*var11) #pesos
#print(indinfra)
indinfran = (indinfra-min(indinfra))/(max(indinfra)-min(indinfra))
df_GB = as.data.frame(cbind(df$Cod_setor, indinfran))
names(df_GB) = c("Cod_setor", "IVSINFRA")
```

```
#Ao final selecionar dados para exportar

write.xlsx(df_GB, "C:/dadost/dados_v/resultados/TIVSINFRA.xlsx", row.names
= FALSE)#substituir nome do diretorio
df_GB = read.xlsx("C:/dadost/dados_v/resultados/TIVSINFRA.xlsx", sheetIndex
= 1)#substituir nome do diretorio

#carregar shapefile

setores = st_read("C:/dadost/dados_v/setores/limite_setores_compl2010_parao
p_SIRGAS_2000_UTM_Zone_23.shp")

#criar coluna "Cod_setor" e transformar código em números

setores$Cod_setor = as.numeric(as.character(setores$CD_GEOCODI))

#adicionar dados de IVS em df_final no shapefile

tb = left_join(as.data.frame(setores), df_GB, by = "Cod_setor")

#adicionar IVS ao shapefile

setores$IVSINFRA = tb$IVSINFRA
#print(tb$IVSINFRA)

#classificar com intervalo fechado à direita e verificar se os dados foram
atualizados em setores

#print(setores$IVSINFRA)

#Histograma---------------------------------------------------------------
-----

II = data.frame(y = setores$IVSINFRA)
hI <- ggplot(II, aes(y)) + geom_histogram(alpha = .4) + theme_classic()+
  xlab("II - Indicator de infrastrutura") + ylab("frequência")
hI

#Mapa---------------------------------------------------------------------
-----

setores$IVSINFRA_classes = cut(setores$IVSINFRA,
                               breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1),
                               labels = c("Muito Baixo", "Baixo", "Médio",
"Alto", "Muito Alto"),
                               right = TRUE)

nc = length(unique(setores$IVSINFRA_classes))-1 #número de classes

display.brewer.pal(n = 5, name = 'Spectral') #paletas sem nodata

a = brewer.pal(n = 5, name = 'Spectral') #armazenar

getwd()
```

```
## [1] "C:/dadost"

ggplot(data = setores) +
  geom_sf(aes(fill = IVSINFRA_classes), lwd = 0) +
  scale_fill_manual(values = c("Muito Baixo" = "#330099",
                               "Baixo" = "#6699CC",
                               "Medio" = "#FFFF99",
                               "Alto" = "#FF9933",
                               "Muito Alto" = "#FF0000"))

describe(indinfran) #estatística do indicador infraestrutura

##    vars    n mean   sd median trimmed  mad min max range skew kurtosis s
e
## X1    1 3571 0.21 0.19    0.1    0.17 0.04   0   1     1 1.37     0.59
0

#Variavel 12--------------------------------------------------------------
-----
#Imoveis não próprios
#Variavel 12.1: V002 Domicílios particulares permanentes

v121 = select(df, Domicilio01_V002)

#Variavel 12.2: Domicilios nao proprios

v122 = apply(select(df, Domicilio01_V008:Domicilio01_V011),
             MARGIN = 1,
             FUN = sum)

var12 = v122/v121
#print(var12)

#Jogar variavel 12 para df

df$var12 = var12
df_v12 = as.data.frame(cbind(df$Cod_setor, var12))

names(df_v12) = c("Cod_setor", "v12")

#Ao final selecionar dados para exportar-----------------------------------
-----

write.xlsx(df_v12, "C:/dadost/dados_v/resultados/v12.xlsx", row.names = FAL
SE) #substituir nome do diretorio

#Variavel 13--------------------------------------------------------------
-----
# Pessoas vivendo abaixo da linha da pobreza
#Variavel 13.1: Populacao residente

v131 = apply(select(df, Pessoa13_V044:Pessoa13_V134),
             MARGIN = 1,
             FUN = sum)
```

```
#Variavel 13.2: número de pessoas que vive com até 1/2 salário

v132 = select(df, PessoaRenda_V001)

var13 = v132/v131
#print(var13)

#Jogar variavel 13 para df

df$var13 = var13
df_v13 = as.data.frame(cbind(df$Cod_setor, var13))
names(df_v13) = c("Cod_setor", "v13")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v13, "C:/dadost/dados_v/resultados/v13.xlsx", row.names = FAL
SE) #substituir nome do diretorio

#Variavel 14--------------------------------------------------------------
-----
# Pessoas responsáveis sem rendimentos
#Variavel 14.1: Pessoas Responsáveis (total)

v141 = select(df, Responsavel02_V001)

#Variavel 14.2: Pessoas responsáveis sem rendimento nominal mensal

v142 = select(df, ResponsavelRenda_V010)

var14 = v142/v141
#print(var14)

#Jogar variavel 14 para df

df$var14 = var14
df_v14 = as.data.frame(cbind(df$Cod_setor, var14))
names(df_v14) = c("Cod_setor", "v14")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v14, "C:/dadost/dados_v/resultados/v14.xlsx", row.names = FAL
SE)#substituir nome do diretorio

#Variavel 15--------------------------------------------------------------
-----
# Pessoas sem rendimento
#Variavel 15.1: V044 a V134 - Pessoas acima de 10 anos

x = select(df, Pessoa13_V044:Pessoa13_V134)
```

```
v151 = apply(x, MARGIN = 1, FUN = sum)

#Variavel 15.2: V010 Pessoas de 10 anos ou mais de idade sem rendimento nom
inal mensal

v152 = select(df, PessoaRenda_V010)

var15 = v152/v151
#print(var15)

#Jogar variavel 15 para df

df$var15 = var15
df_v15 = as.data.frame(cbind(df$Cod_setor, var15))
names(df_v15) = c("Cod_setor", "v15")

#Ao final selecionar dados para exportar-----------------------------------
-----

write.xlsx(df_v15, "C:/dadost/dados_v/resultados/v15.xlsx", row.names = FAL
SE)#substituir nome do diretorio

#Variavel 16---------------------------------------------------------------
-----
#famílias dependentes de idosos
#Variavel 16.1: Pessoas responsáveis

v161 = select(df, Responsavel02_V001) #selecionar dados usados

#Variavel 16.2: Pessoas responsáveis com 65 anos ou mais

v162 = apply(select(df, Responsavel02_V057:Responsavel02_V092),
             MARGIN = 1,
             FUN = sum)

#Variavel 16 final: v16.2/v16.1

var16 = v162/v161
#print(var16)

#Jogar variavel 16 para df

df$var16 = var16
df_v16 = as.data.frame(cbind(df$Cod_setor, var16))
names(df_v16) = c("Cod_setor", "v16")

#Ao final selecionar dados para exportar-----------------------------------
-----

gc()

write.xlsx(df_v16, "C:/dadost/dados_v/resultados/v16.xlsx", row.names = FAL
SE)#substituir nome do diretorio
```

```
#(Substituir os pesos) Calculo do Indicador Economico---------------------
-----
#v12- Imoveis nao proprios 0,2
#v13-Pessoas que vivem abaixo da linha da pobreza (de 2010) 0,3
#v14-Pessoas responsáveis sem rendimentos 0,2
#v15-Pessoas sem rendimento 0.1
#v16-Famílias dependentes de idosos 0,2

indeco = (0.21*var12+0.28*var13+0.21*var14+0.10*var15+0.21*var16) #pesos
#print(indeco)
indecon = (indeco-min(indeco))/(max(indeco)-min(indeco))
df_GC = as.data.frame(cbind(df$Cod_setor, indecon))
names(df_GC) = c("Cod_setor", "IVSECO")

##Ao final selecionar dados para exportar

gc()

write.xlsx(df_GC, "C:/dadost/dados_v/resultados/TIVSECO.xlsx", row.names =
FALSE)#substituir nome do diretorio
df_GC = read.xlsx("C:/dadost/dados_v/resultados/TIVSECO.xlsx", sheetIndex =
1)#substituir nome do diretorio

#carregar shapefile

setores = st_read("C:/dadost/dados_v/setores/limite_setores_compl2010_parao
p_SIRGAS_2000_UTM_Zone_23.shp")

#criar coluna "Cod_setor" e transformar código em números

setores$Cod_setor = as.numeric(as.character(setores$CD_GEOCODI))

#adicionar dados de IVS em df_final no shapefile

tc = left_join(as.data.frame(setores), df_GC, by = "Cod_setor")

#adicionar IVS ao shapefile

setores$IVSECO = tc$IVSECO
#print(tc$IVSECO)

#classificar com intervalo fechado à direita e verificar se os dados foram
atualizados em setores

#print(tc$IVSECO)

#Histograma---------------------------------------------------------------
-----

IE = data.frame(y = tc$IVSECO)
hE <- ggplot(IE, aes(y)) + geom_histogram(alpha = .4) + theme_classic()+
  xlab("IE - Indicador Econômico") + ylab("frequência")

hE
```

```
#Mapa------------------------------------------------------------------------
-----

setores$IVSECO_classes = cut(tc$IVSECO,
                             breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1),
                             labels = c("Muito Baixo", "Baixo", "Medio", "A
lto", "Muito Alto"),
                             right = TRUE)

nc = length(unique(setores$IVSECO_classes))-1 #número de classes

display.brewer.pal(n = 5, name = 'Spectral') #paletas sem nodata

a = brewer.pal(n = 5, name = 'Spectral') #armazenar

getwd()

## [1] "C:/dadost"

ggplot(data = setores) +
  geom_sf(aes(fill = IVSECO_classes), lwd = 0) +
  scale_fill_manual(values = c("Muito Baixo" = "#330099",
                               "Baixo" = "#6699CC",
                               "Medio" = "#FFFF99",
                               "Alto" = "#FF9933",
                               "Muito Alto" = "#FF0000"))

describe(indecon)#estatística do indicador economico

#Indice----------------------------------------------------------------------
-----
#(Substituir, inserir pesos, caso necessario) Calculo do IVS-----------------
-----

ivs = (indsocialn+indinfran+indecon)/3
df_final = as.data.frame(cbind(df$Cod_setor, ivs))
names(df_final) = c("Cod_setor", "IVS")

#Mapa------------------------------------------------------------------------
-----
##Ao final selecionar dados para exportar

write.xlsx(df_final, "C:/dadost/dados_v/resultados/TIVS.xlsx", row.names =
FALSE) #substituir nome do diretorio
df_final = read.xlsx("C:/dadost/dados_v/resultados/TIVS.xlsx", sheetIndex =
1)#substituir nome do diretorio

#carregar shapefile

setores = st_read("C:/dadost/dados_v/setores/limite_setores_compl2010_parao
p_SIRGAS_2000_UTM_Zone_23.shp")

#criar coluna "Cod_setor" e transformar código em números

setores$Cod_setor = as.numeric(as.character(setores$CD_GEOCODI))
```

```
#adicionar dados de IVS em df_final no shapefile

t = left_join(as.data.frame(setores), df_final, by = "Cod_setor")

#adicionar IVS ao shapefile

setores$IVS = t$IVS
#print(t$IVS)

#classificar com intervalo fechado à direita e verificar se os dados foram
atualizados em setores

#print(setores$IVS)

#Histograma---------------------------------------------------------------------------
-----

IIVS = data.frame(y = setores$IVS)
hIVS <- ggplot(IIVS, aes(y)) + geom_histogram() +
  xlab("IVS") + ylab("frequency")
hIVS

#Mapa---------------------------------------------------------------------------------
-----

setores$IVS_classes = cut(setores$IVS,
                          breaks = c(0, 0.2, 0.4, 0.6, 0.8, 1),
                          labels = c("Muito Baixo", "Baixo", "Medio", "Alto
", "Muito Alto"),
                          right = TRUE)

nc = length(unique(setores$IVS_classes))-1 #número de classes

display.brewer.pal(n = 5, name = 'Spectral') #paletas sem nodata

a = brewer.pal(n = 5, name = 'Spectral') #armazenar

getwd()

## [1] "C:/dadost"

ggplot(data = setores) +
  geom_sf(aes(fill = IVS_classes), lwd = 0) +
  scale_fill_manual(values = c("Muito Baixo" = "#330099",
                               "Baixo" = "#6699CC",
                               "Medio" = "#FFFF99",
                               "Alto" = "#FF9933",
                               "Muito Alto" = "#FF0000"))
```