Multidimensional Index

an alternative measurement method to a proportional
social vulnerability index for disaster risk management assessment

Master Thesis

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Multidimensional Index

An alternative measurement method to a proportional social vulnerability index for disaster risk management assessment

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The documentation of all codes used in this thesis can be found at:
https://github.com/HaekalAkbar/multidimensionalindex.

Acknowledgement

I still remember the moment that sparked my interest in public policy. It was when I got involved in a community conflict between the poor and large developers. It made me realize how crucial public policy is, as one unfair policy can oppress individuals, families, villages, or entire segments of society. This experience motivated me to work towards creating fair policies that support marginalized groups. As like I mentioned in my EPA registration essay and scholarship application, this eventually led me to travel from Indonesia to Delft. Growing up, I was taught that the best people are those who are useful to others. This thesis represents the culmination of my journey to become a useful person through my studies. I hope that this research will be beneficial as well to others.

On this special occasion, I would like to express my deepest gratitude to everyone who supported me during my studies at Engineering and Policy Analysis (EPA) and helped me complete this thesis project. I want to express my gratitude to Allah SWT for guiding me to this opportunity. I also want to thank my mother, Rezka Yusanti, my father, Heru Heppyanto, and my brother, Bara Sakti Malano Kartasasmita, for their guidance and support. I am also thankful to all my family in Indonesia and to the Indonesian people, particularly the LPDP scholarship, for letting me feel this study experience by financing my education at TU Delft.

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Executive Summary

Research Background

In light of the growing threat of natural disasters and the increasing impact of climate change on human life, it is crucial to prioritise the progress of disaster risk assessment studies in the development of disaster management policies. Vulnerability, as a key component of risk assessment, encompasses factors and processes that heighten the susceptibility of individuals, communities, assets, or systems to the impact of hazards (UNDRR, 2024b).

Vulnerability is closely linked to location (Cutter, 1996) and comprises two main concepts: biophysical/technological vulnerability and social vulnerability. While biophysical vulnerability primarily pertains to physical and infrastructural vulnerabilities, social vulnerability focuses on the potential for a social group to face losses resulting from a disaster. This research will primarily explore the facets of social vulnerability, aiming to uncover its academic and practical implications.

Social vulnerability is a multifaceted social construct that encompasses dimensions beyond economics and health, including community vulnerability and gender vulnerability. By applying the concept of intersectionality, which recognizes that an individual may face multiple discriminations, this research seeks to examine vulnerability from a similar perspective. The multidimensional nature of vulnerability can significantly impact an individual's disaster risk.

In the discussion of translating social vulnerability conditions into measurable values for formulating policies, various quantitative measurement techniques have been developed into composite indices by academics and practitioners. The process of forming an index, divided into deductive, hierarchical, and inductive methods, enriches the discussion and methodology for measuring social vulnerability. Each form of the index has its own capabilities and advantages, tailored to the user's needs and the concepts incorporated in the measurement method.

While several social vulnerability indices attempt to capture the existing state of vulnerability, none examine it from a multidimensional perspective. Therefore, this research aims to explore and develop alternative methods for measuring social vulnerability using a multidimensional perspective and assess their suitability in enhancing and supporting the disaster risk assessment process. The main research question formulated in this study is: "*How can developing and applying a multidimensional approach to social vulnerability measurement enhance and support the disaster risk assessment process and policies?*".

Methodology

To address the research question, there are at least five main stages that must be carried out. First, it is essential to gain a deeper understanding of the concept of social vulnerability from a multidimensional perspective, including the latest developments in academic discussions and tools for calculating social vulnerability. This enriched literature will aid in developing alternative multidimensional methods.

The next step involves conceptualising a multidimensional approach for calculating social vulnerability. This serves as the theoretical basis for the construction of the alternative method.

The second stage is the development process of the alternative social vulnerability calculation method. A multidimensional index, representing the main perspective, is chosen as the name for this method. Following the method and composite index development framework, this stage discusses design choices and method development.

The following stage includes the implementation of the method using case studies and real data, specifically Indonesian social data at the subdistrict level. Various indicators obtained during the method development stage are used as a reference in collecting variables suitable for assessment needs. After obtaining the results from the multidimensional index calculation, a comparison with the existing social vulnerability index is conducted to identify deviations that occurred with the existing method. Comparison techniques such as visual analysis, class change analysis, and variable contribution analysis are carried out. This comparison process reveals how this alternative calculation method provides different results, insights, and information from existing methods.

The fourth step involves applying the social vulnerability calculations obtained to real disaster cases, focusing on floods in this research. Flood data from Indonesia was analysed to gather information on people at high risk of floods. By combining flood exposure data with the social vulnerability data obtained through our method, we can generate flood risk data. This application process provides insight into how these calculations can be used in real disaster risk cases. Although a detailed analysis of the flood risk assessment results was not conducted, the data does offer information on how the multidimensional index results can be applied to hazard cases.

Finally, to understand the implications of the multidimensional index method, we will explore the policy implications and practicality of the method. This step aims to identify the potential implications of developing this alternative calculation method. The output produced by the method will be examined to explore its implications for policy. Additionally, we will assess and discuss the practicality of the method for users, ensuring that it can be effectively utilised.

<u>Final Deliverables</u>

In this research, we achieved three main deliverables:

1. Developed the Multidimensional Index method to measure social vulnerability

We conceptualised the multidimensional index to incorporate intersectionality theory and a multidimensional perspective. This served as the foundation for developing the multidimensional index method. We explained the method development process by adapting the composite index creation framework, outlining the design choices and methodology development. Additionally, we conducted an analysis and literature review to demonstrate the considerations taken in each decision. We discussed the entire process of developing the method, from the construction index selection stage, vulnerability dimensions, dimension index calculations, and composite index calculations to the sensitivity stage.

We also applied the method to a case study using data and social variables to illustrate the calculation process and showcase examples of results. The Indonesian social vulnerability index, along with vulnerability dimension indices in Indonesia, were used as examples of the method's application in a specific region. We also analysed and interpreted the results obtained from the calculations. The model outputs included the vulnerability index in each dimension, the final social vulnerability index, and the identification of the dominant vulnerability dimensions in each region. These outputs can be further analysed to gain insights, such as conducting spatial analysis to identify areas with high social vulnerability or performing dominant vulnerability analysis to create tailored policies in specific areas.

2. Comparison with the existing method and the application to disaster case results

The results obtained from calculating social vulnerability using the multidimensional index in Indonesia were then compared with existing methods, specifically the Social Vulnerability Index (SoVI), to observe any differences. It was found that there were noticeable differences in vulnerability category patterns. Further analysis of regional context and dimensional analysis can be done to explore the causes of these differences. The analysis of class changes also showed significant differences, with over 50% of regions experiencing changes throughout Indonesia.

Another comparison was made regarding contribution variables, showing significant differences in how each method attributes contribution to vulnerability dimensions. The multidimensional method shows the proportional contribution of each dimension, while the existing method (SoVI) demonstrates notable differences in contribution between dimensions.

The application of the multidimensional index to a real disaster case, specifically flooding, demonstrates the ability of this method to provide valuable insights into disaster risk assessment. Applying the final multidimensional index allows for a general risk assessment to determine the risk an area faces if hit by a high-risk flood, along with its vulnerability conditions. Additionally, this index provides specific information about risk conditions in each dimension of vulnerability, such as economic, gender, and community vulnerability. This data can be used to formulate disaster management policies.

3. Implications for Policy and Practicality

This section explores the implications of developing a method for calculating social vulnerability and its usefulness in shaping disaster management policies. By examining the calculation process and the resulting multidimensional index, three key implications for policy development are identified:

a) Policy prioritisation based on vulnerability categories: Identifying high social vulnerability areas can help prioritise disaster management and vulnerability reduction policies.

b) Targeted policy development for vulnerable hotspots: Visual analysis techniques can be used to identify concentrations of areas with high vulnerability, enabling targeted policy development.

c) Tailored disaster management policies based on dominant dimensions: Utilizing the multidimensional index output to identify the dominant vulnerability dimensions in each region can help tailor policies based on the specific vulnerability attributes of each region.

These implications provide valuable guidance for policymakers, but they do not exclude other potential uses of the developed method for calculating social vulnerability.

The practicality of the method is also discussed to provide practitioners with guidance on its application. A step-by-step process is outlined, including selecting appropriate variables, grouping based on vulnerability dimensions, calculating the multidimensional index, identifying areas of interest, and selecting suitable output. This explanation aims to facilitate the method's use for interested practitioners.

Conclusion

The research question is answered by explaining the research method and the deliverables obtained. The social contribution is evident in providing a new method for calculating social vulnerability from a multidimensional perspective. This is demonstrated in the application of the method in disaster cases and is discussed in the implications section of the research. The scientific contribution of this research is evident throughout, particularly in the section that discusses conceptualisation and method development. Some limitations related to the availability and completeness of data, as well as certain stages of method development that could not be carried out due to time constraints, are important recommendations for further research.

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List of Abbreviations

UNFCCC	United Nations Framework Convention on Climate Change
UNDRR	United Nations Office for Disaster Risk Reduction
IPCC	Intergovernmental Panel on Climate Change
GDP	Gross Domestic Product
BNPB	*Badan Nasional Penanggulangan Bencana*/National Disaster Agency
BPBD	*Badan Penanggulangan Bencana Daerah*/ Local Disaster Agency
SoVI	Social Vulnerability Index
FGWC	Fuzzy Geographical Weighted Clustering
DRM	Disaster Risk Management
PCA	Principal Component Analysis
GIS	Geographic Information System
SIA	Social Impact Assessment
PODES	*Potensial Desa*/Village Potential Data
BPS	*Badan Pusat Statistik*/Indonesian Central Bureau of Statistics
HOP	Hazard of Place
GFM	Global Flood Map

1 Introduction

1.1. Background

The risk of global disasters that threaten the entire world is increasing, affecting both developing and developed countries. Climate change is a pressing issue that threatens human life everywhere. As society continues to advance in urban and rural areas, new challenges are emerging. The combination of increased population and disaster threats contributes to a rise in disaster risk. Efforts to address these challenges have been ongoing for a long time. Humans coexist with nature, facing threats such as floods, earthquakes, volcanic eruptions, hurricanes, and more. Various forums and organisations at different levels work collaboratively to prepare for future challenges and discuss disaster threats. For example, the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC) focus on climate change at a global level. Additionally, similar forums at regional, national, and local levels address the threat of natural disasters to humanity.

Academics worldwide study the impact of disasters on humans, producing valuable academic insights on resilience, climate risk, and disaster management. These insights serve as theoretical and practical references for dealing with natural disasters. The development of disaster resilience theory and disaster management practices continues. Disaster studies are increasingly evidence-based, providing thorough analyses for effective disaster management. Using data and evidence enhances understanding of population conditions and disaster risks in specific areas. Various quantitative and qualitative methods are employed in disaster studies. Efforts to protect humans from disaster threats will continue as disaster studies evolve and the threat of disaster increases due to climate change. Studying the theory and methodology of disaster prevention is crucial to obtaining better results for protecting the human population.

1.2. Importance of Social Vulnerability Analysis in Disaster Management

The urgency in studying deeper aspects of disasters, is evident given the prevailing disaster conditions. As potential disaster risks develop, it is essential to correlate disaster management studies. This allows for the precise production and mapping of appropriate measures in disaster management. It is essential to consider the social impact of disasters, as they not only damage physical infrastructure and cause casualties but also impact the economy and social systems. Analysing the characteristics and conditions of population vulnerability will help understand the initial state of communities exposed to disasters, both before and after a disaster. Understanding social vulnerability comprehensively will enable policy formulators to create effective and targeted policies for affected populations.

Since the 1990s, there has been an increasing focus on researching population vulnerability to natural hazards. Cutter (1996) initiated discussions on vulnerability to environmental hazards, and since then, this aspect of social vulnerability has continued to evolve through further research, particularly in the calculation of social vulnerability to disasters. Several techniques for calculating social vulnerability have been developed by experts, including the Social Vulnerability Index (SoVI) (Cutter et al., 2003), and the measures developed by the Centers for Disease Control and Prevention (CDC) and the Agency for Toxic Substances and Disease Registry (ATSDR) (Flanagan et al., 2020).

Analysing social vulnerability in a population vulnerable to disasters can be complex. Although several social vulnerability Indices, such as SoVI, provide an assessment of vulnerability, the construction of social vulnerability is multifaceted. Vulnerabilities resulting from various factors are interconnected and can be compounded. Considering the intersectionality theory by Crenshaw (1989), which explains the potential for intertwined discrimination in a population, can be a new analytical tool for understanding social vulnerability. Therefore, it is essential to develop techniques for calculating social vulnerability that consider the multiple aspects contributing to vulnerability.

2 Literature Review

2.1. Disaster Risk Management

The United Nations Office for Disaster Risk Reduction (UNDRR) defines disaster risk as the potential loss of life, injury, or damage to assets that can occur within a specific period in a system, society, or community. This potential loss is determined probabilistically based on hazards, exposure, vulnerability, and capacity. Disaster risks can also be explained as a set of hazards, exposure, and vulnerability (H-E-V), as explained in the IPCC (Intergovernmental Panel on Climate Change, 2014). Hazard refers to a physical event, trend, or influence; exposure refers to the presence of various resources in places and environments; and vulnerability is determined as the tendency or potential to be adversely affected.

Disaster risk management is not just a theoretical concept but a practical approach that is pivotal in addressing disaster risks. It involves the application of disaster risk reduction policies and strategies to prevent new disaster risks, reduce existing disaster risks, and manage residual risks. This active engagement in Disaster Risk Management (DRM) strengthens resilience and significantly reduces disaster losses. The field of DRM is divided into three parts: prospective DRM, which focuses on preventing the development of new or increased disaster risks; corrective DRM, which focuses on removing or reducing existing disaster risks; and compensatory DRM, which aims to enhance the social and economic resilience of individuals and societies in the face of residual risks that cannot be effectively reduced. The importance of this work cannot be overstated, as it directly impacts the safety and well-being of communities and individuals.

2.1.1. Hazard

According to the UNDRR (2024a), a hazard is a process, phenomenon, or human activity that can result in loss of life, injury, damage to property, social and economic disruption, or environmental degradation. Depending on the type and occurrence of the disaster, hazards can be natural, anthropogenic, or a mix of both. They can occur singly, in a sequence, or combination and can be characterised based on their location, intensity, frequency, and probability.

It is important to note that a hazard is an event or phenomenon that threatens human life or property. Natural events that do not impact humans are not considered hazards. Going deeper, White et al. (1974) discovered that the perception of hazard is influenced by cultural values and the interaction of people and nature. This means that different populations with different beliefs and histories with nature will perceive natural events differently. However, there is an attempt to obtain a universal definition of hazard that can be agreed upon globally, even though, in practice, it may be localised depending on how the population encounters and responds to natural events that occur. This global and local aspect of hazard perception highlights the complexity and variability of the topic and underscores the need for a nuanced approach to disaster risk management.

2.1.2. Vulnerability

When discussing vulnerability, it is crucial to recognise its interdisciplinary nature and its utilisation in various disciplines, including medical and health sciences, social work, sociology, psychology, development studies, disaster and humanitarian studies, and more. In this research discussion, we will focus on vulnerability in the context of disasters. According to UNDRR (2024b), vulnerabilities are conditions influenced by physical, social, economic, and environmental factors or processes that increase the susceptibility of individuals, communities, assets, or systems to the impacts of hazards. Considering the concept of risk in the framework developed by Wisner et al. (2004), risk is a combination of hazard and vulnerability. This framework indicates that hazards are external forces and vulnerabilities are internal forces. Vulnerability, as an individual's internal ability to face danger, explains how vulnerability is viewed as a characteristic that can be identified in the context of risk and disaster. This interdisciplinary nature of vulnerability underscores its relevance and importance in various fields, including the audience's respective areas of expertise.

Vulnerability is also a concept that is closely tied to location (Cutter, 1996). According to Cutter, vulnerability is widely understood as "a potential for loss" that exists in terms of place vulnerability. This vulnerability is a combination of social vulnerability and biophysical/technological vulnerability. Social vulnerability is defined as the potential of a social group for losses as a result of a disaster, and biophysical vulnerability is the potential of the biophysical environment for losses in interaction with a disaster. Pelling (2003) also explains the concept of "human vulnerability," which is a combination of the physical vulnerability in the built environment and the social vulnerability of people and the social, economic, and political systems.

2.2. Vulnerability Measurement

2.2.1. Approaches to Vulnerability Measurement

The concept of vulnerability in the field of disaster must be defined in measurable terms. The metrics used to measure vulnerability can vary based on different factors, such as the approach taken, the focus of the analysis (e.g., place, community, households, population groups), the types of vulnerability or system being considered (physical, social, infrastructure, economic), and the type of hazard or stressor (e.g., all hazards, climate change, a specific type like flood) (Cutter, 2024).

Approaches to vulnerability metrics can be qualitative, quantitative, or integrated (Birkmann, 2006). Qualitatively, vulnerability is examined using non-numerical data, often involving participatory methods to gather local knowledge and community perception. This approach includes understanding the context, cultural factors, social networks, and other intangible aspects. The quantitative approach aims to represent vulnerability using statistical methods and numerical indicators. The integrated approach combines the qualitative and quantitative approaches to understand vulnerability comprehensively. An example of the integrated approach can be seen in the work of (Kienberger & Steinbruch, 2014) in Búzi, Mozambique, where both qualitative and quantitative techniques were combined in vulnerability measurement.

To assess the vulnerability condition of an area quantitatively, we require an index generated from vulnerability indicators. Various methodologies exist for calculating vulnerability indexes. In general, according to Tate (2012), the most prominent distinguishing characteristic of vulnerability calculation methodology is its structural design. The types of structural design used in the process of creating a vulnerability index are divided into three: Deductive, hierarchical, and inductive. Deductive models usually have less than ten indicators, which are normalised and aggregated to become an index. This structure exists in the initial phase of vulnerability index development. Hierarchical models typically consist of ten to twenty indicators grouped into sub-indices. After the indicators are normalised at the beginning, multilevel aggregation is carried out at the sub-indices and final index phases. The final method is the Inductive method, which usually has more than twenty indicators that are later reduced to an index using a statistical tool, principal component analysis (PCA). The factors resulting from PCA are then aggregated into an index. This inductive method was popularised by Cutter et al. (2003) under the name Social Vulnerability Index (SoVI), and it has since become a common tool for calculating the social vulnerability index (Painter et al., 2024). Figure 1 below illustrates the three vulnerability calculation structures that have been explained.

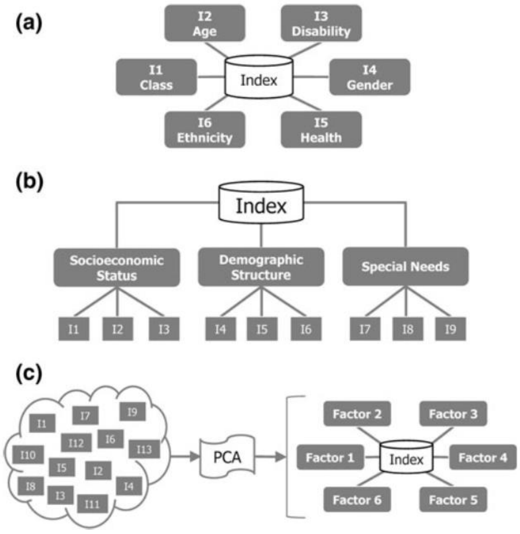


Figure 1 Vulnerability index structural design (Tate, 2012). Explains three types of structural design of social vulnerability index: deductive, hierarchical, inductive.

2.2.2. Application of Vulnerability Index in Disaster Risk Assessment

Vulnerability is always a key aspect of disaster risk assessment and is crucial in determining risk and hazard. It encompasses the evaluation of not only the physical aspects, such as buildings and materials but also social vulnerability. Social vulnerability is vital for addressing the societal component in environmental hazard assessment. This concept of disaster is not confined to a single type but is applicable to various disasters. For example, the Social Vulnerability Index (SoVI) has been used in combination with the US Geological Survey's coastal vulnerability index to assess coastal place vulnerability to erosion hazards in US coastal counties (Boruff et al., 2005). Social vulnerability is also employed in assessing vulnerability to hurricanes (Rygel et al., 2006), earthquakes (Schmidtlein et al., 2011), flood (Koks et al., 2015), and climate change (Vincent, 2004). In disaster risk assessment, the vulnerability score can be based solely on social vulnerability or on a combination of social and physical vulnerability scores.

2.3. Intersectionality

The intersectionality theory, first discussed by (Crenshaw, 1989), explains how discrimination can be based on a combination of identities rather than just one minority identity. Crenshaw analyses how black women are marginalised due to both gender and race (see Figure 2). This theory is not limited to identifying identity discrimination and can also be applied to other contexts. In our case, we will adopt this concept into the social vulnerability discussion, specifically, how a population can have multiple vulnerability dimensions.

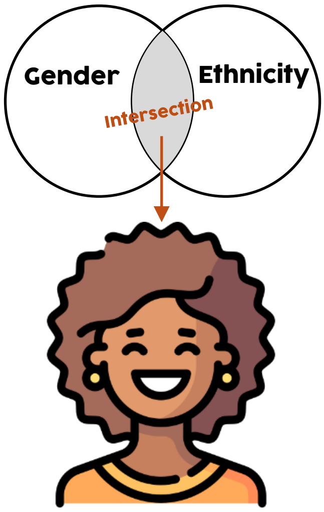


Figure 2 Intersectionality illustration of the discrimination of Black Women

The intersectionality theory has continued to develop over time. Collins and Bilge (2016) explained intersectionality based on five core principles: social inequality, relationality, social context, power, and complexity. These principles are crucial for providing a nuanced perspective on how the theory can help explain the impact of disasters on vulnerability, particularly social vulnerability.

Social inequality refers to how social categories and stratification do not operate independently but instead create compounded disadvantages. This is similar to how dimensions of social vulnerability do not exist in isolation but rather interact to create compounded vulnerability. Relationality explains the relationships between different social identities and how they interact to shape individual experiences. In the context of social vulnerability, different vulnerability dimensions are interconnected and dynamically related rather than isolated traits. Social context means that intersectionality is context-specific. In the context of disaster impact, different vulnerabilities, regions, and types of disasters can vary.

The power principle explains that the framework is concerned with power dynamics. In the context of social vulnerability, it can help us understand how power influences decisions regarding vulnerability, whether decision-makers see vulnerability dimensions separately or as a compound. Finally, Complexity explains that intersectionality advocates for understanding the complexity of social identities rather than reducing them to single categories. It is important to highlight this when discussing social vulnerability, which is complex and cannot be explained by a single number or value. Acknowledging complexity means moving beyond single-issue analysis, preventing oversimplification, and promoting a more comprehensive understanding of the issue at hand.

Understanding intersectionality theory through the lens of social vulnerability will allow us to perceive vulnerability in a new light. Current vulnerability assessments primarily rely on a final index for comparing different regions and categorising them based on their levels of vulnerability. However, while this final index may offer a glimpse into the predominant factors contributing to the index, it does not offer additional analytical support in exploring the potential intersectionality of social vulnerability within a region. We need an alternative method that not only records the social vulnerability index but also provides insight to help policymakers analyse vulnerability characteristics using the analytical framework of intersectionality theory.

2.4. Research Gap

After analysing the literature, several key issues regarding social vulnerability have been identified. The first issue concerns the representation of indicators or social dimensions that may be undervalued due to the statistical tools approach. It is necessary to explore alternative methods that can give appropriate weight to the social dimensions forming social vulnerability, ensuring that no aspects of social vulnerability are neglected in an index. The second issue involves understanding the complexity of social vulnerability using intersectionality analysis. Developing a measurement method for social vulnerability that not only generates a final index but also facilitates exploration of the dominant dimensions contributing to vulnerability will greatly enhance deeper vulnerability studies.

Research and development are needed for a multidimensional approach to social vulnerability that generates a final index and appropriately balances the role of variables in it. Such an approach can provide valuable insights into the complexity of social vulnerability. Creating an alternative index based on intersectionality theory will contribute to the development of a social vulnerability measurement methodology.

A key point for future research is the likelihood that the index, in a multidimensional manner, will effectively address the challenge of representing vulnerability dimensions in the index and provide additional information for analysing vulnerability complexity. Additionally, exploring how this alternative methodology can support disaster risk assessment and impact disaster management policies is crucial. From this problem formulation, the next crucial question is whether this multidimensional index can improve the social vulnerability measurement process. This is particularly true in terms of addressing the representativeness of dimensions and providing additional supporting information for disaster risk management policy.

Summarising the issues above, a research question to address those issues can be formulated as follows:

"*How can developing and applying a multidimensional approach to social vulnerability measurement enhance and support the disaster risk assessment process and policies?*"

3 Method

3.1. Sub Questions

In order to address the research question mentioned earlier, the study will be divided into several sections, including:

a. Understanding social vulnerability and the need for a multidimensional approach
b. Designing the multidimensional index
c. Applying the Multidimensional Index to social vulnerability measurement and assessing the comparison results with the existing method
d. Implementing the Multidimensional Index to the Disaster Risk Assessment
e. Drawing policy implications from the development of the multidimensional index method

Understanding social vulnerability and the need for a multidimensional approach

In this section, we will explore the concept of social vulnerability and the importance of taking a multidimensional approach. Specifically, we will discuss the current tools and methods for assessing social vulnerability and the necessity of incorporating a multidimensional approach through a literature review.

Designing the Multidimensional Index

The process of designing a methodology for measuring social vulnerability in a multidimensional manner is discussed in SQ2. The discussion of the theoretical basis and design choices in this method will help us understand the framework of this method.

Assessing Social Vulnerability using a Multidimensional Index and Comparing it to the Existing Method

The assessment of social vulnerability in Indonesia involves using the SoVI and Multidimensional methods in SQ3. This enables a better understanding of social vulnerability by utilizing both methods. The SQ3 also includes a comparison between SoVI and Multidimensional to evaluate the effectiveness of the multidimensional index in measuring social vulnerability, with SoVI serving as the reference method.

Applying Social Vulnerability to Disaster Risk Assessment

In this section, we will apply the concept of social vulnerability to disaster data, focusing on flood hazards. First, we will identify the flood hazards and exposure before incorporating the social vulnerability aspect. We aim to investigate how the social vulnerability value, derived from multidimensional methods, impacts disaster risk assessment, with a specific focus on flood risk assessment. The process of implementing the multidimensional index to assess disaster risk will be conducted in Q4, and we will analyse both the process and the results of this implementation.

Drawing Policy Implications from the Development of the Multidimensional Index Method

This final section discusses the policy implications of developing multidimensional methods in SQ5. The main question regarding the policy implications that can be obtained by developing this alternative method is derived from the results of the analysis of multidimensional index values, their comparison with SoVI, and their application to disaster risk assessment.

Table 1 Sub-questions of the research

	Sub-Question	Methodology	Sources/Input
SQ1	What are the needs and implications of applying a multidimensional approach to social vulnerability measurement?	Literature review	Literature
SQ2	How can we design a multidimensional approach to measure social vulnerabilities?	Literature review	Literature
SQ3	*How can we apply the multidimensional approach to measure social vulnerability, and what are the comparison results with the existing method?*	Multidimensional Index, SoVI, and Comparison methods	Indonesia Data: Socio-economy and Demographic
SQ4	*What are the processes and results of implementing the multidimensional index in a disaster risk assessment?*	Flood Risk Analysis (with GIS)	Indonesia Flood Hazard & Population Data
SQ5	*What are the implications of using a multidimensional approach in measuring social vulnerability for disaster risk management policymaking?*	Literature Review and Policy Analysis	SQ3 and SQ4 results

3.2. Research Flow

This research has seven main stages to arrive at the desired final result in answering the research question. (i) Understanding the social vulnerability and multidimensional concept; (ii) Developing alternative approaches for measuring social vulnerability; (iii) Measuring the social vulnerability using SoVI and multidimensional approach; (iv) Comparing the SoVI and Multidimensional results; (v) Analysing the flood hazard and exposure conditions in Indonesia; (vi) Creating flood risk assessment using Multidimensional; (vii) Defining policy implications. Figure 3 Research Flow visualizes the research flow of these seven steps.

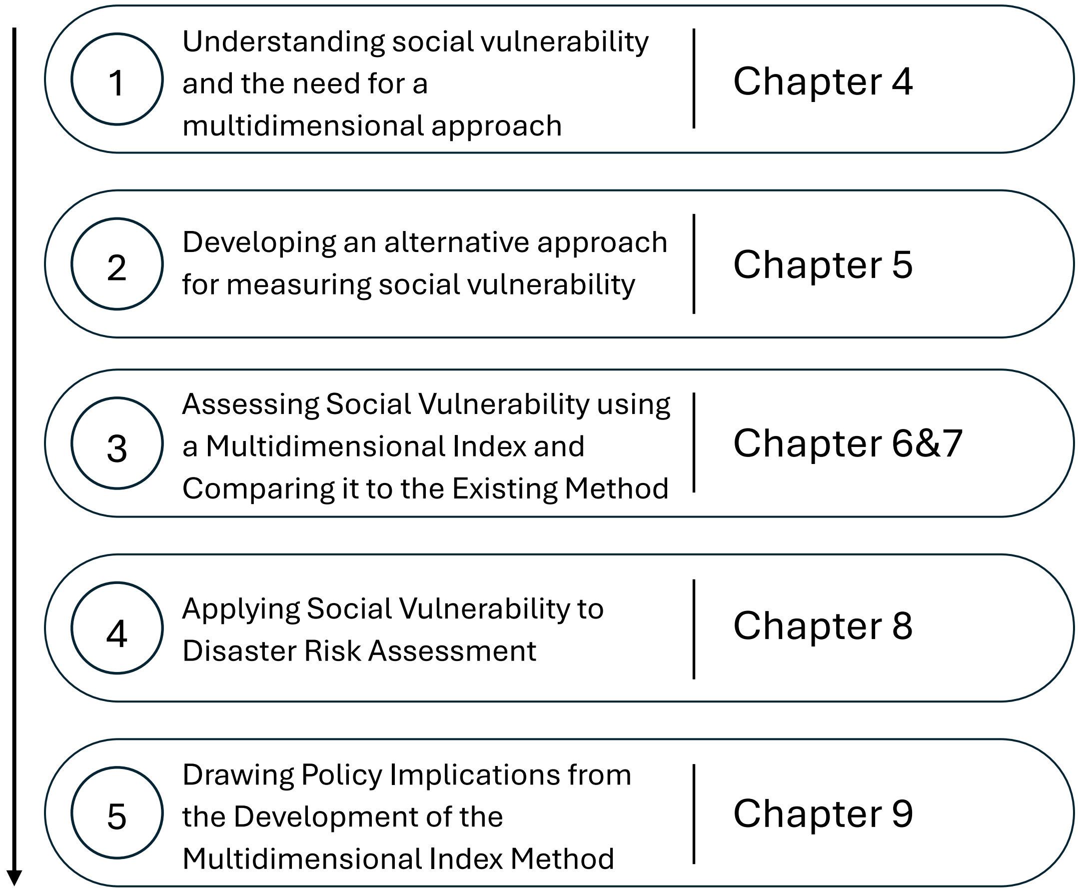


Figure 3 Research Flow with Chapters that explain each process

3.2.1. Understanding Social Vulnerability and the need for multidimensional approach

The research will start by examining social vulnerability and how it is measured. In Chapter 4, we will explore the concept and the different calculations based on the structural index that defines it. Once we understand the basic concept of social vulnerability, we will discuss the need for a multidimensional approach to measuring social vulnerability, including the incorporation of intersectionality theory and its implications.

3.2.2. Developing an alternative approach for measuring social vulnerability

Chapter 5 translates the multidimensional concept discussed in the previous section into a methodology. This chapter utilises a composite index preparation framework, drawing from articles by Salzman (2003) and Moreira et al. (2021).

Salzman's article delves into the methodological choices in constructing composite indices within economics and social well-being. This article intentionally explores methodological decisions, aiming to review this topic comprehensively. The article explains the process of making choices in the development of composite indices, as outlined in Figure 4 Index construction steps below:

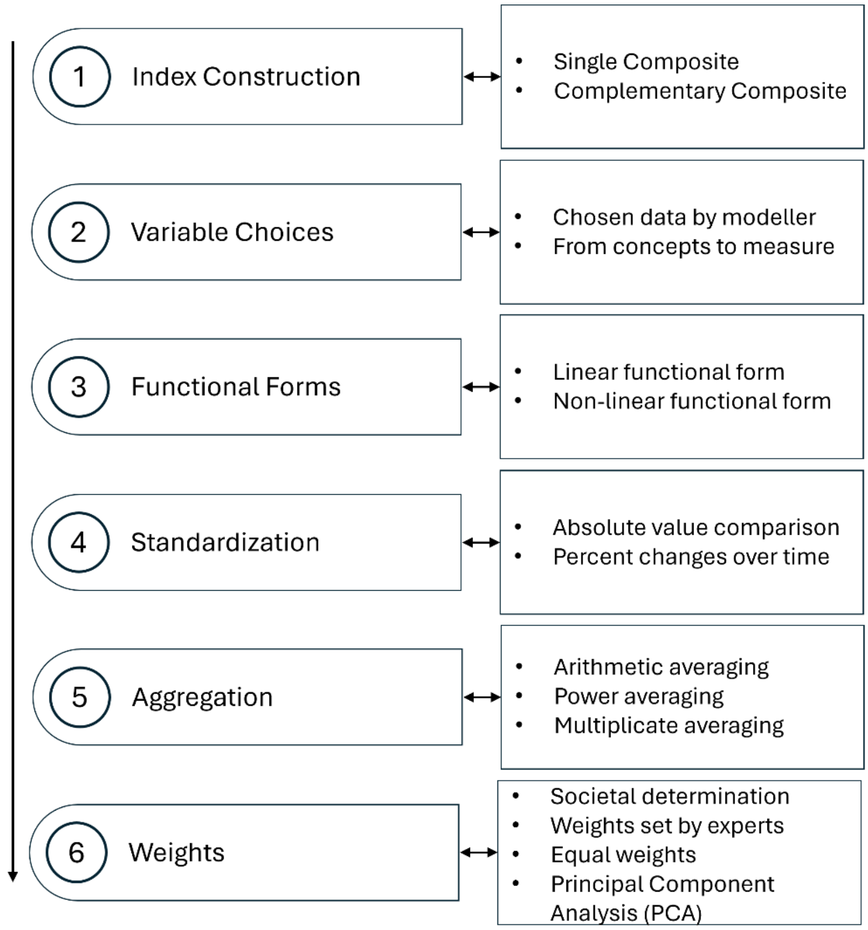


Figure 4 Index construction steps and all choices within each step

The graph above outlines the methodological choices involved in building composite indices. The process begins with choosing the general form of the index, which could be a single or complementary composite. Next, variables are selected based on the judgment of the modeller or the concept being measured. The functional form, which involves applying a functional transformation to the raw data to represent the significance of marginal changes in its level, is then chosen. After determining the functional forms associated with the variables, a standardisation method is chosen to ensure the meaningful comparison of values used in the model. The method for aggregating the existing variables is then selected based on the model's needs, and weights within the aggregation scheme are set using various weighing methods, each with its advantages and trade-offs. The article by Moreira et al. (2021) serves as another reference framework that aids in the multidimensional method development process and Figure 5 below illustrates the index construction stages.

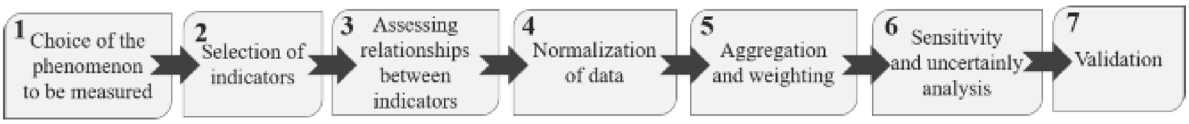


Figure 5 Index construction steps (Moreira et al., 2021).

In Moreira *et al.*'s (2021) article, the process of creating an index follows several steps. First, one must select the phenomena to be included in the index in order to establish the index's context. Next, suitable indicators for the chosen phenomena are selected, followed by assessing the indicators' relationships. Normalising the data after obtaining the indicators ensures that the data can be compared across a consistent range. The aggregation and weighting phases are then conducted to create the index. Lastly, sensitivity and validation analyses are performed to test and confirm the resulting index.

In this study, the construction of the Multidimensional index combines the framework stages of the two articles mentioned above. The adjustments made to data requirements, calculation techniques, and research limitations guarantee that the research can yield optimal results within existing constraints.

3.2.3. Assessing Social Vulnerability using a Multidimensional Index and Comparing it to the Existing Method

In Chapter 5, we explained the process of calculating the multidimensional index. Now, we will calculate the Multidimensional Index using Indonesian data as our case study. The rationale for choosing the Indonesian case as our study is provided at the beginning of Chapter 6. Additionally, we performed the SoVI calculation as an existing method to use for comparison. To calculate the SoVI using Indonesian data, we will begin by selecting input data, which includes social variables in Indonesia such as poverty map data from SMERU, village data from the Indonesian government, and demographic data on the Indonesian population. Once we have collected these variables, we can proceed with the SoVI calculations.

The SoVI calculation method follows the steps outlined in the SoVI recipe guide. (Hazards & Vulnerability Research Institute, 2016), the initial source for the SoVI calculation method. You can find an overview of the SoVI calculation stages in Figure 6 below.

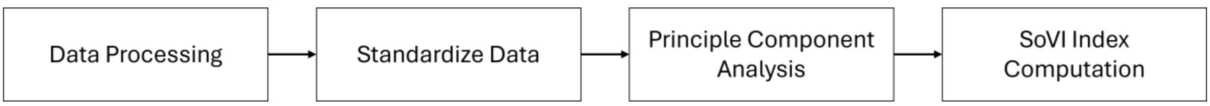


Figure 6 SoVI steps overview

To calculate the SoVI, we follow a specific process. First, we normalise the input data using methods like percentages or per capita values. Then, we standardise the data using z-score standardisation to create variables with a mean of 0 and a standard deviation of 1. Next, we use PCA (Principal Component Analysis) with varimax rotation and the Kaiser Criterion to determine the number of components. The PCA process helps us identify the factors contributing to the index. We then analyse factor loadings to determine the significance of each factor. Variables with factor loadings above a certain threshold are considered important for the factors. Variables that increase vulnerability are given positive scores, while those that decrease vulnerability are given negative scores based on their contribution to the index. Finally, we aggregate the SoVI calculations using an additive model with individual scores for each factor.

The next step in this phase is to look at the result of the comparison between SoVI and Multidimensional, which is intended to see how the results of the vulnerability index obtained from the multidimensional method we are developing compare with the results of the existing social vulnerability calculation method. Apart from that, we also tested the suitability of the calculation process and results of this social vulnerability index in accordance with the initial objectives of this method being developed. This process involved comparing several aspects, including the theoretical variances between the two methods, a visual comparison of social vulnerability results, and the contribution of each input variable to the calculation model.

The theoretical comparison involved examining the theoretical basis and the rationale for creating the calculation method. We understand that SoVI is derived from the statistical processing of social variables to represent vulnerability conditions as an index in the real world. Similarly, Multidimensional also aims to achieve this but incorporates analysis of intersectionality theory.

Visually, the comparison is carried out by aligning the results of mapping the social vulnerability index values from the two methods. This comparison involves creating a social vulnerability map for all of Indonesia and detailed data for each archipelagic group or large island. By doing this, we can identify differences between the two methods, such as variations in categorisation and discernible patterns. We also use distribution data for each vulnerability category for comparison to observe the number of objects indicated in each vulnerability category. Additionally, we conduct a class change analysis to ensure there is a difference between the results of the two methods being tested. This analysis helps identify areas with different classes or categories from the two methods under examination. The way to do this is first by assigning numbers to each category from lowest to highest, following the following mapping:

a) Low = 1
b) Mid-low = 2
c) Medium = 3
d) Mid-high = 4
e) High = 5

Then, we subtract the class value according to multidimensional calculations and according to SoVI in each region to find out the difference in regional class. A larger result indicates a greater class difference. Then, we convert all the subtraction results into absolute values and aggregate them to create a statistical table of class changes for the two methods being compared.

The final step in the comparison process involves assessing the contribution of each variable to the social vulnerability index results in each method. This calculation is aimed at testing the initial goal of the multidimensional method, which is to evenly recognise all dimensions of vulnerability in the index results and compare how the variables contribute to the final SoVI value. First, we will calculate the contribution of the variables in SoVI. To carry out the calculation, we first determine the loading value of each variable in each factor in the PCA analysis, as well as the amount of variance for each factor. The loading value of each variable in each factor is then multiplied by the respective variance factor to determine the size of the variable's contribution in each principal component. Finally, an additive model following the assigned cardinality of the factors in the actual SoVI model is applied to get the size of the variable's contribution. These results serve as a reference for variable contributions. This process is repeated for each variable.

To calculate the contribution of variables to the multidimensional method, we first consider the number of constituent variables in each dimension. For dimensions with three or more variables, we follow the same steps as with the SoVI based on the variables in each dimension. Since we use the geometric mean for dimensions with two variables, the contribution value for each variable will be 0.5. Finally, for dimensions with only one variable, the contribution value of that variable to the final index result is one, as this dimension will use the value of that variable as is. The results of calculating the contribution of each variable are presented graphically to compare the contributions of all variables to our final index.

The final step is to compare the contribution of the vulnerability dimensions to the final index, as the initial intention of developing the multidimensional method was to ensure evenness in the contribution of vulnerability dimensions. Dimensional contribution is obtained by adding variable contribution scores based on each dimension. We can then determine the contribution in each dimension for each index, both for the SoVI and Multidimensional methods. It is important to note that because the range of SoVI and multidimensional vulnerability index values is different, we will not compare the score results; rather, we will compare the patterns that occur between the two methods. Patterns of dimensional contributions that are balanced or unequal in just a few dimensions will be highlighted as the main information in this comparison process.

3.2.4. Applying Social Vulnerability to Disaster Risk Assessment

In this study, we investigate the application of a multidimensional index to a real-life disaster scenario by analysing flood data from Indonesia. The flood hazard and exposure data were obtained from the Global Flood Map v.2 by Fathom, and population data was sourced from WorldPop. To determine flood hazard, we established a minimum threshold for high-risk flooding at a depth of 0.5 meters (Rentschler & Salhab, 2020), with a recurrence interval of 100 years. Using this threshold, we filtered the flood data to identify high-risk areas and combined pluvial and fluvial flood data to create a flood hazard map for Indonesia.

To determine the number of people exposed to floods, we utilised population data with the exact resolution and data type as our flood data. By overlaying the filtered flood hazard data with the population data, we could identify the affected areas and calculate the population residing there. This information allowed us to map out flood exposure.

To align our data aggregation with our social vulnerability calculations, we combined the flood exposure data within the administrative boundaries of Indonesian subdistricts. We used GIS tools to aggregate the number of people affected by high-risk floods within each subdistrict, which aligns with the social vulnerability data.

The obtained flood exposure data were combined with social vulnerability data obtained using a multidimensional index approach. This was done to include the multidimensional index result as the required vulnerability data for disaster risk assessment. This will enable us to identify the number of people exposed to high-risk floods in each category for further analysis. Furthermore, we will conduct spatial analysis to identify areas with a high vulnerability category and map the number of people exposed to flooding in those areas. This spatial data will help us identify hotspots in high-vulnerability areas with a large number of exposed people.

In addition to using the final social vulnerability index data, further analysis material can be obtained from the results of the multidimensional index, including analysis based on each dimension. Policymakers interested in specific dimensions can use the assessment results for each dimension or index as analysis material. For instance, an economic index can be used to conduct a particular flood risk analysis to identify areas with high economic vulnerability and a large number of people exposed to high-risk floods.

3.2.5. Defining Policy Implications

Defining the policy implications of developing a multidimensional index can be achieved by first examining the theoretical basis used to calculate social vulnerability, the results obtained from the method, and the potential policy implications that can arise from using this alternative method.

The multidimensional vulnerability perspective, influenced by compounded discrimination from intersectionality theory, offers a new outlook for developing disaster management policies. Subsequently, when considering the results produced by the multidimensional index method, we can explore the potential implications of using these results in policy development regarding the final index of social vulnerability and the indices in each dimension. This calculation method can serve as a valuable reference for policymakers conducting vulnerability analyses for disaster risk assessment. For instance, it can aid in establishing policy priorities and selecting appropriate measures based on the vulnerability conditions in different geographical areas.

4 Understanding Social Vulnerability and the Concept of Multidimensionality

4.1. The Concept of Social Vulnerability

The term "vulnerability" in the context of disaster usually refers to the susceptibility of buildings and material possessions to damage caused by disaster (Filatova, 2014). However, this definition fails to take into account the potential vulnerability experienced by people living in flood-prone areas. To make flood risk calculations more relevant to humans, other variables that can accurately reflect the vulnerability of the population must be used.

Social vulnerability itself is a concept that helps identify the vulnerability of an individual or group not based on physical conditions but rather on pre-existing conditions that are deeply embedded in social, economic, and political relations between groups (Fordham et al., 2013). Cutter (2024) defined social vulnerability as the potential for harm and loss that is influenced by people's susceptibility to harmful agents, events, or processes and their level of exposure to them. This social vulnerability within a population is also influenced by their limited ability to mitigate the risk of natural disasters, including their inability to prepare, respond, or recover. (Adger (1999); Cutter et al. (2003), (2008)). Social vulnerability is a broad concept that spans different fields, drawing from related ideas such as social marginalisation (sociology), health disparities (public health), uneven development (political economy), and social and spatial inequality (geography).

This concept is useful for distinguishing vulnerable groups that are likely to be affected worse than other groups in case of a disaster. It is important for the government to recognise these groups and provide appropriate handling and response during disaster events to ensure their safety. Koks et al. (2015) conducted a study that integrated the concept of flood risk with social vulnerability data. This approach has proved useful and provides a novel way of looking at flood risk management, where social vulnerability is a vital variable that can be considered.

4.2. The Multidimensional Concept of Social Vulnerability

Intersectionality theory, as explained in Chapter 2.3, offers a new perspective on understanding social vulnerability by considering the interaction of different dimensions. Instead of relying on a single index to explain social vulnerability, this theory guided us to examine vulnerability from a more dynamic and complex viewpoint. We need to understand vulnerability more comprehensively by recognising the interconnections among different dimensions. Additionally, representing the variables used to form the index in their respective vulnerability dimensions provides a more detailed, planned, and accurate description of the population's condition.

For instance, consider someone who is elderly, poor, and has an immigrant background with a language barrier. When using intersectionality theory to assess social vulnerability, we capture the person's vulnerability to the disaster by looking at all dimensions together. This person's profile makes them highly vulnerable to disasters, as each dimension of vulnerability is important and interconnected. We are not leaving out other vulnerabilities and just focusing on one dominant vulnerability dimension, but instead, consider all dimensions as one compounded vulnerability. Poverty alone increases social vulnerability, as poor individuals are more likely to be affected by natural hazards (Hallegatte et al., 2020). Additionally, being elderly makes it difficult to find a job (Phillips, 2023), and cultural differences and language barriers can hinder job opportunities (Schellekens, 2001). This is not only a cause of poverty and maintaining poverty but can also worsen the situation, especially in disaster conditions. Managing disasters for these individuals becomes much more challenging than for those with fewer vulnerabilities. Furthermore, age and language barriers become significant obstacles in disaster preparedness, response, and recovery (Phraknoi et al., 2023; Teo et al., 2019). The difficulty in mobilisation and communication processes makes these individuals highly vulnerable, with more potential for worse disaster impacts. By understanding the dominant vulnerability dimensions that contribute to its formation, we can better analyse and develop disaster management policies. Intersectionality analysis captures this combination of vulnerabilities, which is challenging to obtain with tools focusing on only one dominant indicator of vulnerability.

Incorporating intersectionality theory into social vulnerability measurement assumes that each dimension of vulnerability plays an equal role in forming social vulnerability, resulting in a proportional recognition of all dimensions of vulnerability. This is done by describing and identifying all dimensions of vulnerability one by one and highlighting the significant vulnerability dimensions, which will help increase the comprehensiveness and detail of disaster risk assessment results. When it comes to tools or calculation models that aim to meet requirements as simply as possible, as long as the tool assesses multiple vulnerability dimensions and can provide insight or additional analysis regarding the possibility of a population having multiple vulnerabilities, the model can be considered to address multidimensionality. The multidimensional index developed in this research will provide a deeper understanding of the conditions within each dimension of social impacts on the population, aligning with the original intention of establishing this method, ultimately leading to a final vulnerability index result.

The multidimensional approach has prompted the development of an alternative method for identifying the social vulnerability index in a more multidimensional manner. This approach takes into account the dimensions of vulnerability gathered from social impact dimensions, as well as their interconnections within the population. The multidimensional approach discussed in this research will present a new way to calculate social vulnerability. It allows the modeller or user of this method to map the dimensions of vulnerability at the outcome, enabling the examination of the dynamics of social vulnerability in a more structured and planned manner. Comprehensively identifying vulnerabilities will lead to better disaster risk assessment results tailored to the affected population's vulnerability profile.

5 Methodology Development

In this section, we will outline the methodology design of the multidimensional approach previously mentioned. We will discuss the design methodology using the combined framework of Salzman (2003) and Moreira et al. (2021), which has been modified to suit the requirements of this multidimensional methodological explanation.

5.1. Index Construction

Index construction is a general form of index that will be created. At this stage, we will determine whether the index will be a single or complementary composite. A single composite is an aggregation of variables used in an index, while a complementary composite comprises two separate indices: a conglomerative index and a deprivational index. The deprivational index measures only the welfare of the worst off, whereas the conglomerative index measures overall well-being. In this multidimensional index, we will measure all dimensions and variables that affect the social vulnerability of the population, whether they increase or decrease social vulnerability. It means that the complementary composite is the choice. We are taking this approach to understand the actual conditions of the population in the index.

5.2. Social Impact Dimensions

When developing the multidimensional index, we refer to the social impact assessment (SIA) framework. Social Impact Assessment (SIA) involves identifying and managing the social impacts of current or proposed policies and interventions (Vanclay, 2002). These social impacts can change over time and space and often accumulate due to various urban interventions, human activities, and natural processes. SIA literature emphasises the importance of focusing on vulnerable groups to better manage socio-environmental risks (Climent-Gil et al., 2018). This vulnerability focus is crucial because climate change and urban issues like inequality and segregation have significant spatial dimensions. Communities become vulnerable to climate change when the risks intersect with their physical, economic, and institutional inability to cope. Recognising the spatial aspects of climate change impacts and assessing communities' capabilities to handle these changes can provide valuable insights for managing climate risks throughout the space.

We will use the SIA framework to identify the dimensions of vulnerability that are crucial in creating vulnerable conditions for populations (Vanclay, 2002). This framework will provide the theoretical basis for assessing the impacts of disasters on people's livelihoods and communities through spatial analysis. Spatial data allows for the quantification and visualisation of the data under study. The dimensions under the SIA framework which we will use as the basis of our vulnerability dimensions are:

a. Health and well-being
b. Quality of built environment
c. Economic
d. Cultural
e. Community
f. Institutional, political, and equity
g. Gender

From each dimension of social impacts in the SIA framework, we identified a set of indicators for each dimension through a literature review analysis. These indicators are listed in Table 2 Below:

Table 2 Social Dimensions and Indicators

Dimension	Indicator	References
Health & Well-being	Elderly	Cutter et al. (2003); Tapia et al. (2017); Otto et al. (2017); English et al. (2009); Eisenman et al. (2016)
	Infancy	Cutter et al. (2003); Tapia et al. (2017); Otto et al. (2017); English et al. (2009); Eisenman et al. (2016)
	Illness	Robinson et al. (2019)
	Special needs	Reckien et al. (2017); Cutter et al. (2003)
	Personal Immobility	Reckien et al. (2017); Eisenman et al. (2016); Uejio et al. (2011)
Built Environment	Housing quality	Tapia et al. (2017); Reckien et al. (2017); Eisenman et al. (2016); Santamouris (2020)
	Infrastructure availability	Cutter et al. (2003); Otto et al. (2017); Eisenman et al. (2016)
	Housing density	Cutter et al. (2003); Uejio et al. (2011); Reckien et al. (2017)
	Lack of conservation programs	Tapia et al. (2017)
	Lack of disaster relief/warning systems	Tapia et al. (2017)
	Lack of zoning/building standards	Tapia et al. (2017); Reckien et al. (2017); Eisenman et al. (2016)
Economic	Purchasing power	Tapia et al. (2017); English et al. (2009); Cutter et al. (2003); Santamouris (2020)
	Homeownership	Tapia et al. (2017); Cutter et al. (2003); Uejio et al. (2011)
	Employment	Tapia et al. (2017); Cutter et al. (2003)
	Lack of social security systems	Tapia et al. (2017); Cutter et al. (2003)
	Lack of economic diversity	Tapia et al. (2017)
Gender	Unequal childcare responsibilities	Robinson et al. (2019)

	Entitlement and participation of women in public life	Tapia et al. (2017); Reckien et al. (2017)
	Unequal access to paid work	Reckien et al. (2017)
	Women more affected by impacts	Reckien et al. (2017); Otto et al. (2017)
	Underrepresentation of women in governance agencies	Pearse (2017); Reckien et al. (2017)
Institutional	Corruption	Tapia et al. (2017)
	Political instability	Tapia et al. (2017)
	Inability to hold accountable	Reckien et al. (2017)
	Inability to exert influence/ to participate	Thomas et al. (2019); Reckien et al. (2017); Tapia et al. (2017)
	Lack of representation	Thomas et al. (2019)
Cultural	Race/ethnicity	Tapia et al. (2017); Otto et al. (2017); Cutter et al. (2003); Uejio et al. (2011)
	Language barrier/ literacy	Cutter et al. (2003); Reckien et al. (2017); Uejio et al. (2011)
	Risk awareness	Thomas et al. (2019); Reckien et al. (2017)
Community	Lack of social memory	Thomas et al. (2019); Reckien et al. (2017)
	Lack of community cohesion	Tapia et al. (2017)
	Social isolation	Weber et al. (2015); English et al. (2009); Eisenman et al. (2016); Uejio et al. (2011)

We will analyse each population object's dimensions to create a multidimensional index. The indicators listed in each dimension will serve as a reference for grouping our social variables. In the next stage, these groups will be used as input for calculating the dimension index and the final multidimensional index.

5.3. Dimension Index

The process of creating a multidimensional index begins by gathering all social variables related to social vulnerability based on the dimensions and indicators mentioned above. Then, the variables are categorised and grouped according to the existing dimensions. This grouping allows the variables to be placed in the same context and serves as input to form the dimension index. In this case, the dimension index is an index for each social impact dimension. It helps explain the condition and characteristics of the population within each dimension, whether they are in a vulnerable condition or not. This index for each dimension contributes to forming the final multidimensional index. Through the aggregation process, we obtain a comprehensive multidimensional index. One advantage of this methodology is identifying the components that make up the final index, specifically the dimension index. This helps us recognise the dimensions that play a significant and dominant role in defining social vulnerability within a population.

To create the dimension index, we will do several steps:

a. Aggregation of variables

When working with data that is at a different scale than what we need for analysis, it is important to consider the type of data in each variable. For instance, our dataset contains data at the city level, but we will be working at the province level, so we need to aggregate the data accordingly. The common types of data in our variables are continuous and binary.

We will use the additive method for continuous data to sum the values at the scale we require. For example, if we have data on the number of healthcare facilities in each city, we will sum these values to obtain the total for the province.

For binary data (where the variable is either yes or no, represented by 1 and 0), we will calculate the mean for each scale. For instance, if we have data on the availability of electricity in each city, we will take the mean value at the subdistrict level to obtain the value at the province level.

b. Standardisation

The standardisation process is essential when dealing with data that have different ranges and measurements. It involves scaling the data to the same level to avoid bias and mix-ups due to varying measurement units. Booysen (2002) explains that the aim of scaling variables is to show the relationship between objects, how far apart they are, and their direction relative to each other. This process involves ordering the values to determine the distance between them.

Several main standardisation methods can be seen in Table 3 below:

Table 3 Main standardisation method (Moreira et al., 2021)

Method	Equation	Description	Reference
Ranking	$y_{\text{in}} = \text{Rank}(x_{\text{in}})$	Based on ordinal variables that can be turned into quantitative variables.	Carlier et al. (2018)
Z scores	$y_{\text{in}} = \frac{x_{\text{in}} - \bar{x}_{\text{in}}}{\sigma_{\bar{x}_{\text{in}}}}$	Converts all indicators to a common scale with a mean of 0 and a standard deviation of 1.	Gerrard (2018)
Min-max	$y_{\text{in}} = \frac{x_{\text{in}} - \min(x_{\text{in}})}{\max(x_{\text{in}}) - \min(x_{\text{in}})}$	Rescales values between 0 (worst rank) and 1 (best rank). It subtracts the minimum value and divides it by the range of the	Jha & Gundimeda (2019)

		maximum value subtracted by the minimum value.	
Distance from the group leader	$y_{\text{in}} = \frac{x_{\text{in}}}{\max(x_{\text{in}})}$	Rescales values between 0 and 1. It is defined as the ratio of the value of the indicator to its maximum value.	Munyai et al. (2019)
Division by total	$y_{\text{in}} = \frac{x_{\text{in}}}{\sum(x_{\text{in}})}$	It is defined as the ratio of the value of the indicator to the total value for the indicator.	Jamshed et al. (2019)
Categorical scale	$y_{\text{in}} = \begin{cases} 0 \text{ if } x_{\text{in}} < P^{15} \\ 20 \text{ if } P^{15} \leq x_{\text{in}} < P^{25} \\ 40 \text{ if } P^{25} \leq x_{\text{in}} < P^{65} \\ 60 \text{ if } P^{65} \leq x_{\text{in}} < P^{85} \\ 80 \text{ if } P^{85} \leq x_{\text{in}} < P^{95} \\ 100 \text{ if } x_{\text{in}} \leq x^{t}_{\text{qc}} \end{cases}$	Assigns a value for each numeric or qualitative indicator. Values are based on percentage.	Andrade & Szlafsztein (2018)
Binary Standard	None	It is calculated using simple Boolean 0 and 1 (false and true) values.	Garbutt et al. (2015)

In this method, we use the Z score standardisation method for the dimension with more than three variables, which produces a set of variables with a mean of 0 and a standard deviation of 1, and we use distance from the group leader method for another category.

c. Creating dimension indexes

In this multidimensional approach, we will consider various variables that comprise each dimension's index. We do this to ensure that all relevant variables describing the true condition of the population are included. To create the index for each dimension using multiple variables, we will use a weighting method to translate those variables into representative indexes.

There are several well-known weighting methods in this field. This process can be explained by three main categories: deductive, inductive, and hierarchical, the same as the structural composite index design, which we talked about before (Moreira et al., 2021). The deductive method essentially involves using expert or public opinion to establish a suitable weighting scheme for the variables in the index. The weights are determined by experts based on how significant or critical individual variables contribute to the index. Another method is the inductive approach, which involves using statistical tools to reduce a group of variables to produce an index. The most common method is Principal Component Analysis (PCA), a factor analysis tool that reduces the dimension of data into several factors. The primary objective of this statistical tool is to uncover variations in a data set using fewer dimensions. PCA itself is a linear algebraic technique that generates weights for different variables by assigning them the components of the first eigenvector of the covariance matrix. The last category is the hierarchical method, which uses an equal weighting scheme to assess the influence of variables on the index. The idea behind this weighting is to assign equal value to all variables. The purpose of this equal weighting technique is to make the choice of weights less subjective.

In this multidimensional method, we use weighting to generate dimension indexes based on the number of variables representing each dimension.

- Dimension with three or more than three variables.

When dealing with dimensions containing more than three variables, we utilise the PCA method. This is to maintain the fairness of the weighting scheme depicting each dimension. We aim to guarantee that the dimension index is created from the different variables present and documented in the dataset.

PCA helps us reduce the dimension of our data by identifying several factors that represent the variance of the entire data set. This method helps minimize the subjective weighing of variables. The weights are derived from the rotated factor matrix, with each factor indicating the proportion of the total variance in the indicators explained by that factor. The final dimension index is obtained by adding all factors after adjusting their directionality or cardinality based on the dominant variable in each factor. The illustration of the formation of the dimension index can be seen in Figure 7 below.

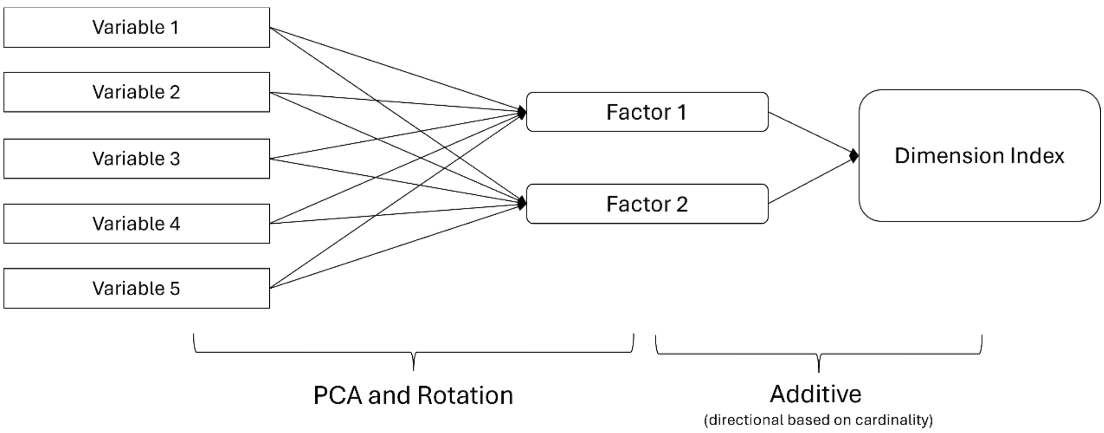


Figure 7 PCA process on dimension index creation

- Dimension with two variables.

To dimension that is constructed from two variables, first, we will standardise the variables to ensure they are in the same range. We will use the distance from the group leader technique, which rescales values between 0 and 1 by calculating the ratio of the indicator's value to its maximum value. Then, to combine the variables into a single index, we will use a technique that avoids compensating issues, where one variable's high value compensates for the other variable's low value. To address this issue, we will use the geometric mean. The geometric mean calculates the central tendency of a set of numbers by multiplying them together and then taking the n^{th} root of the resulting product, where n is the total number of values. This approach helps mitigate the compensating issue by preventing a single variable from dominating the index, resulting in a balanced and realistic measure of the combined performance of the variables.

$$Geometric\ mean = \sqrt[n]{a^1 a^2 \dots a^n}$$

- Dimension with only one variable.

For any dimension that is formed with only one variable, we will use the value of that variable as it is, or in other words, the variable value will directly represent the dimension index. To use the variable's value, we will apply the distance from the group leader as the standardisation method so that the index will have a similar range to other dimension indexes.

5.4. Multidimensional Index

After standardising the variables in each dimension, we calculate the dimension index. We carry out the same dimensional index calculations for dimensions with one or two variables as discussed above. For dimensions with three or more variables, we create a dimension index using PCA to reduce variables, provide cardinality, or adjust the direction of each factor. Finally, we use an additive model to produce a dimension index.

When calculating the multidimensional index, we combine all the dimension indexes to obtain the final value. It is important to note that the final multidimensional index value is used to assess the overall social vulnerability of a population and compare it to other populations in the area. One of the key advantages of this method is that we can still examine the index value of each dimension, allowing us to understand the impact of each dimension on social vulnerability. By analysing the intensity of each dimension, we can identify the dominant dimensions that contribute to the dynamics of social vulnerability within a population. Understanding the dimensions that significantly influence a population's dynamics can provide further insight by examining how interconnected vulnerabilities manifest within a population, which aligns with the intersectionality theory.

5.5. Sensitivity and Validation

Sensitivity analysis examines how a model's results change when different values or methods are used within the model. It helps us understand the uncertainty of the model's output, which is influenced by the inputs and techniques used.

Sensitivity analysis can be divided into sensitivity to indicator selection and index construction. When we talk about indicator selection, we look at how the input data used to build the index affects our results. Understanding that poor-quality input will result in poor-quality output, this sensitivity analysis aims to reveal how input dynamics influence index results. One way to conduct a sensitivity test on indicator selection is to perform calculations on the same model using varying numbers of selected or randomised indicators and then compare the results. Another aspect of sensitivity analysis focuses on the impact of methodological decisions made during the model's setup. These decisions can affect the output results and may occur at various calculation stages, such as the initial phase of indicator normalisation, differences in rotation methods after the PCA process, and the method used for dimension index aggregation.

The validation process confirms that the model accurately reflects the real system and produces precise results. Validation can be done using secondary data, such as observable outcomes, or consulting with experts with direct knowledge of the study area. Since vulnerabilities may not have observable phenomena, validation can be done using proxies like damage, mortality, post-event surveys, and other relevant indicators.

6 Multidimensional Index of Indonesia

6.1. Disasters in Indonesia: Context and Data

Indonesia is a country that is prone to disasters. In the period from 2015 to 2023, Indonesia experienced 28,536 disaster incidents, resulting in 7,729 fatalities, as reported by Indonesia's National Disaster Management Agency (Data Informasi Bencana Indonesia (DIBI), 2024). These disasters include floods, extreme waves, land and forest fires, droughts, extreme weather, earthquakes, tsunamis, and landslides. The majority of these disasters, around 74.10%, are hydrometeorological, such as floods and extreme waves, while the rest are geological. Despite this, geological disasters, particularly earthquakes and tsunamis, have had a significant impact on the Indonesian population and the economy. Indonesia's location in the Pacific Ring of Fire makes it prone to volcanic eruptions due to the presence of many active volcanoes. Throughout history, the country has experienced significant events like the eruption of Mount Krakatoa in 1883, which resulted in the deaths of 36,000 people in Java (Morgan, 2013) and the Indian Ocean Tsunami in 2004, which claimed approximately 230,000 lives. (Rabinovich et al., 2015).

In addition to volcanic eruptions and seismic activity, Indonesia faces hydrometeorological disasters such as regular flooding and coastal inundation. For example, the flood in Jakarta in 2013 displaced 40,000 people (YEU, 2013). More than 42 million Indonesians live in low-lying areas, making them vulnerable to flooding (USAID, 2017). Furthermore, high rainfall increases the risk of landslides in hilly or mountainous areas, while the dry season brings drought, particularly in regions like West Nusa Tenggara and Timor. Certain areas like West, Central and East Java, Yogyakarta, Bali, and Nusa Tenggara are most vulnerable to extreme droughts (Sufa, 2019). In addition to these current challenges, Indonesia also faces the looming threat of climate change, which will exacerbate sea level rise, droughts, landslides, and other disasters.

The government reports that 97 percent of Indonesia's population is at risk of natural disasters, with earthquakes posing the highest risk (BNPB; UNPFA; BPS, 2015). In addition to earthquakes, floods are also a major concern for Indonesia. Flooding not only causes inundation but also spreads diseases. Pollution is another significant threat, whether in the air of urban areas or as a result of forest fires during the long dry season.

Exposure to disasters is correlated with socio-economic vulnerability. Poverty is a significant factor that impacts other vulnerabilities, such as lack of education, access to resources, healthcare, nutritious food, and other essential needs(Hallegatte et al., 2020). Gender also plays a role in vulnerability in Indonesia due to limited job opportunities, low wages, unequal household responsibilities, unequal education levels, and various forms of discrimination, making women more vulnerable (Arif et al., 2010).

Additionally, conflict between communities can lead to social vulnerability in Indonesia due to its cultural diversity and the potential for social friction. For example, the inter-tribal conflict between the Dayak and Madurese tribes in 2001 is a notable example of this (Intani et al., 2022). Lack of access to healthcare also contributes to vulnerability, with stunting being a major health problem in many areas of Indonesia (Ministry of Health, 2013).

Moreover, institutional problems, such as high levels of corruption, further contribute to societal vulnerability. Indonesia's corruption perception index in 2023 is expected to receive a low score, ranking 115th out of 180 countries (Transparency International, 2023). It is crucial to identify further the various vulnerability profiles that make the Indonesian population susceptible to natural disasters, particularly in understanding the social dimensions of impacts, which significantly influence community resilience to disasters. Indonesia, with its various disaster risks, unique geological and climatic conditions, and a wide range of data on community vulnerability, presents an intriguing case study for the study of disasters and vulnerability.

In this research, we will try to see the state of social vulnerability in Indonesia in terms of index numbers. We plan to utilise a multidimensional index approach, using the model construction discussed in the previous chapter. The data for our model will be sourced from three primary references: the SMERU poverty map 2015, PODES 2014, and Indonesian demographic data 2019.

The SMERU Poverty Map 2015 is an updated version of the poverty map series released by SMERU in 2000 (SMERU Insititute, 2015). It combines data from various sources, including the 2010 population census, 2010 Susenas, and 2014 Podes survey. This poverty map records data at the village or administration level 4, covering over 75,000 villages in Indonesia. It includes multiple indicators such as poverty rate estimations based on the national poverty line (NPL) and the international poverty line (IPL-US$3.1PPP), poverty gap using NPL and IPL, poverty severity, and the Gini ratio index.

Village Potential Data, abbreviated as PODES, is a statistical survey conducted by the Indonesian Central Bureau of Statistics (BPS). Its purpose is to collect data about the availability, development, and existence of potential at the village level (BPS, 2014). This statistical survey was conducted three times over a period of ten years and is used for national and regional planning, as well as for determining regional classification and other statistical activities. In our research, we extracted several groups of variables from the PODES data source. These groups include natural assets (e.g., natural resources, natural disasters, and pollution), financial assets (such as the number of banks, cooperatives, and availability of credit facilities), physical assets (e.g., essential infrastructure in the village), human assets (considering the quality and condition of the villagers), and social assets (including conflicts in the village). We will use the data from PODES as input for the multidimensional index model.

The final data source used as an input variable for the Indonesian multidimensional index is Indonesian demographic data from 2019 (Ministry of Internal Affairs, 2019). This statistical data contains demographic information at the village level, covering various aspects such as population and area. From this data source, we will use demographic information such as the number of people per gender, the distribution of people across different age groups, education levels, and the unemployment rate. These three data sources provide the input variables for our model, and the specific variables can be found in the Table 4 below.

Table 4 Variables of Indonesia data for social vulnerability measurement

Variable	Description	Type	Source
pds_banjir	Ever Experiencing Natural Disasters: Flood	Binary	PODES 2014
pds_banjirbandang	Ever Experiencing Natural Disasters: Flash Flood	Binary	PODES 2014
pds_minumbersih	Availability of Safe Drinking Water Source	Binary	PODES 2014
pds_koperasi	Number of Cooperative	Continuous	PODES 2014
pds_credit	Availability of Credit Facilities	Binary	PODES 2014
pds_sd	Number of Primary School	Continuous	PODES 2014
pds_puskesmas	Number of Puskesmas	Continuous	PODES 2014
pds_trayek	Availability of Public Transportation	Binary	PODES 2014
pds_road	Village Road can be Traversed for the Whole Year	Binary	PODES 2014
pds_sinyal	Availability of Cellular Signal	Binary	PODES 2014
pds_market	Market Existence	Binary	PODES 2014
pds_cacat	Number of Disabled People	Continuous	PODES 2014
pds_kelahi	Existence of Social Conflict	Binary	PODES 2014
p0_gkn	Poverty Rate using National Poverty Line (NPL)	Continuous	Estimate using Poverty Map
p1_gkn	Poverty Gap using National Poverty Line (NPL)	Continuous	Estimate using Poverty Map

p2_gkn	Poverty Severity using National Poverty Line (NPL)	Continuous	Estimate using Poverty Map
gini	Gini Index	Continuous	Estimate using Poverty Map
WANITA	Number of Women	Continuous	Indonesia Demographic Data 2019
TIDAK_BELU	Number of People Who Do Not Attend School	Continuous	Indonesia Demographic Data 2019
BELUM_TAMA	Number of People Who Have Not Finished School Yet	Continuous	Indonesia Demographic Data 2019
BELUM_TIDA	Number of Unemployed People	Continuous	Indonesia Demographic Data 2019
underage	Number of People Under 15 Years Old	Continuous	Indonesia Demographic Data 2019
oldies	Number of People Over 60 Years Old	Continuous	Indonesia Demographic Data 2019

Using the variables in the table above, we will apply a multidimensional index model to analyse social vulnerability in Indonesia.

6.2. Measuring Social Vulnerability in Indonesia

In order to calculate the social vulnerability using the multidimensional index approach, we will follow the guide created on the Chapter 5 which can be seen in the Figure 8 below.

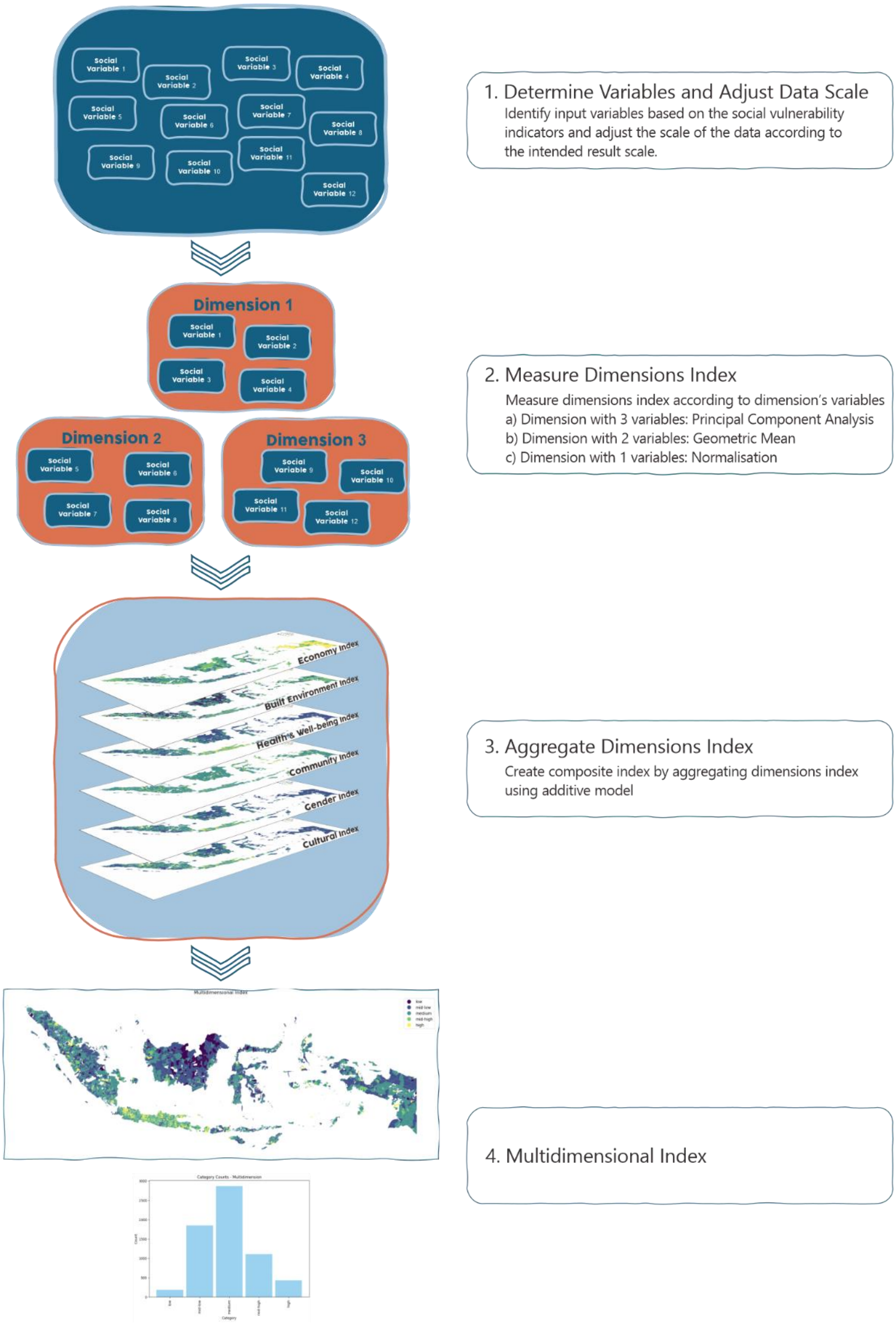


Figure 8 Multidimensional Index flow chart. Each figure explains the step that is taken in the measurement process.

First, we need to start by grouping the variables we have into the social impact dimensions within the Multidimensional Index. The categorisation of variables into social impact dimensions is outlined in Table 5 Below:

Table 5 Social variables of Indonesia in dimensions of social impacts

Dimension	Variable Name	Description	Type
Economy	p0_gkn	Poverty Rate using National Poverty Line (NPL) -> FGT0 = Number of poor people / Total population	Continuous
	p1_gkn	Poverty Gap using National Poverty Line (NPL) -> FGT1 = (NPL - Per capita expenditure) / NPL*Total population	Continuous
	p2_gkn	Poverty Severity -> FGT2 = Square of FGT1	Continuous
	gini	Gini Index	Continuous
	pds_koperasi	Number of Cooperative	Continuous
	pds_credit	Availability of Credit Facilities	Binary
	BELUM_TIDA	Unemployment number	Continuous
Cultural	TIDAK_BELU	Number of people without education	Continuous
	BELUM_TAMA	Number of people have not finished education	Continuous
Gender	WANITA	Number of women	Continuous
Community	pds_kelahi	Existence of Social Conflict	Binary
Health & Wellbeing	underage	Number of underage people	Continuous
	oldies	Number of elderly	Continuous
	pds_cacat	Number of Disabled People	Continuous
Built Environment	pds_trayek	Availability of Public Transportation	Binary
	pds_road	Village Road can be Traversed for the Whole Year	Binary
	pds_sinyal	Availability of Cellular Signal	Binary
	pds_sd	Number of Primary School	Continuous
	pds_banjir	Ever Experiencing Natural Disasters: Flood	Binary
	pds_banjirbandang	Ever Experiencing Natural Disasters: Flash Flood	Binary
	pds_minumbersih	Availability of Safe Drinking Water Source	Binary
	pds_puskemas	Number of health facilities in the village	Continuous

After grouping the variables based on their social dimensions, we analyse them on a subdistrict scale, one level higher than the village. Because our original data is at the village level, we need to aggregate the values to standardise the raw data and analysis scale. As mentioned earlier, we will find the totals for variables with continuous data in each subdistrict, while for binary data, we will use the mean at the subdistrict level.

The index for each dimension was measured using the aggregated data. The method used to calculate the number of variables in each dimension will be different according to the number of variables in each dimension. The index of each dimension will be crucial for further analysis, as it allows us to see the intensity of vulnerability for each dimension. We map the index using the index of all dimensions to see the spatial distribution of the dimension index. Five groups of the social vulnerability level on the map are defined using the standard deviation. The groups are high (>1,5 std), mid-high (0.5 to 1.5 std), medium (-0.5 to 0.5 std), mid-low (-1.5 to -0.5 std), and low (<-1.5 std).

The Multidimensional Index does not just generate a single vulnerability index as the primary result but also provides indexes for each vulnerability dimension. These can offer valuable insights for analysis. The index calculation outcomes for each dimension are illustrated in Figure 9 to Figure 14 Below.

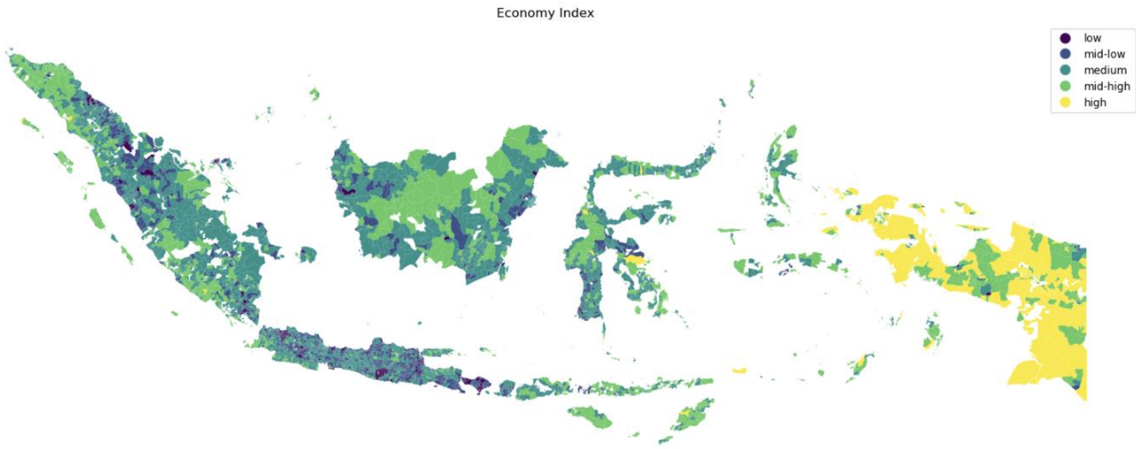


Figure 9 The map of Economy Index of Indonesia categorised by colour

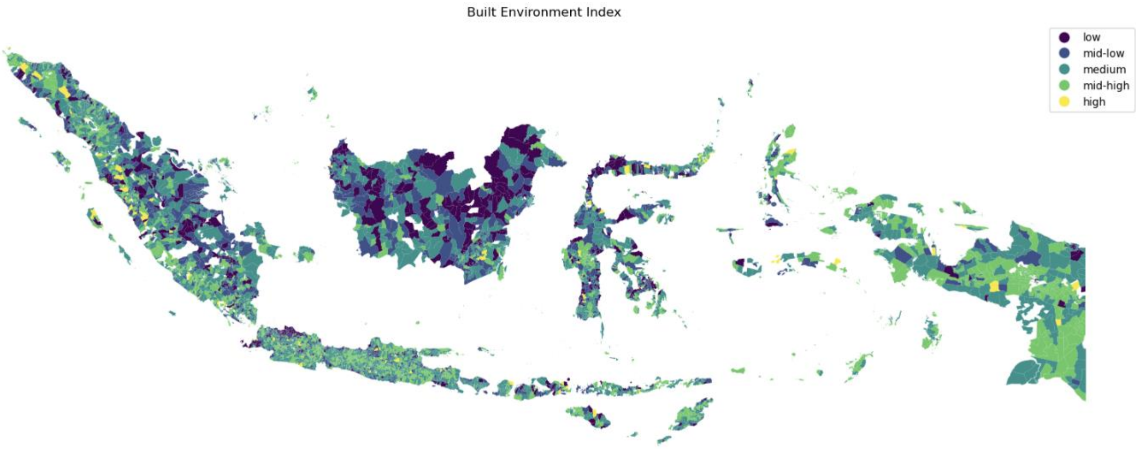


Figure 10 The map of Built Environment Index of Indonesia categorised by colour

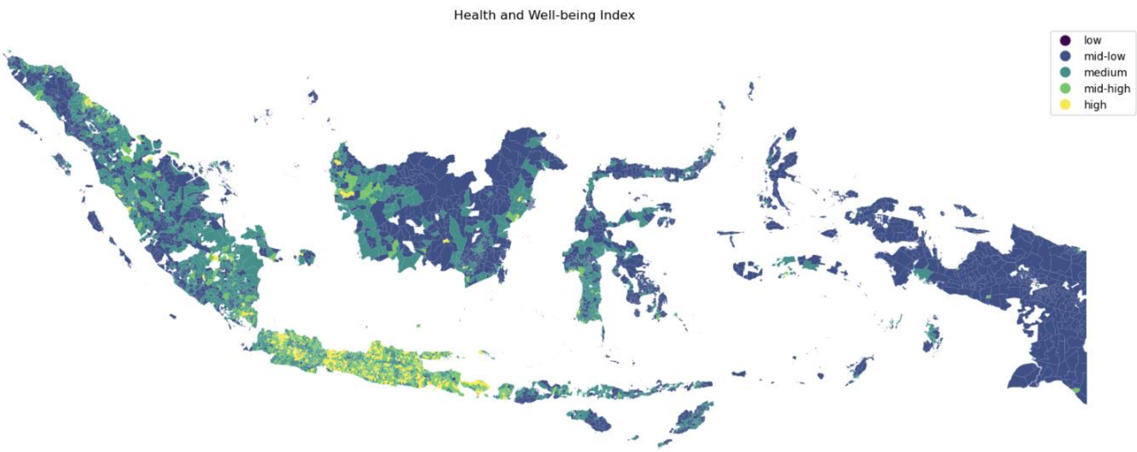


Figure 11 The map of Health and Well-being Index of Indonesia categorised by colour

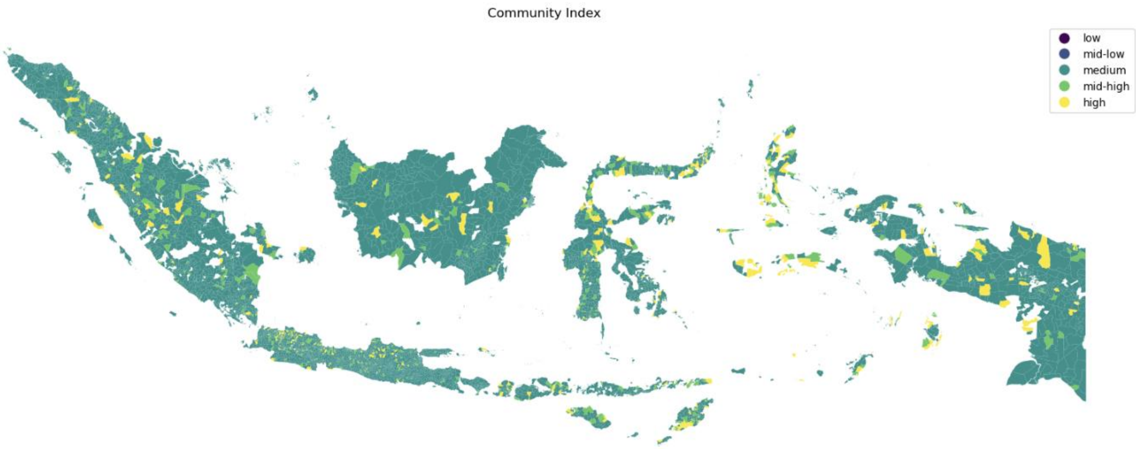


Figure 12 The map of Community Index of Indonesia categorised by colour

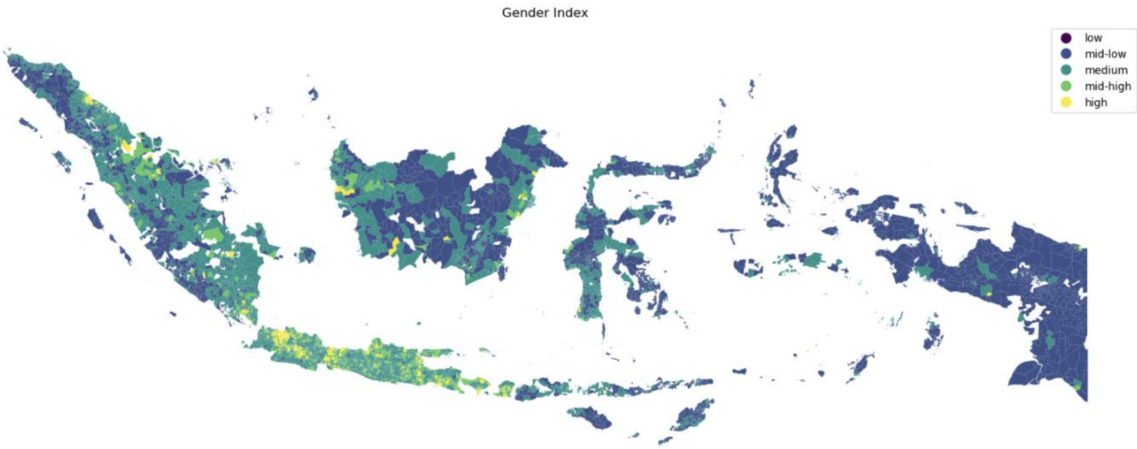


Figure 13 The map of Gender Index of Indonesia categorised by colour

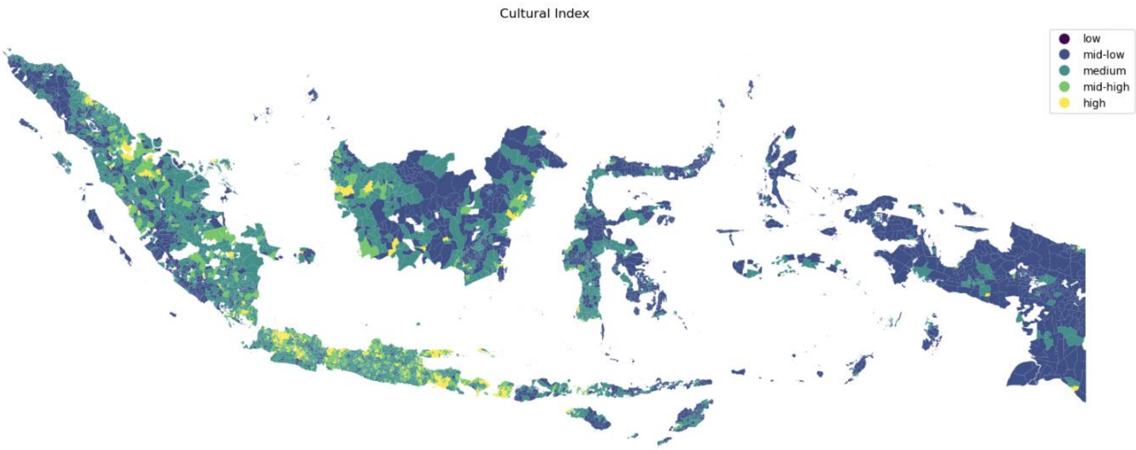


Figure 14 The map of Cultural Index of Indonesia categorised by colour

The data from each index map for each dimension allow us to assess social vulnerability in each subdistrict in Indonesia. We can observe the vulnerabilities in each dimension to gain a more thorough understanding.

Then, we utilise the dimensional indexes to aggregate and derive the ultimate multidimensional index. This index aids in comprehending the distribution and comparison of social vulnerability in each subdistrict in Indonesia. Furthermore, it enables us to analyse the intensity of vulnerability in each dimension, identify predominant vulnerability dimensions, and conduct other analyses at the dimension level rather than solely at the final index. Below, you can observe Indonesia's multidimensional index and its categories distribution using our social variables.

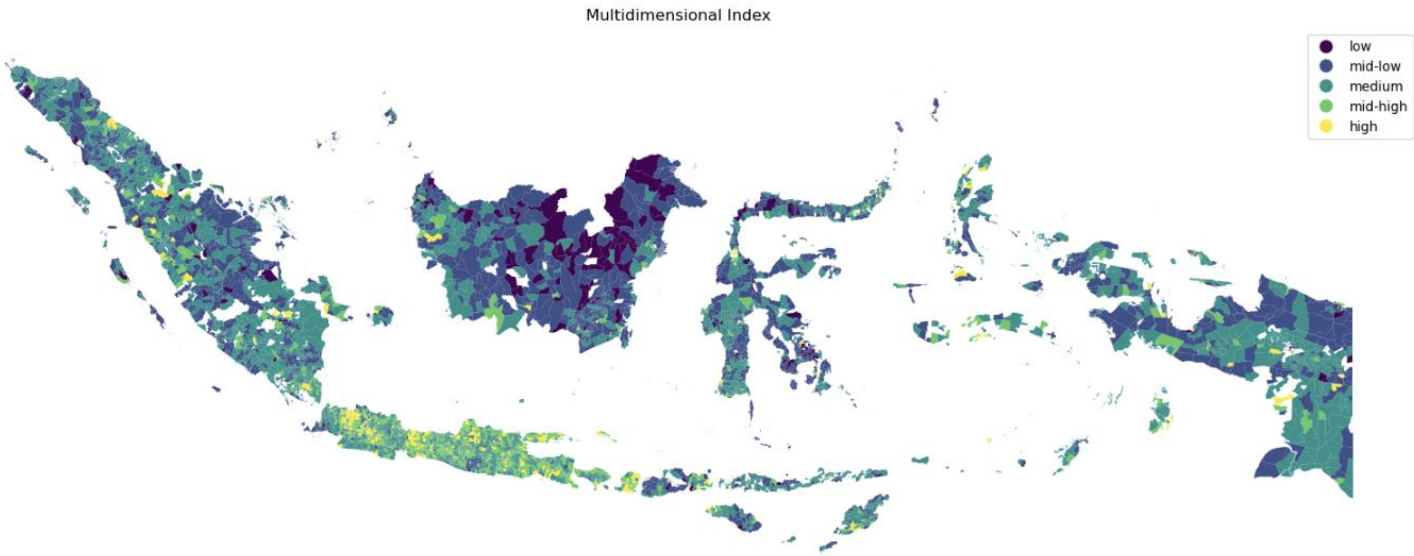


Figure 15 The map of Multidimensional Index of Indonesia categorised by colour

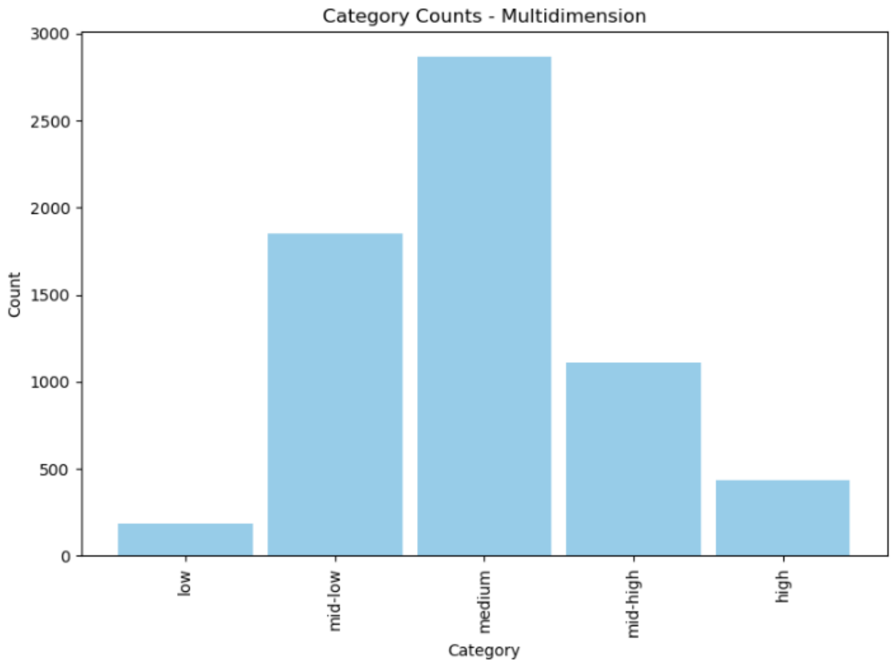


Figure 16 Distribution of Multidimensional Index categories

Based on the map in Figure 15 above, we can analyse the level of social vulnerability in different regions. The spatial distribution can be easily understood by observing the colour-coded categories on the map. For reference, the legend at the top-right of the map indicates a low vulnerability in purple and a high vulnerability in yellow, with other categories represented by different colours. Additionally, in Figure 16's distribution diagram, we can observe the distribution of social vulnerability categories in Indonesia, starting from low-level vulnerability to high-vulnerability areas. Further analysis of the Indonesian Multidimensional Index will be carried out in the section 6.3.

6.2.1. Sensitivity Analysis

We are conducting a sensitivity analysis on the multidimensional index to understand how changes in the model impact the final index results. Throughout this test, we will observe how the results vary when we modify the process from the dimension index aggregation stage to the final multidimensional index. This is to assess the impact of differences in structure and method on the resulting index. To carry out this analysis, we will test two aggregation methods: geometric mean and PCA. The geometric mean is an alternative aggregation method chosen due to its ability to provide a fair representation of smaller values in the final index. Meanwhile, PCA has been selected as a statistical tool to produce a composite index. We will compare the results of the two aggregation methods with the original method of the multidimensional index, the additive model or the sum model. The analysis will encompass correlation analysis, rank correlation analysis, and visual analysis.

Table 6 Correlation analysis of additive model, geometric mean, and PCA.

	Additive	Geometric Mean	PCA
Additive	1.000000	0.719837	0.499578
Geometric Mean	0.719837	1.000000	0.710498
PCA	0.499578	0.710498	1.000000

Table 6 displays the correlation values between each aggregation method. These values are derived from comparing the results of the two methods using the Pearson correlation coefficient. A value closer to 1 indicates a higher correlation between variables. The geometric mean shows a moderate positive correlation with the original additive model, showing a significant relationship. However, the PCA method demonstrates a lower correlation value of 0.499, suggesting that it captures different dimensions compared to the original method.

Table 7 Rank correlation of additive model, geometric mean, and PCA.

	Additive	Geometric Mean	PCA
Additive	1.000000	0.768694	0.286213
Geometric Mean	0.768694	1.000000	0.7202782
PCA	0.286213	0.7202782	1.000000

In the analysis presented in Table 7, we observed the rank correlation among different methods. Rank correlation is a method used to measure the relationship between the rankings of different variables. We employ Spearman rank correlation, which evaluates how well the relationship between two variables can be described using a monotonic function. In rank correlation here, the higher the Spearman's rank correlation value, the stronger the relationship between the two aggregation methods. The comparison revealed a strong correlation between the additive model and geometric mean method, suggesting that the rankings of subdistricts using these two methods are quite similar. However, the PCA method exhibited a lower rank correlation, indicating notable differences in its rankings.

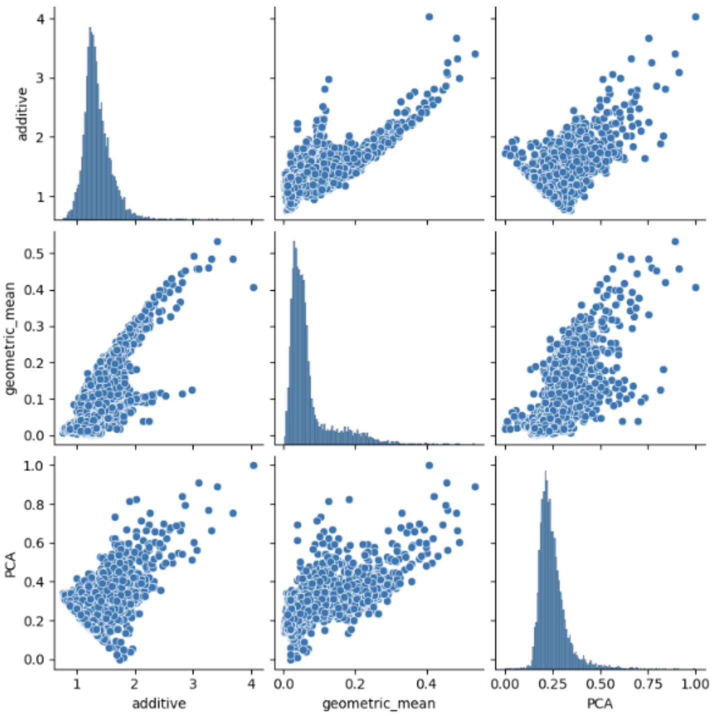


Figure 17 Visual sensitivity analysis of additive model, geometric mean, and PCA.

In the next step, we conducted an analysis based on data distribution across all methods, as shown in Figure 17 above. The graphs of the additive model and geometric mean method exhibit a positive linear relationship with some dispersion, suggesting a correlation between them, although they are not identical. On the other hand, the graph of the additive model and the PCA method shows more dispersion, indicating that these methods capture different aspects in their results.

The sensitivity analysis indicates that even a small change in the aggregation method used to produce a composite index at the final stage of the multidimensional index method can significantly influence the final index results. This is especially evident with significant method changes, such as using PCA, as the original additive model and PCA have different concepts and techniques. In general, the geometric mean yields relatively balanced results similar to the additive model, albeit with slight differences from a macro perspective.

The choice of aggregation method for creating a composite index should be tailored to the needs of the model creator and user. Our sensitivity experiment used the geometric mean when dealing with different scales, many outliers, and when the sub-indices contribution is multiplicative. However, it is important to note that the geometric mean is sensitive to zero values, as they can produce zero results in the aggregation. On the other hand, PCA is used to reduce the data dimensions and apply weights to sub-indices. The differences in results and patterns of existing methods will have benefits for their respective needs.

6.3. Analysis and Interpretation

In order to analyse the results of calculating the Multidimensional Index in Indonesia, we will revisit the initial importance of this tool in converting social vulnerability into measurable values. As discussed in previous chapters, natural disasters can impact people differently, even within the same area and timeframe. This difference is due to varying levels of social vulnerability among individuals. Social vulnerability refers to an individual's susceptibility to the harmful effects of a disaster.

Vulnerability is not limited to a single dimension; an individual may experience multiple dimensions of vulnerability, such as economic, gender, and cultural vulnerability. For instance, an elderly person living in poverty and facing language barriers falls into section 4.2. Individuals with multiple dimensions of vulnerability are likely to be more severely affected by natural disasters compared to those with fewer vulnerabilities. Analysis using an intersectional perspective is valuable for understanding these conditions and viewing social vulnerability from a multidimensional perspective.

The Multidimensional Index offers crucial insights for analysing social vulnerability across multiple dimensions, providing a comprehensive understanding of various aspects of vulnerability. To demonstrate the application of the Multidimensional Index in Indonesia, we will examine Java Island as a case study. Java serves as the economic hub and the seat of the Indonesian capital, contributing 56.48% to the overall Indonesian economy as of 2023 (BPS, 2023) (see Figure 18a). Despite having the highest population, Java achieved the highest high school completion rate at

73.5% in 2023 (BPS, 2024) (see Figure 18b). Additionally, Java boasts well-developed infrastructure, pervasive road networks that ensure year-round accessibility (BPS, 2014) (see Figure 18c). These indicators denote Java as a prosperous region with a well-educated population and robust infrastructure.

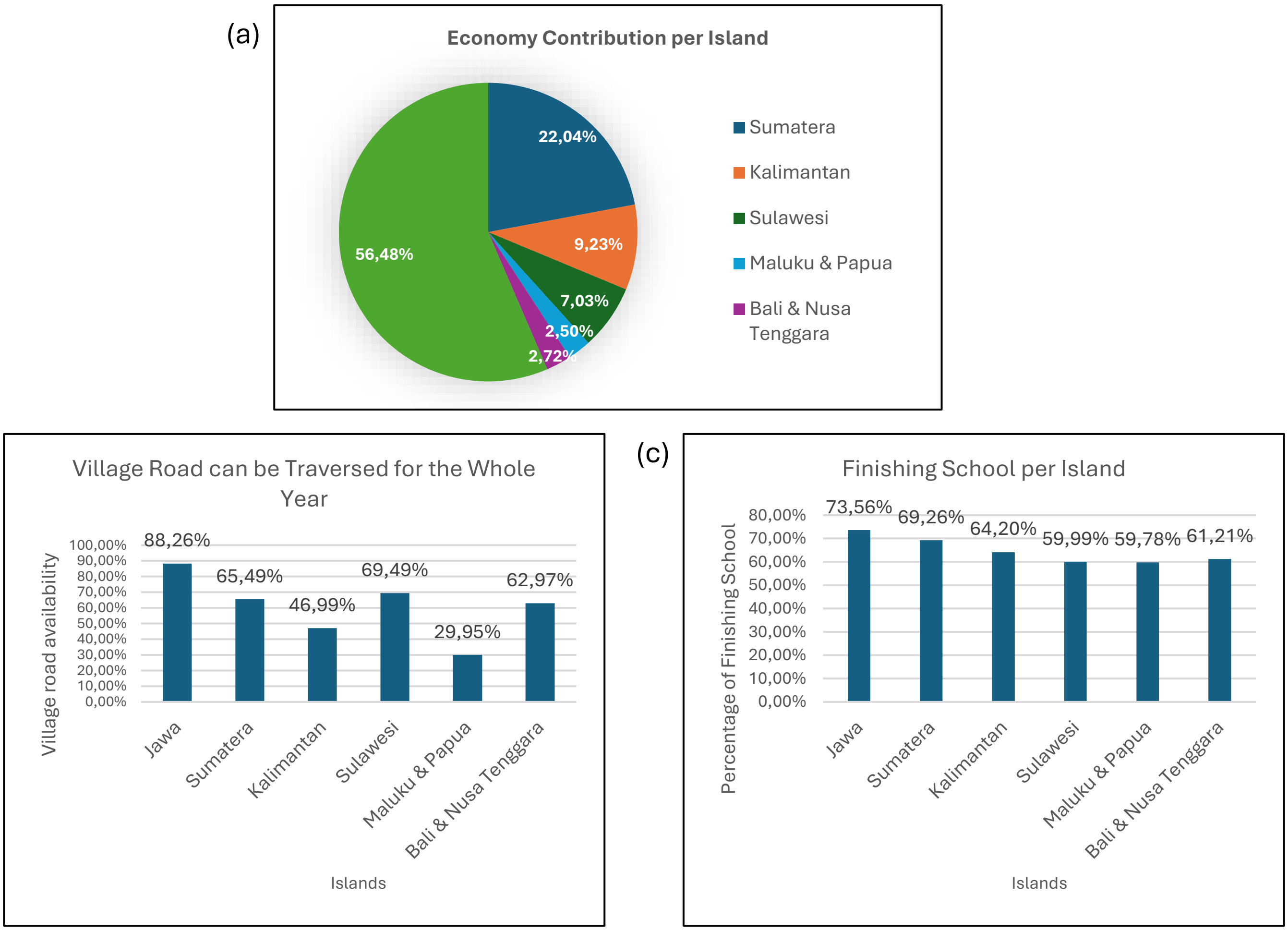


Figure 18 Socio economy data of Jawa (a) Economy contribution per island to Indonesia economy (BPS, 2023); (b) Percentage of Finishing School (BPS, 2024); *(c) Village road can be traversed for the whole year* (BPS, 2014).

It is helpful to understand how the social vulnerability index is interpreted to relate information about Java to the vulnerability assessment process. This index is a tool used to evaluate and compare the level of social vulnerability across different regions. It categorises regions into five levels, ranging from low to high. The higher the index category, the more susceptible an area is to disasters. Based on the available data, Java seems to have relatively low social vulnerability compared to other islands. Siagian's (2014) calculation using the Social Vulnerability Index (SoVI) categorised most areas in Java as moderate (see Figure 19). Similarly, the calculations in this study (Section 7.2) also placed most areas of Java in the moderate category. However, is this also found in the Multidimensional Index results on Java?

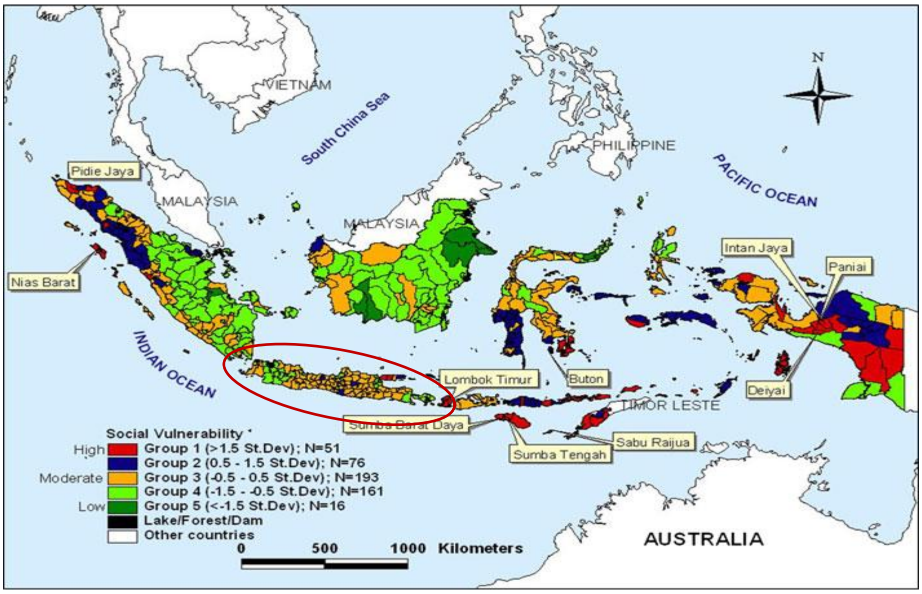


Figure 19 Social Vulnerability Index of Indonesia by Siagian et al. (2014).

Interestingly, the results of the Multidimensional Index on the island of Java show different things (see Figure 20) where there are several areas with a high vulnerability index on the island of Java. Contrary to previous assumptions based on the Social Vulnerability Index (SoVI), some areas of Java have a high vulnerability index. This is unexpected, given Java's overall prosperity, education, and infrastructure. To better understand this, we should analyse the vulnerability in each dimension of Java. It is important to remember that the Multidimensional Index considers all vulnerability dimensions equally.

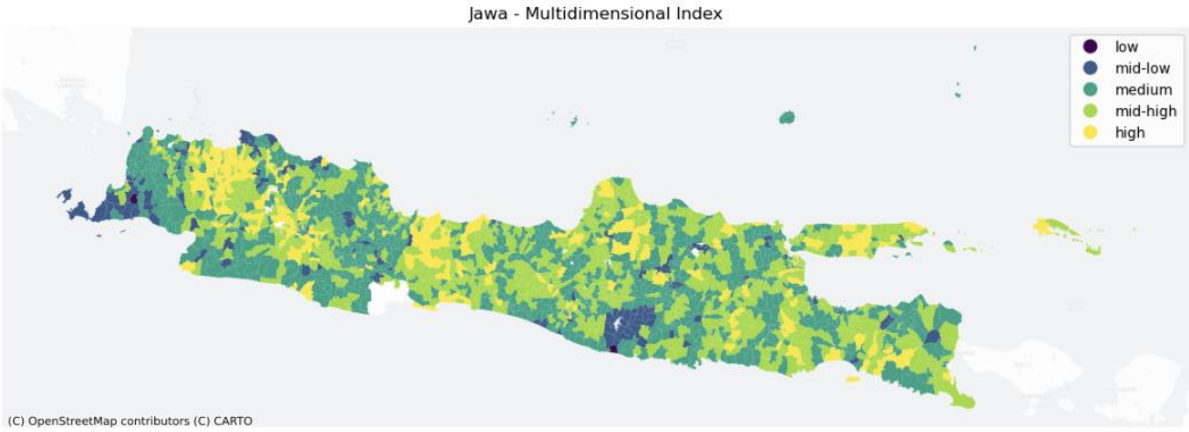


Figure 20 The map of Social Vulnerability Index in Jawa using Multidimensional Index method

In order to observe the relationship between favourable economic and infrastructure conditions and vulnerability in the economic and built-environment aspects, we can refer to Figure 21 and Figure 22. The Economy and Built-Environment Index illustrates vulnerability in the economic and infrastructure sectors. In general, subdistricts on the island of Java fall into the medium category. This aligns with the good economic and infrastructure conditions on the island of Java, resulting in relatively low vulnerability values in these two dimensions. Data and vulnerability calculations yield similar results. However, it is interesting to note that the final social vulnerability index indicates that a number of subdistricts on the island of Java are in the high vulnerability category. We should explore other dimensions that also influence social vulnerability on the island of Java.

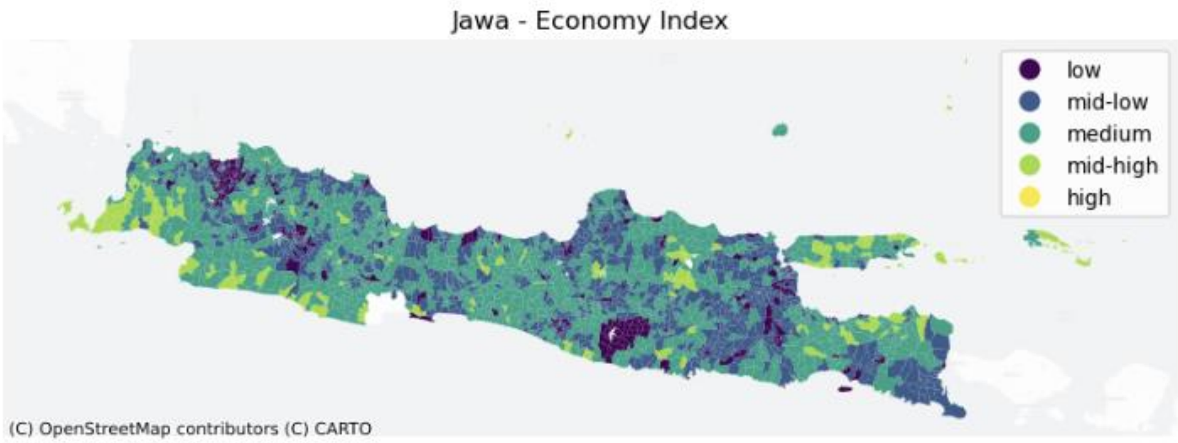


Figure 21 The map of Economy Index of Jawa categorised by colour

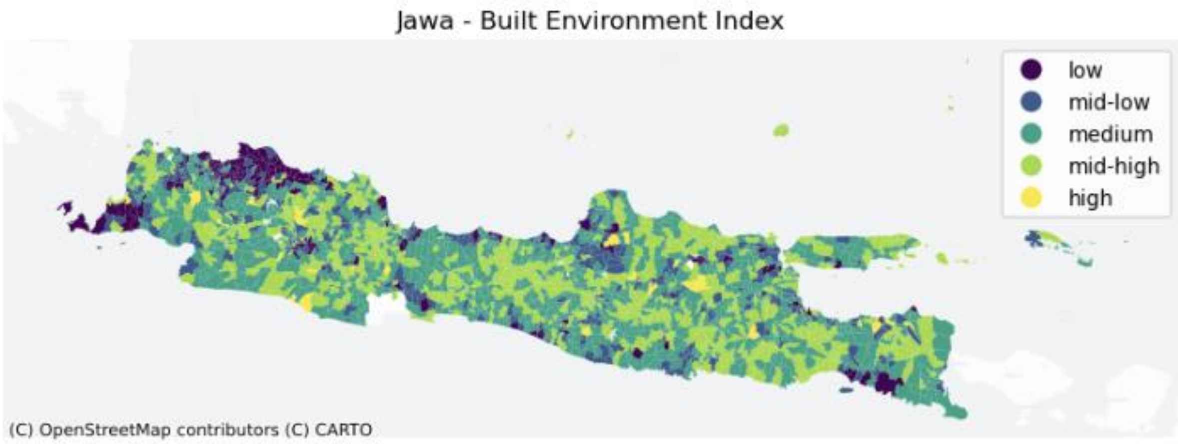


Figure 22 The map of Built Environment Index of Jawa categorised by colour

Aside from economic and built environment factors, other dimensions also contribute to the final social vulnerability value. Figure 23 and Figure 24 show the calculation results for the Health & Well-being and Gender dimensions on Java Island, showing significant dimension index results. These dimensions differ from the economic and built environment dimensions, as many subdistricts with a high vulnerability category spread fairly evenly across Java Island. We can examine the indicators that make up these dimensions to see more details. The Health & well-being dimension includes variables related to infancy, older people, and individuals with disabilities. On the other hand, the gender dimension reflects the number of women in each subdistrict. The high health & well-being and gender dimension index results indicate a significant population on Java Island with these characteristics, which falls into the vulnerable category in natural disaster conditions and makes a corresponding contribution to the final vulnerability index assessment.

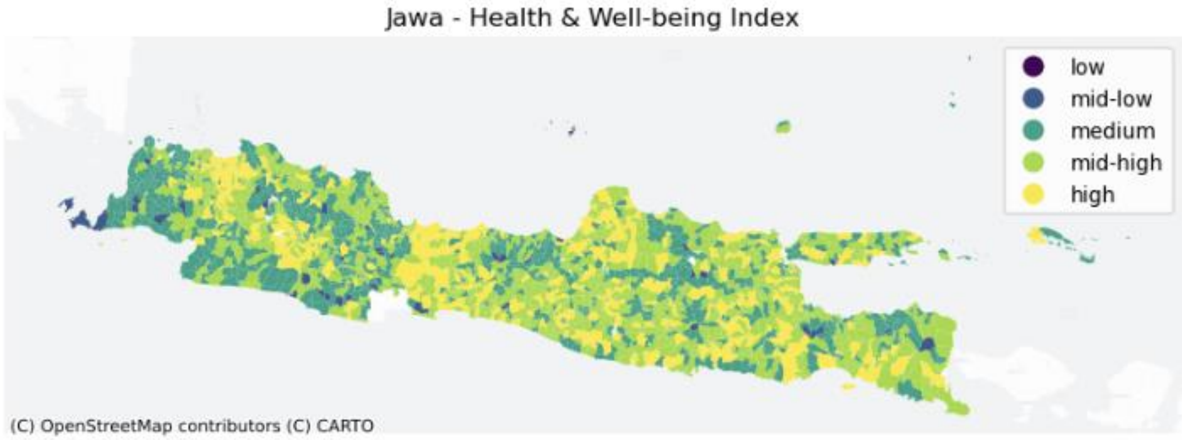


Figure 23 The map of Health & Well-being Index in Jawa categorised by colour

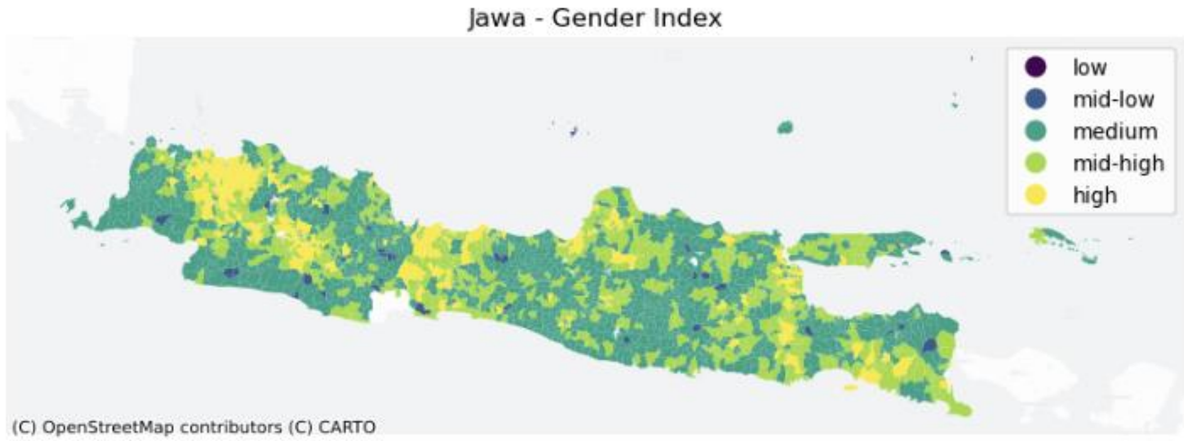


Figure 24 The map of Gender Index in Jawa categorised by colour

Based on the analysis of Java Island, it is evident that the island is in good condition and has a medium level of vulnerability. However, certain factors from the health & well-being and gender dimensions contribute to some subdistricts falling into the high vulnerability category. It is important to note that different vulnerability index results may be obtained from alternative calculation methods due to varying weighting and assessment processes of variables and indicators.

This analysis example helps to illustrate how the Multidimensional Index operates by incorporating intersectionality analysis or, in simpler terms, providing a proportional portion on all vulnerability dimensions. By taking into account all vulnerability dimensions rather than focusing solely on one dominant vulnerability indicator, the multidimensional index maps the intensity of vulnerability across all dimensions and generates a vulnerability index that is proportionate to all aspects of vulnerability. In a more theoretical explanation, intersectionality in multidimensionality pays attention to other dimensions of vulnerability that contribute to overall vulnerability. This approach ensures that a person or population with multiple vulnerabilities can be correctly recognized based on the vulnerability attributes they possess.

Similar analyses can be conducted on various islands or regions using different scales and case examples. The indices generated by the Multidimensional Index method can serve as a tool for calculating social vulnerability using a multidimensional approach. This is particularly helpful for those requiring vulnerability analysis encompassing intersectionality and multiple dimensions.

7 Comparison of SoVI and Multidimensional Index

7.1. Introduction to Social Vulnerability Index (SoVI)

The development of the vulnerability index to assess the social vulnerability index (SoVI) began when Cutter (1996) introduced the Hazard of Place (HOP) model to explain vulnerability to natural hazards. The HOP model conceptualises the dynamic interaction between physical and social systems in creating vulnerability. This model uses statistical data and social variables to quantify vulnerability, combining perspectives from risk-hazard and political ecology research. The HOP model emphasises that vulnerability, like damaging events, is place-based and context-specific. It focuses on socio-vulnerability and is formed from 8 socio-economic indicators. To further her research, Cutter et al. (2003) gathered 250 socio-economic and built environmental variables from the 1990 decennial census to develop the Social Vulnerability Index (SoVI). This index was created to compare pre-existing social vulnerability through a composite index empirically. The SoVI is mapped and categorised using standard deviation to show spatial social vulnerability in the US. Then, in the next phase, Cutter & Finch (2008) We tested SoVI's temporal stability, finding that it consistently explained between 73 and 78 percent of variance over an extended time period, with the number of components ranging from 9 to 12. SoVI has become a commonly used method for quantifying vulnerability in a social context.

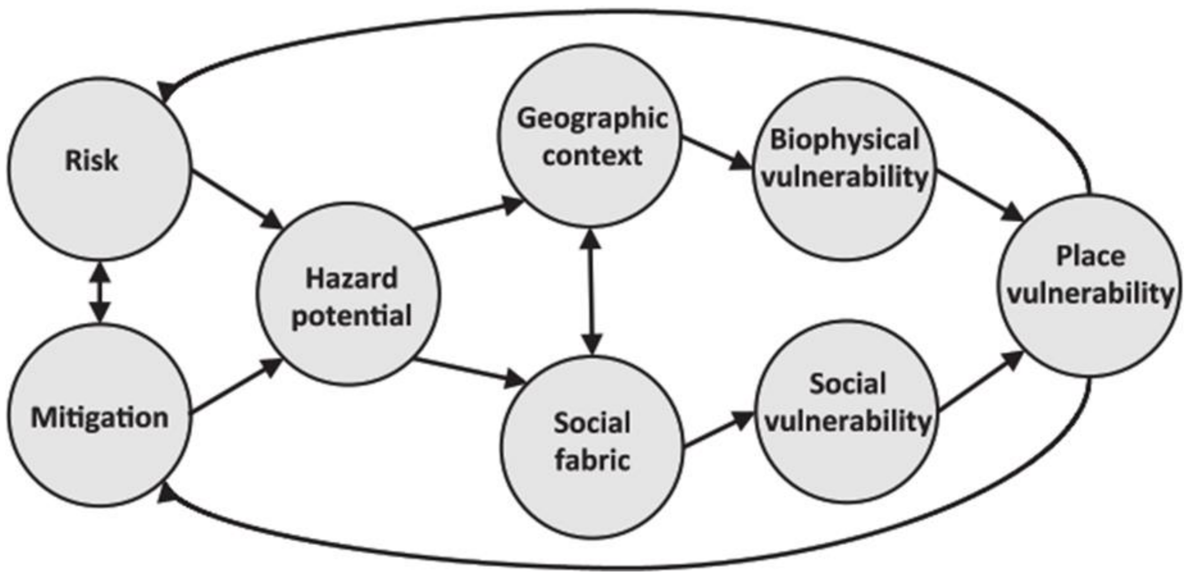


Figure 25 Hazard of Place Model by Cutter (Cutter, 1996).

PCA, as the primary statistical tool used in SoVI, employs mechanisms that need to be taken into account. As a method of assigning weights to input variables, PCA relies solely on statistical analysis. PCA assigns weights based on the variance of the variable, with variables exhibiting higher variance typically receiving more weight because PCA aims to capture the most significant sources of variation in the data (Wold et al., 1987). Additionally, PCA reduces dimensionality by transforming the original correlated variables into a smaller set of uncorrelated principal components. When we scrutinise the nature of PCA, it becomes clear that unequal weights can possibly be assigned to input variables. In reality, the significance of social vulnerability cannot be solely determined by an indicator's variance and statistical characteristics in the overall data. It is a complex system that may have high significance even if the statistical attributes do not appear dominant in the calculation process in PCA.

The SoVI calculation process involves several stages according to the Hazards & Vulnerability Research Institute (2016), the research institution that developed this method. The four main stages are Data Processing, Data Standardization, PCA, and SoVI computation, which can be seen in Figure 26. Data Processing involves normalizing input variables using percentages, per capita values, or density functions. Subsequently, the data is standardized using z-score standardization, resulting in a variable with a mean of 0 and a standard deviation of 1. The standardized data is then entered into the PCA model and subjected to varimax rotation. The number of components produced is determined using the Kaiser criterion or eigenvalue, which must exceed 1. This process can be visualized with a scree plot. The next step is to identify the dominant variable in each factor produced by the PCA model by setting a certain threshold for the factor loadings of each variable. These dominant variables determine the importance of each factor in contributing to social vulnerability. The final stage involves calculating the SoVI Index using an additive model based on the importance of each factor. The SoVI results can be used to create a social vulnerability map, which provides insights into social vulnerability within specific study areas.

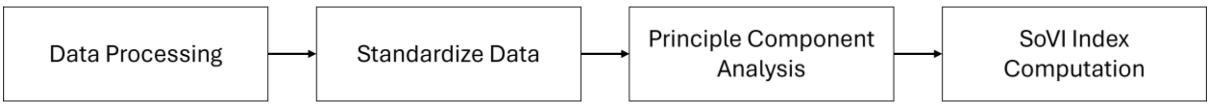


Figure 26 SoVI steps overview

7.2. SoVI of Indonesia

We will use social variables in Indonesia to calculate the SoVI Index value for each region in the country. The data and variables used in the SoVI calculation are the same as those used to produce the Indonesian Multidimensional Index in Chapter 6. The results of the SoVI calculation in Indonesia at the subdistrict scale, as well as the distribution of each SoVI category, can be seen in Figure 27 and Figure 28.

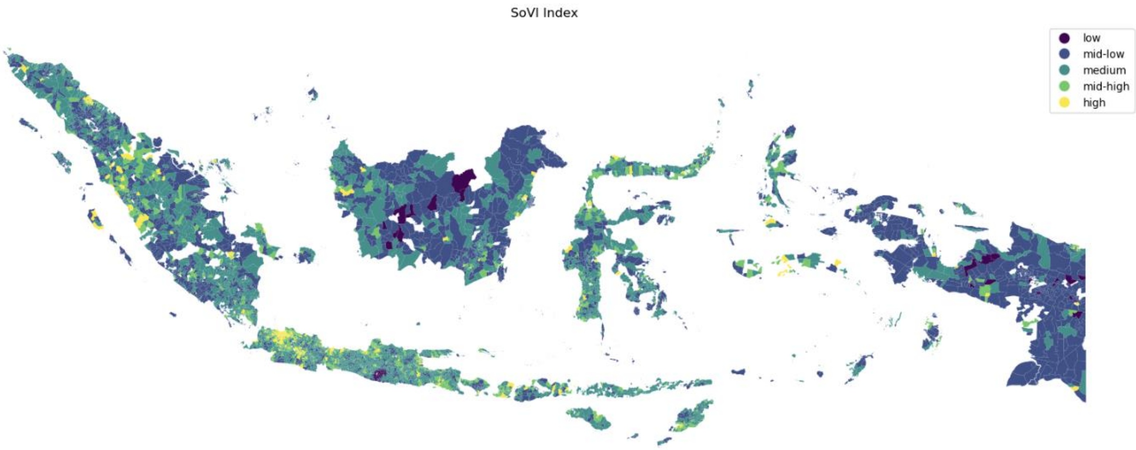


Figure 27 The map of SoVI of Indonesia categorised by colour

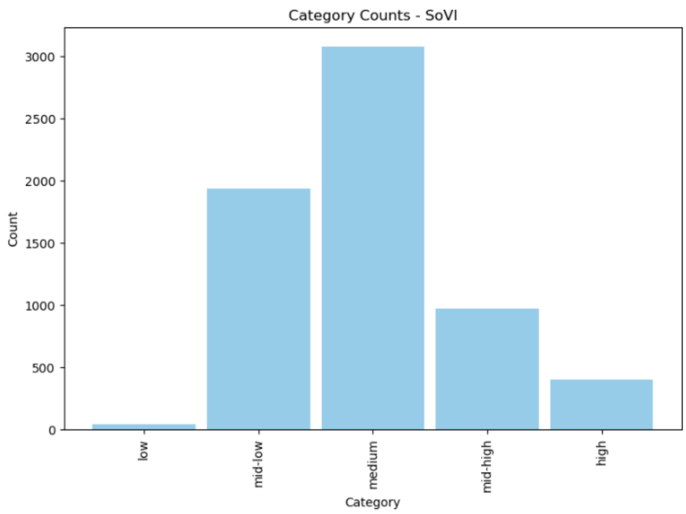


Figure 28 Distribution of SoVI categories

The SoVI mapping for all subdistricts in Indonesia displays the categorisation of social vulnerability based on SoVI. Looking at the map, we can observe several patterns. In Sumatra, most areas fall into the medium and mid-low categories, with only a few subdistricts classified as highly socially vulnerable, particularly in West Sumatra and Riau. Similarly, in Kalimantan, most areas are in the mid-low category, along with some in the low category. Sulawesi Island exhibits a similar pattern, with most areas in the medium category and a few in the high category. In Papua, social vulnerability values are evenly distributed across the region, mostly falling into the mid-low category, with only a few subdistricts in other categories. In the Maluku islands, Bali, and Nusa Tenggara, the majority of areas are in the medium category, with several in the mid-high and high categories. Notably, Java presents a different pattern, with a concentration of high social vulnerability categories, particularly around Jakarta and West Java.

Furthermore, the distribution pattern of the number of regions in each category, illustrated in Figure 19, reveals a general normal distribution pattern. The medium category contains the largest number of regions, while the mid-low and mid-high categories follow suit. Comparatively, the low and high categories encompass a considerably smaller number of areas. This demonstrates that, according to the SoVI index, Indonesian regions generally exhibit medium vulnerability, with some areas displaying high social vulnerability. Additionally, spatially, areas with high vulnerability tend to be concentrated, such as in the Jakarta area on the island of Java.

7.3. Comparative Analysis of SoVI and Multidimensional Index

Once we have the results of calculating social vulnerability using the SoVI method, we will compare them with the results of the multidimensional index for Indonesia from Chapter 6. Our goal in this research is to explore the multidimensional approach being used. We aim to enhance the process of calculating social vulnerability by developing a method encompassing all dimensions of social impacts in the index.

As discussed in the initial section, it is essential to note that PCA, the primary tool for reducing data dimensions in SoVI, tends to give more weight to variables with higher variance. This differs from the original intention of the multidimensional approach, which seeks to record vulnerability conditions by emphasising the representation of vulnerability dimensions in the calculation process. Another theoretical difference between SoVI and the multidimensional approach is that the multidimensional approach considers the interconnected relationship between vulnerability dimensions. By defining the index for each social impact dimension, this approach captures the unique characteristics of each population, allowing for a more detailed analysis of the compound vulnerabilities that may exist. Even though in its development, SoVI also considered multidimensional aspects by enabling the production of multivariate components (Cutter, 2024), the dynamics that occur in PCA in the component formation process allow for a situation of undermining variables by the statistical process in the PCA. Moreover, the striking difference with the Multidimensional Index is that the multidimensional aspect of SoVI occurs very dynamically and is very dependent on the state of the data and statistical processes in PCA, in contrast to the Multidimensional Index process, which from the start has accommodated the presence of vulnerability dimensions in the beginning. By mapping the intensity of vulnerability obtained from multidimensional index calculations, a more detailed population situation based on the vulnerability dimensions in this method can always be obtained in each calculation.

We will use three approaches to compare the results of the two methods for calculating social vulnerability. First, we will visually examine the distribution of social vulnerability. Second, we will do the class change analysis. Third, we will assess the contribution of each indicator to the index results. Visual observation aims to identify discrepancies between the two index results, focusing on distribution patterns for each category and comparing the distribution of numbers in each category of social vulnerability. Figure 29 provides a visual comparison of the two methods.

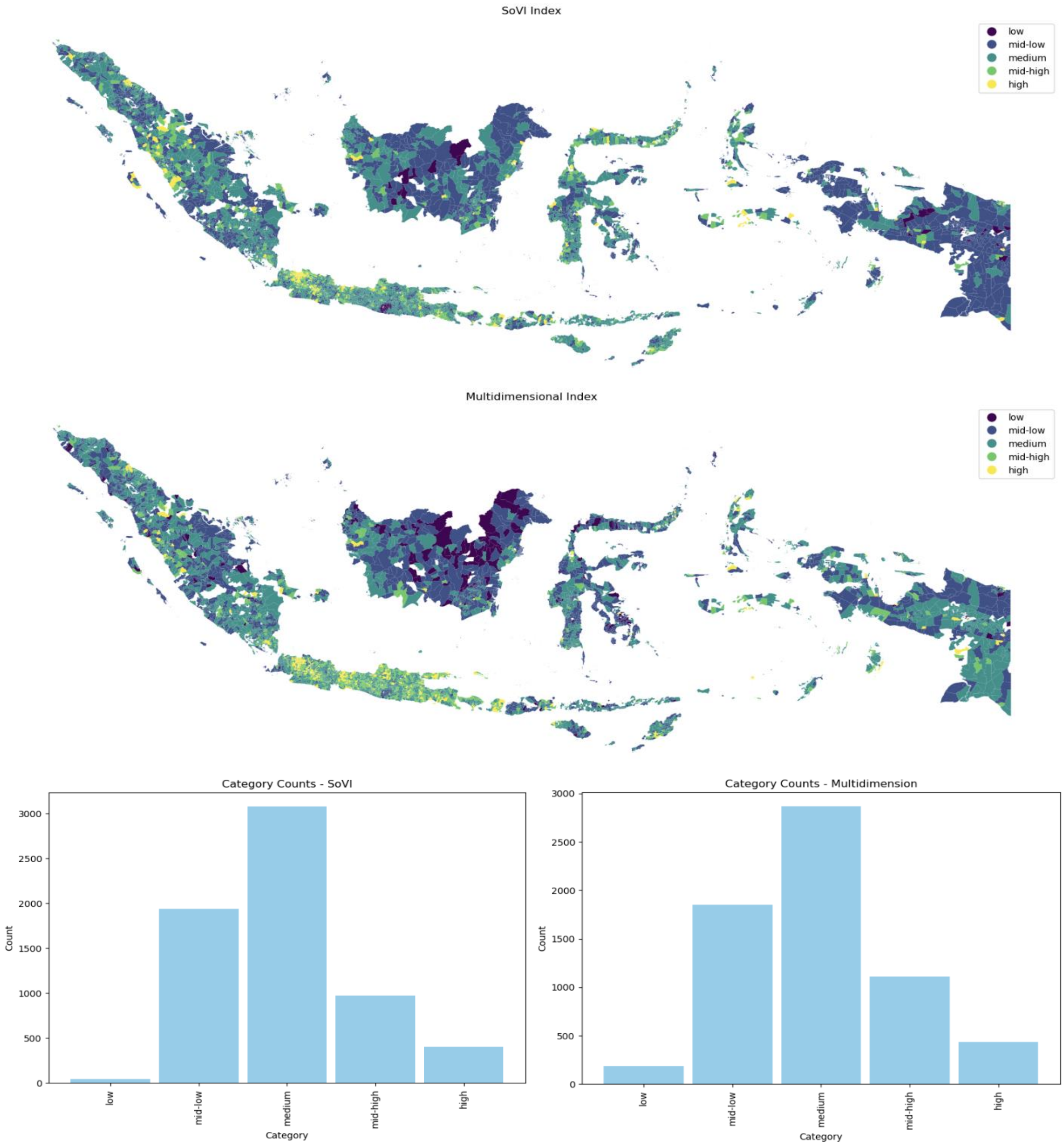


Figure 29 Map Comparison of SoVI and Multidimensional Index categorised by colour and the distribution of categories of SoVI and Multidimensional Index

Visually, we can see several differences between the SoVI map and the Multidimensional Index.

In this analysis, we will examine various examples of significant differences in the distribution of social vulnerability categories on the major islands of Indonesia. On the island of Sumatra, we observe notable differences in the West Sumatra and Riau areas, with more areas falling into the high and mid-high categories in the SoVI assessment results. In Kalimantan, differing patterns are evident in the northern, eastern, and central areas, with more areas falling into the low category in the results of the multidimensional assessment. On the island of Java, the most striking difference in pattern is observed, with several areas in the multidimensional assessment results categorised as high, spread throughout Java, as opposed to the concentrated areas around Jakarta in the SoVI assessment results. Lastly, in Papua, differences are noticeable in the South Papuan and Mountainous Papua regions, where the multidimensional index results show more regions in the mid-high category. Variations in the distribution patterns of vulnerability categories can be further explored in each region in Indonesia. This analysis highlights several differences in results between the two methods, which can impact the information provided to each region in formulating disaster management policies.

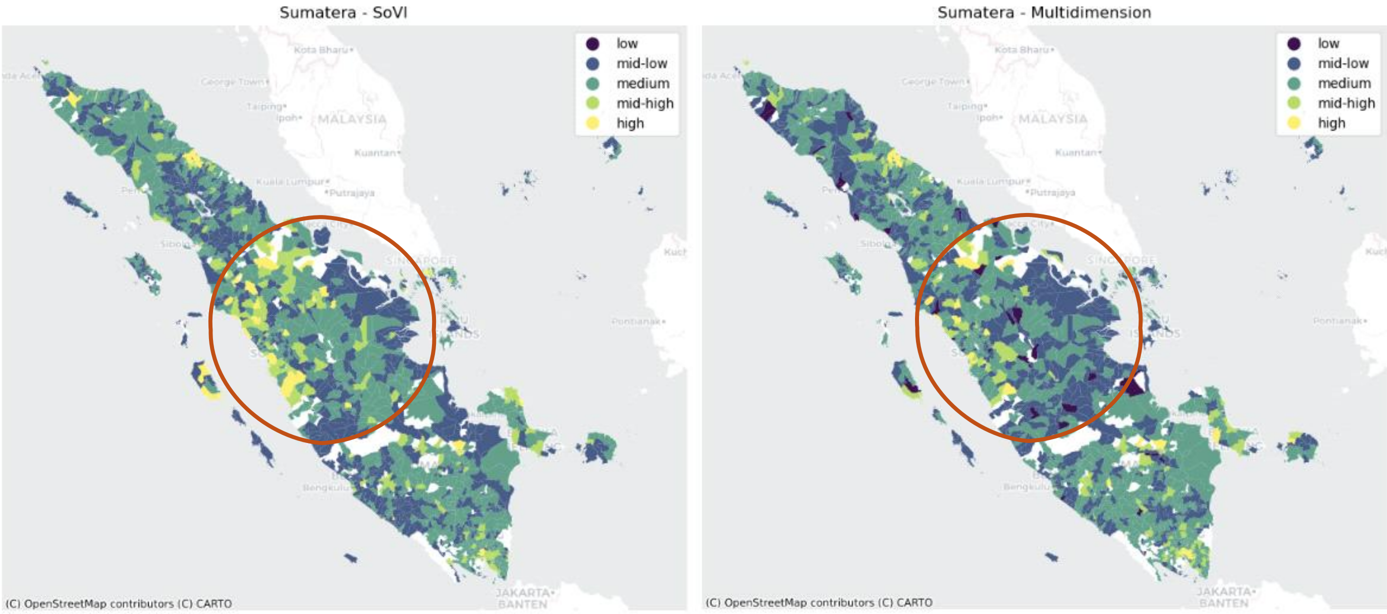


Figure 30 SoVI and Multidimensional Index Comparison of Sumatera. The circle highlights notable differences that can be found between both methods.

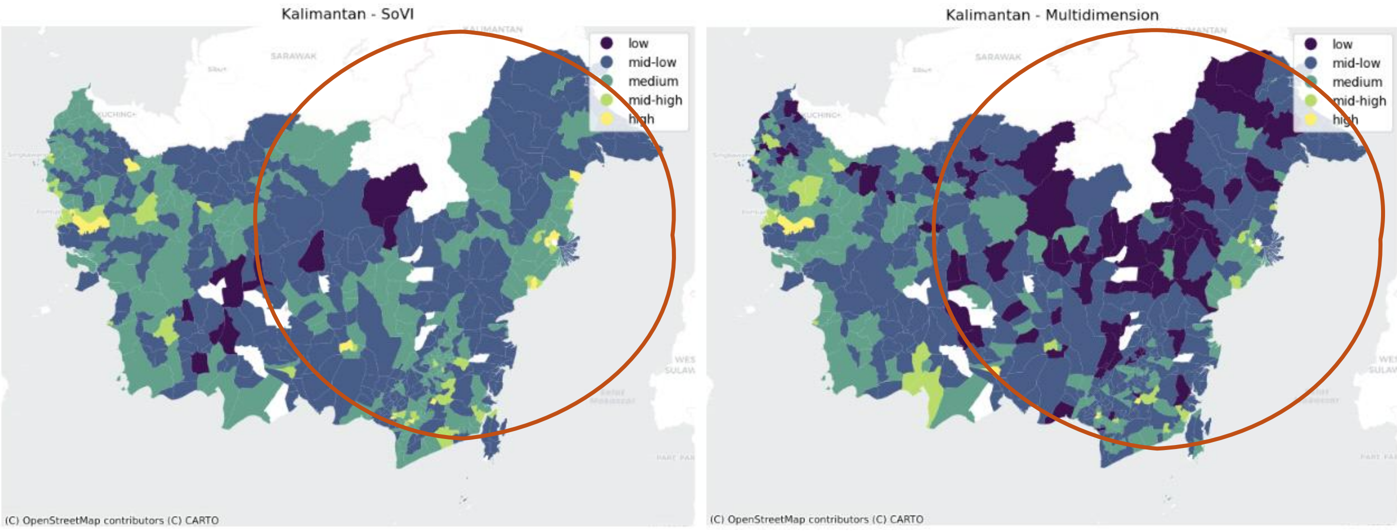


Figure 31 SoVI and Multidimensional Comparison of Kalimantan. The circle highlights notable differences that can be found between both methods

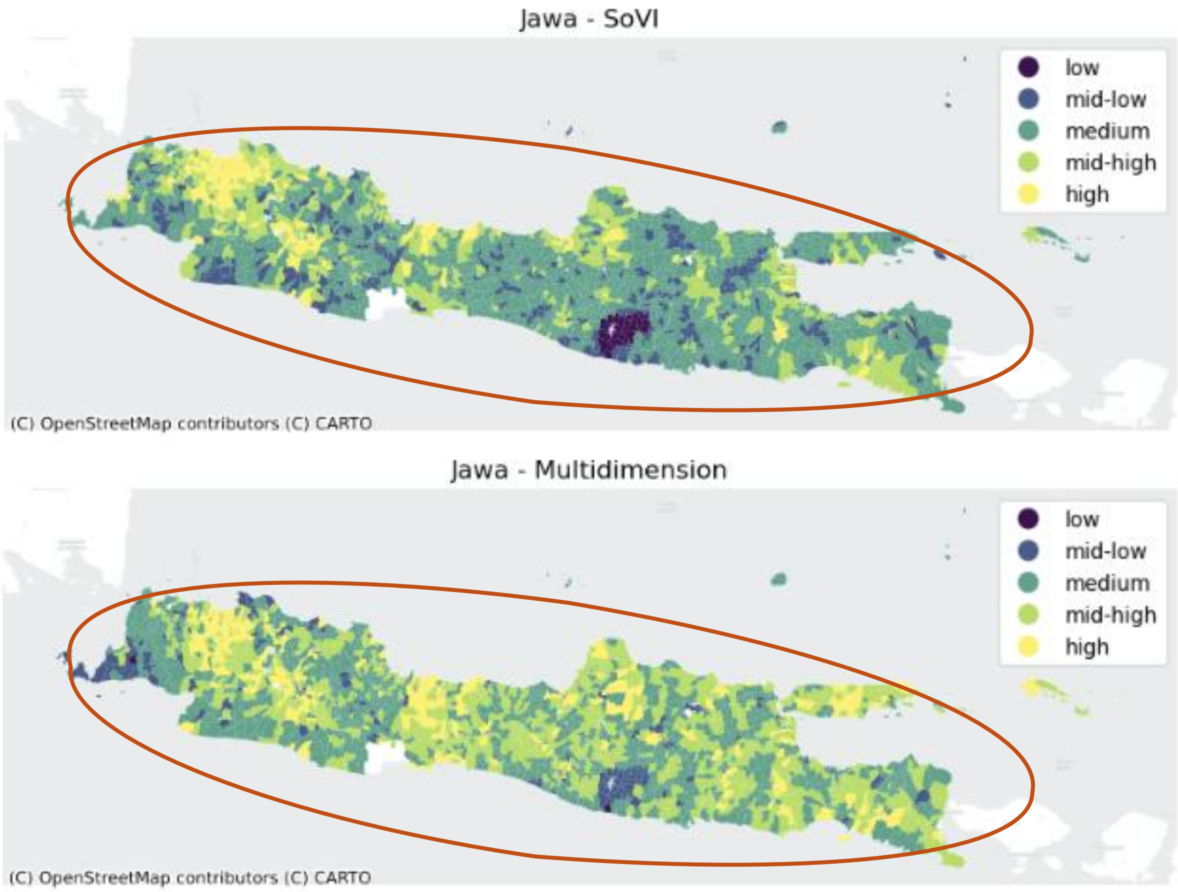


Figure 32 SoVI and Multidimensional Comparison of Jawa. The circle highlights notable differences that can be found between both methods

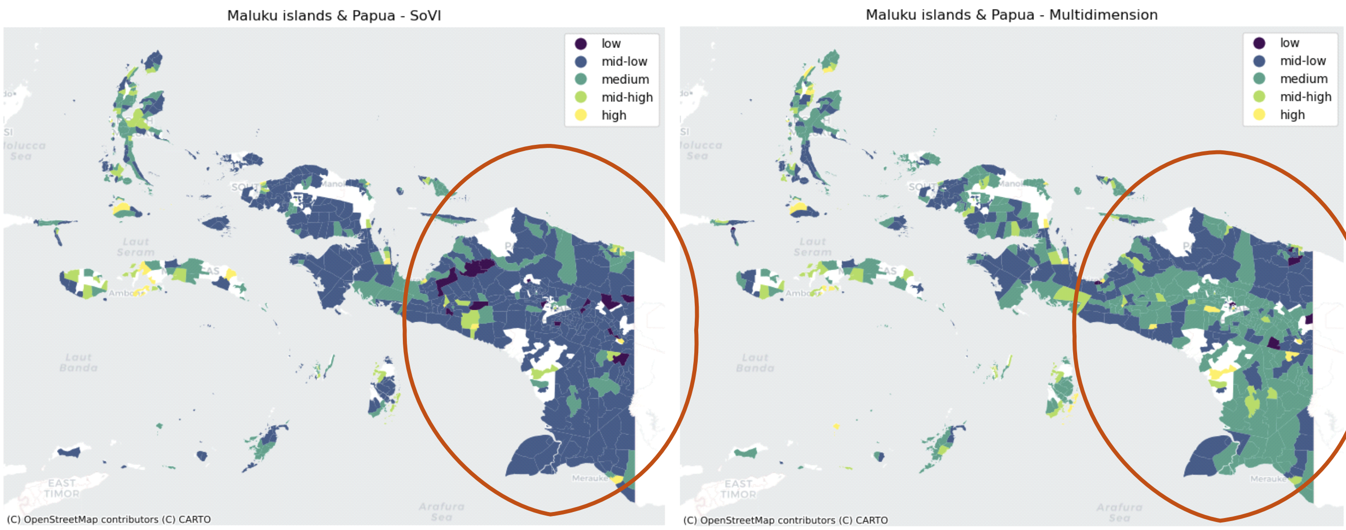


Figure 33 SoVI and Multidimensional Comparison of Maluku Islands & Papua. The circle highlights notable differences that can be found between both methods

To further explore these differences, we will conduct a class change analysis to identify variations in vulnerability classification across different regions in Indonesia. Class change analysis refers to cases where the same geographic area is assigned different vulnerability classes. For example, subdistrict X in Indonesia may be classified as high vulnerability by the SoVI method and medium vulnerability by the Multidimensional Index. Table 8 summarises the class changes between the two methods being evaluated. A higher class change value indicates more significant disparities in vulnerability classification between the SoVI and the Multidimensional Index. Over 50% of the regions have experienced class changes, with the majority exhibiting a difference of one class. The highest observed disparity is three classes, representing the most significant difference between the two methods. From a policy-making standpoint, these differences in classification are expected to have a substantial impact. It is important to recognise that the categorisation of social vulnerability levels will affect the prioritisation and types of intervention provided in disaster management policies.

Table 8 Degree of class change between SoVI and Multidimensional Index

	Divergence →							
Total Subdistricts	No Class	% Change	1 Class	% Change	2 Class	% Change	3 Class	% Change
6446	3058	**47,44%**	3017	**46,80%**	348	**5,40%**	23	**0,36%**

The next comparison is to examine the contribution of each variable to the final index results in two methods. This comparison is significant as it allows us to assess the balance of each dimension's contribution in the multidimensional method and compare it to the contribution of each variable in the SoVI method. One of the motivations for developing the multidimensional method in this study was to create an index calculation approach that evenly weighs social dimensions when calculating the social vulnerability index. The SoVI method calculates the contribution of variables by considering their loading on all factors and the variance amount for each factor in the overall data. On the other hand, in a multidimensional index, the contribution of each variable to the final index is calculated by breaking down its contribution for each dimension. Figure 26 illustrates each variable's contribution to the calculation of social vulnerability in the final SoVI and Multidimensional index.

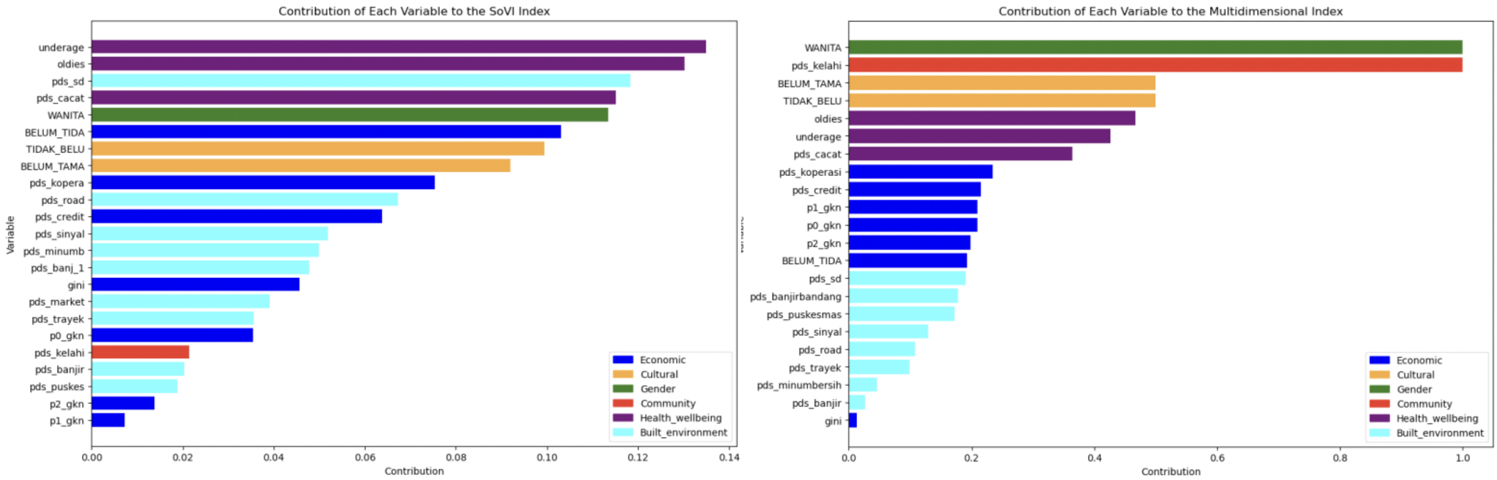


Figure 34 Variables Contribution to the SoVI and Multidimensional index. The vertical axis represents the variables that make up the index, while the different colours of the bars indicate the dimensions of vulnerability.

In Figure 34, we can observe the variations in variable contributions to two social vulnerability indices. The graph uses different colours to represent the dimensions from which the variables originate. It is important to note that the two methods used to calculate the social vulnerability index in this study employ different mechanisms, which can result in varying contribution values for each variable. The SoVI is generated using Principal Component Analysis (PCA), which focuses on the variance in each variable. The loadings assessment for each variable in each factor that forms the SoVI is influenced by the variance of each variable in the overall data. Consequently, we may observe variations in variable weights in the final SoVI index results. On the other hand, the multidimensional method follows a different approach, aiming to ensure equal representation of each dimension forming social vulnerability. In the calculation process of the multidimensional method, variables are divided based on their respective dimensions, and calculations are performed within each dimension. Despite using the same PCA tools, the weighting dynamics of the Multidimensional Index are based solely on the variance of each isolated variable within each dimension. This means that there may not be weight inequality between variables across dimensions. By examining the variable contribution data in Figure 34, we can observe how the contribution of each dimension is distributed in the process of forming the index. Figure 35 presents the combined variable contribution values within each dimension.

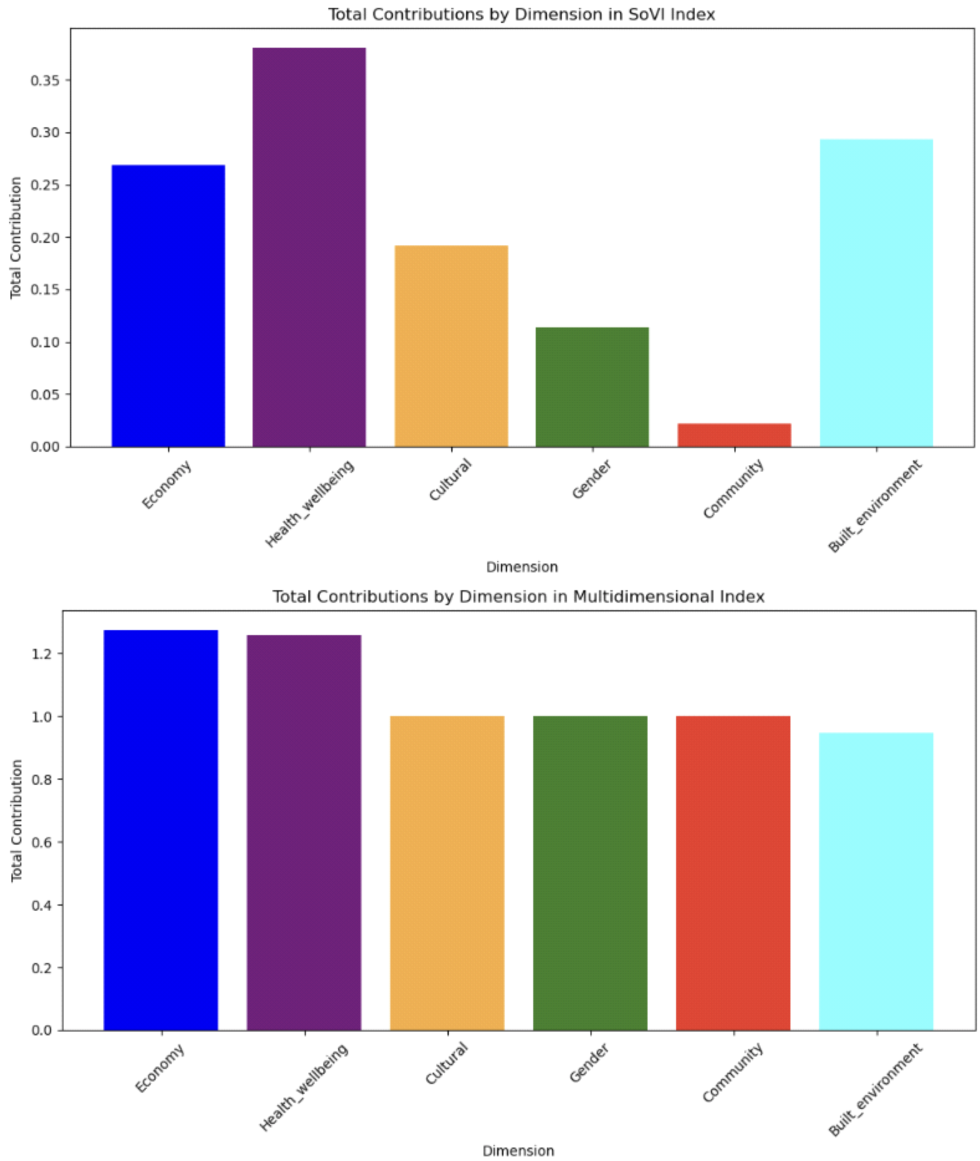


Figure 35 Dimensions Contribution to the SoVI and Multidimensional Index.

In Figure 27, we can observe each dimension's varying degrees of involvement in creating the index using the two calculation methods. The top image shows the Social Vulnerability Index (SoVI), where noticeable differences exist between the involvement of each dimension. The health and well-being dimension has the highest involvement value, followed by the built-environment and economic dimensions. It is evident from the SoVI graph that the community dimension has an insignificant involvement. This pattern is also observed in the gender and cultural dimensions, where their involvement is significantly lower compared to the health and well-being dimensions. This can be attributed to the relatively small contribution of variables in these dimensions to the overall index, influenced by data variance conditions and the Principal Component Analysis (PCA) method, which places importance on the variance of variables in the dataset.

On the other hand, when we examine the graph of the multidimensional index, we can see a more balanced distribution of involvement across all index dimensions. This is due to the conceptual development of the method, emphasising equal contributions from all dimensions influencing the social vulnerability calculation process. As depicted in the bottom graph, all dimensions have nearly equal involvement in shaping the index, with only two dimensions contributing slightly more than the others. This demonstrates how the multidimensional method achieves a balanced representation of the vulnerability dimension in its calculations, which SoVI does not emphasise.

The comparison of the two methods for measuring social vulnerability, SoVI and Multidimensional Index, reveals significant differences in visual analysis, class change analysis, and contribution variables. The choice of measurement method depends on the user's needs for the desired output. SoVI is suitable for producing social vulnerability index values for practitioners who do not consider the dimensions of social vulnerability and treat vulnerability indicators equally and in a balanced manner. On the other hand, the Multidimensional Index is designed for practitioners who pay attention to vulnerabilities in each vulnerability dimension and want to identify index values for each vulnerability dimension.

8 Flood Risk Analysis of Indonesia Using Social Vulnerability

8.1. Flood Hazard and Exposure in Indonesia

In this chapter, we will use the practical application of the multidimensional social vulnerability index to analyse flood risk. We will focus on flood data in Indonesia to determine the potential risk to the population. For the analysis, we will use the Global Flood Map v.2 (GFM) from Fathom, which provides data on both pluvial and fluvial floods in Indonesia. Pluvial floods are caused by heavy rainfall, while fluvial floods occur when water levels in streams or bodies of water rise and flood surrounding land. Specifically, we will be examining the 1-in-100-year flood data from the GFM, as these high-risk flood events have a high probability of occurring. To narrow down the data, we will only include inundation depths of at least 0.5 meters, which we consider the minimum limit for high flood risk to humans. The filtered pluvial and fluvial flood data will be represented in Figure 36 and Figure 37. As shown in Figure 38, the merger of both flood data will be our main reference for the flood hazard data of Indonesia.

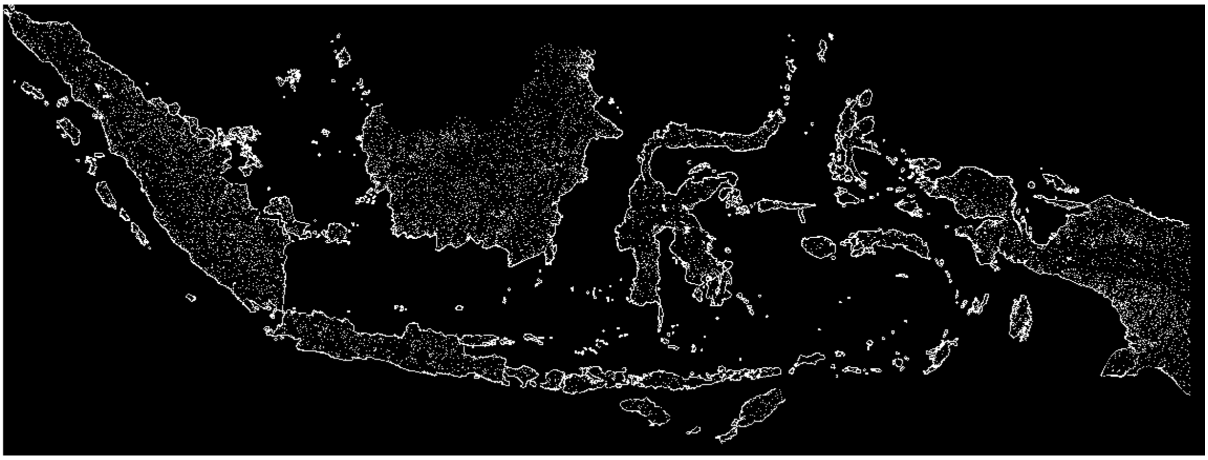


Figure 36 Pluvial Flood with return period 1-in-100 years and >0,5m inundation depth.

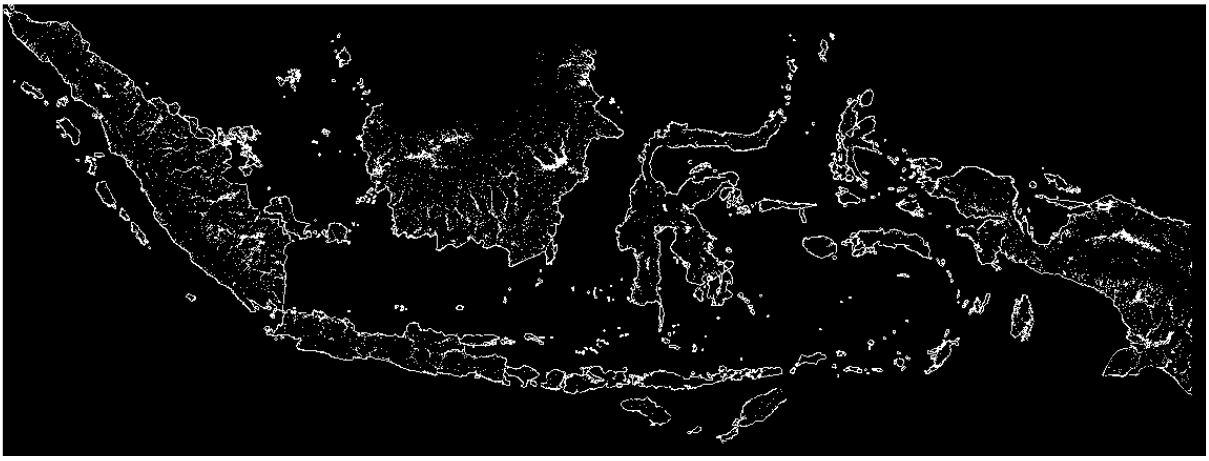


Figure 37 Fluvial Flood with return period 1-in-100 years and >0,5m inundation depth.

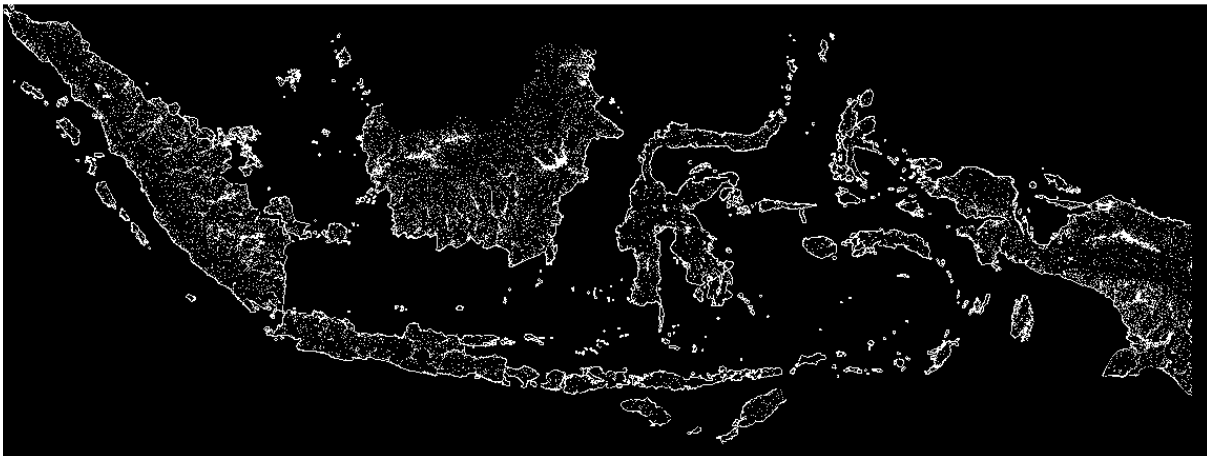


Figure 38 Merged Pluvial and Fluvial Flood with return period 1-in-100 years and >0,5m inundation depth.

To gather exposure data, we will combine our flood data with the population data. We are using the 2020 population counts from WorldPop (Unconstrained individual countries 2000-2020), which have a resolution of 3 arcseconds (approximately 90 x 90 meters at the equator). Figure 39 presents the population data for Indonesia and Figure 40 Illustrates the combined flood and population data.

Figure 39 Population Data of Indonesia

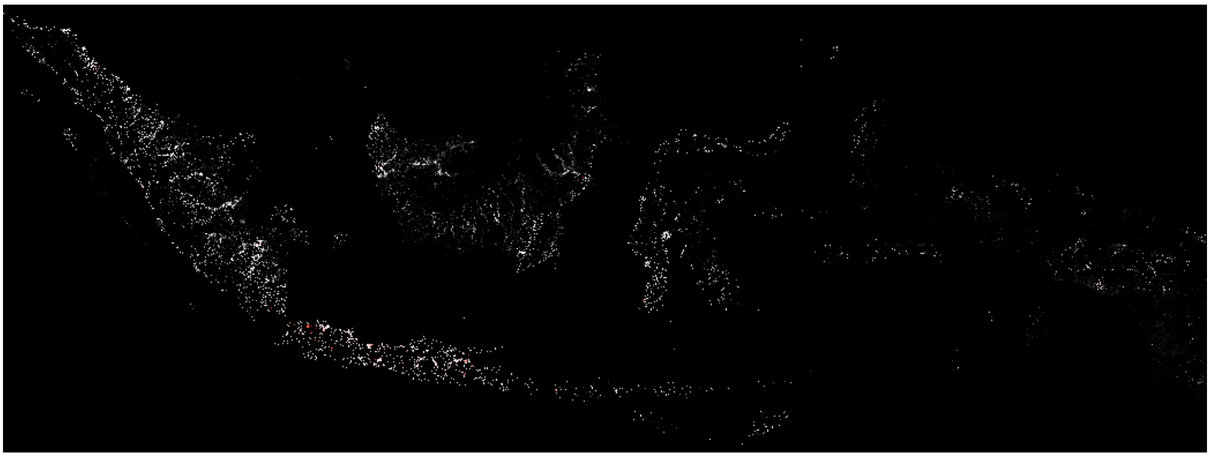


Figure 40 Overlayed map of Flood Hazard and Population Data of Indonesia.

The obtained exposure data from flood and population data will be overlayed once again but using the shapefile that explains the boundaries of subdistricts in Indonesia. This step is crucial for understanding the number of people in each district at high risk of flooding. We will use GIS tools to transform our results into a shapefile of each subdistrict (Figure 41) containing the aggregated number of people.

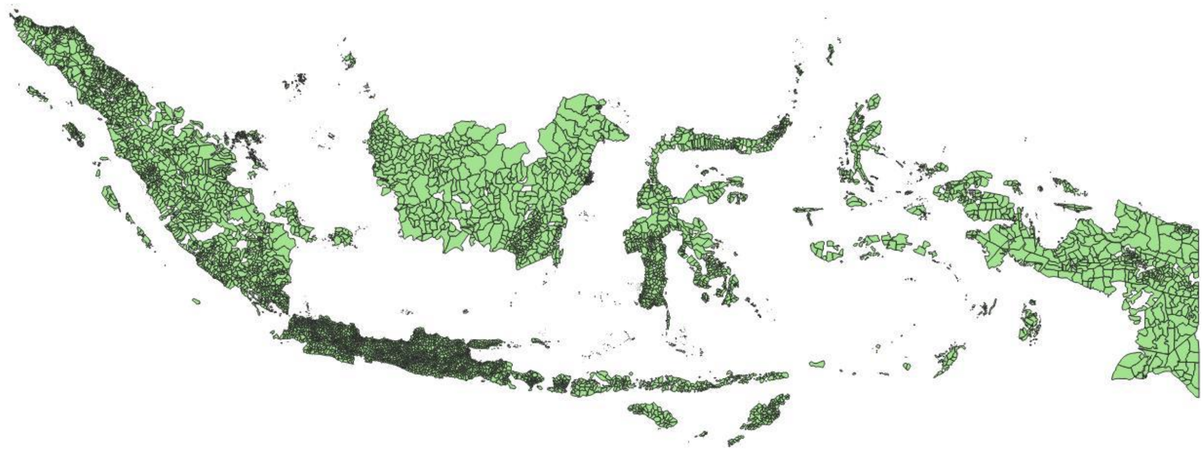


Figure 41 Administration border of Indonesia per subdistricts.

We have gathered data on people exposed to high-risk floods, enabling us to determine the number of individuals at risk in each area. For instance, Figure 42 displays the top 10 subdistricts with the highest number of people exposed to high-risk flooding.

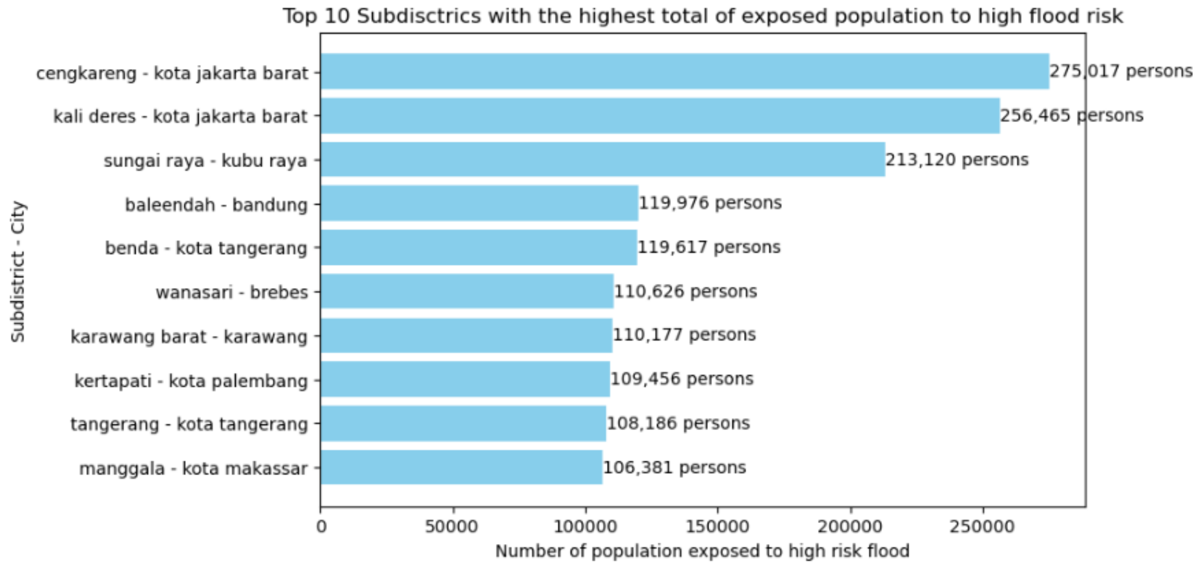


Figure 42 The top 10 are the most exposed people to high-risk floods in Indonesia.

However, it is important to consider more than just headcount data when assessing flood risk. Some areas with smaller populations may have high exposure to flooding. That is why we need to also look at the percentage of the population exposed to high-risk floods for a more comprehensive analysis. Figure 43 helps us to see the subdistricts with the highest percentage of people exposed to flooding.

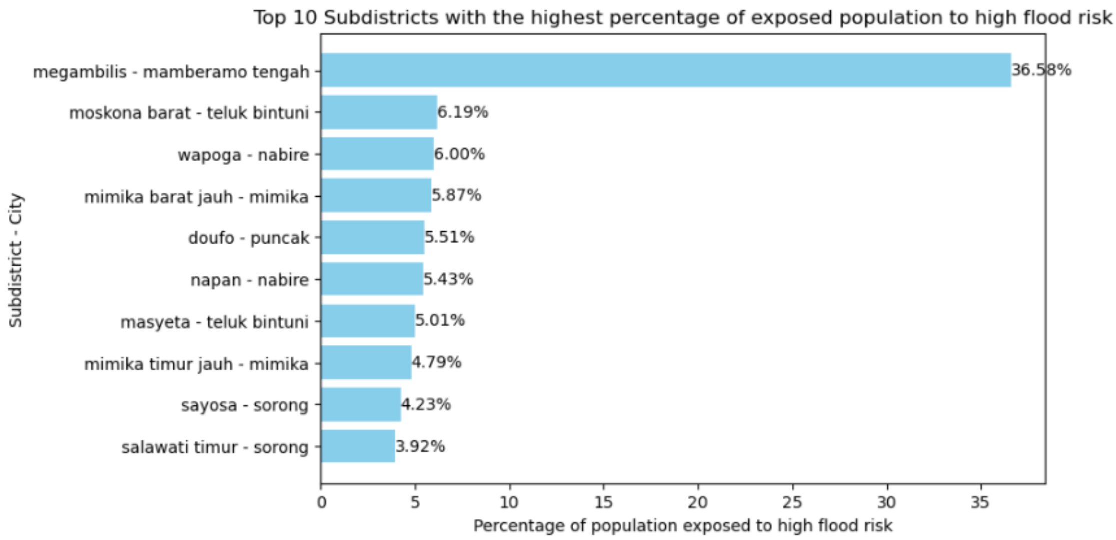


Figure 43 The top 10 areas with the highest percentage of exposed people to high-risk floods in Indonesia.

8.2. Flood Risk Analysis of Indonesia

To conduct flood risk analysis in Indonesia, we can utilise the social vulnerability status data in each subdistrict and recently obtained data on the population exposed to high-risk floods. We can create a multidimensional index with five categories based on social vulnerability to identify the number of people at high risk of floods in each category. This analysis focuses on incorporating the social vulnerability index into general flood risk calculations rather than conducting a detailed analysis of flood situations in specific regions.

The initial goal of developing this method was to allow for flexible vulnerability assessment across different dimensions. This approach enables a more in-depth understanding of vulnerabilities within each social impact dimension by utilising the dimension index we obtain from the calculation. We will investigate using the vulnerability index for each dimension in flood risk analysis in Indonesia. One way to gather this analysis is to overlay vulnerability data for each dimension with data on people exposed to high-risk floods that we have previously calculated. The following figures depict the results of combining information about vulnerability for each dimension with flood exposure data.

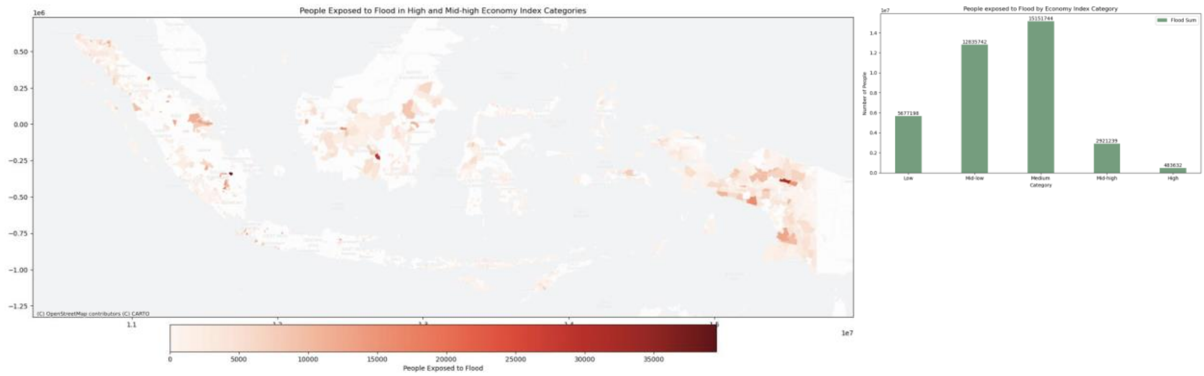


Figure 44 The map of flood risk analysis using Economy Index in Indonesia and its distribution

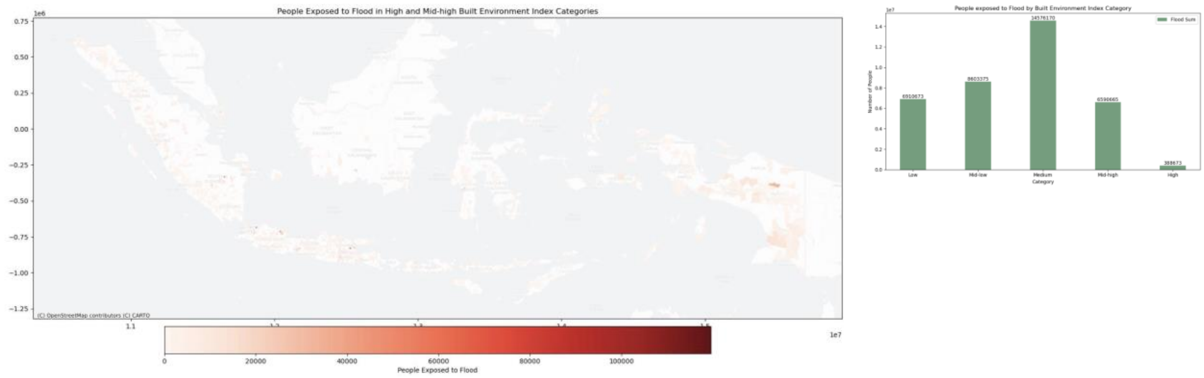


Figure 45 The map of flood risk analysis using built environment index and its distribution

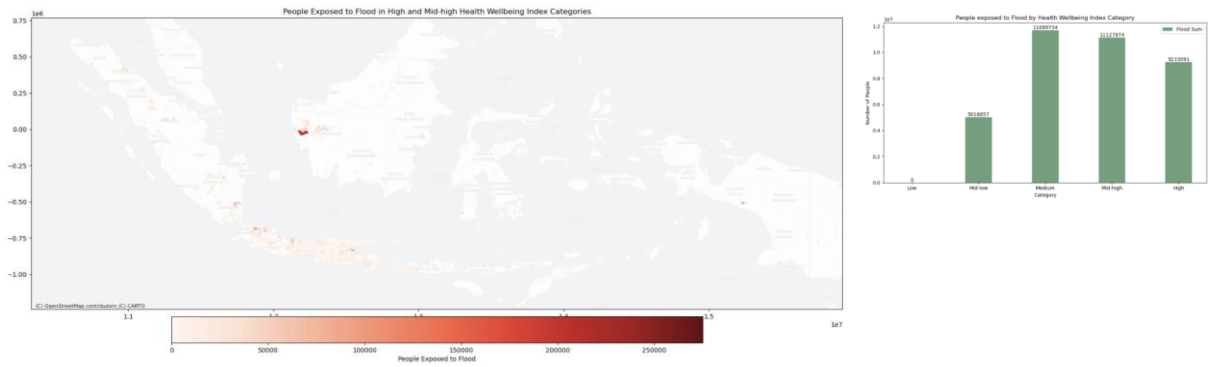


Figure 46 The map of flood risk analysis using health and well-being index and its distribution

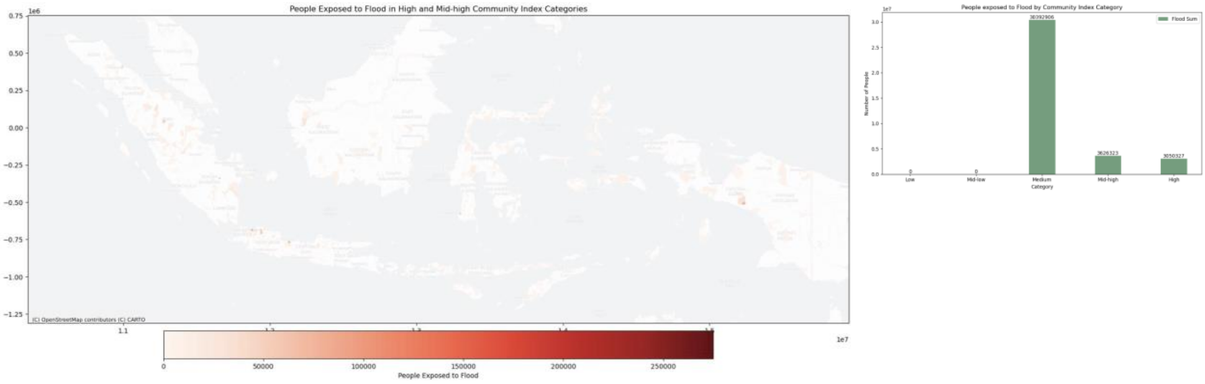


Figure 47 The map of flood risk analysis using community index and its distribution

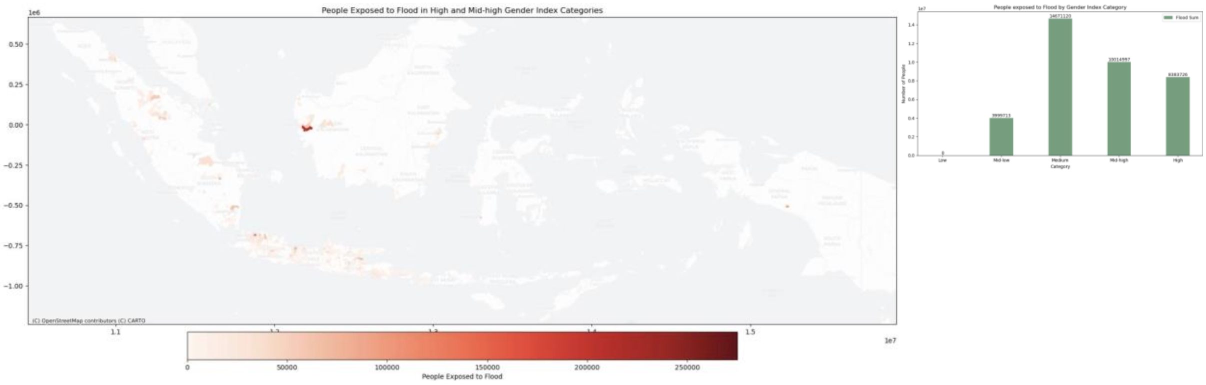


Figure 48 The map of flood risk analysis using gender index and its distribution

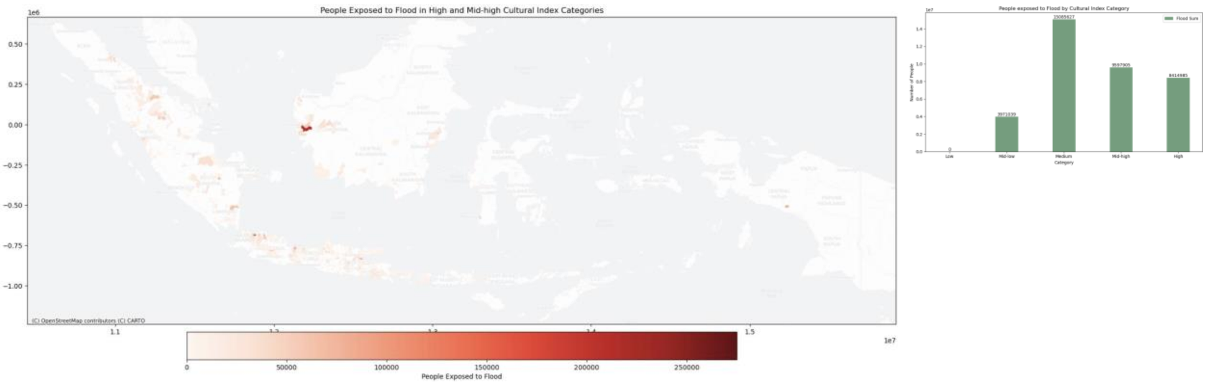


Figure 49 The map of flood risk analysis using cultural index and its distribution

In this analysis, we will not conduct an in-depth examination of every aspect of social vulnerability in all regions of Indonesia. Instead, we will demonstrate how to obtain information output using the dimension index. For instance, in Figure 44, we can observe the results of overlaying economic dimension data in Indonesia with data on people exposed to high-risk floods. The distribution graph on the right of Figure 44 displays the distribution of people exposed to floods categorised based on their level of economic vulnerability. Looking at areas in the mid-high and high categories or areas with high economic vulnerability, we find that 3 million people, approximately 9% of the total population, are exposed to flooding. This means that 3 million Indonesians are economically vulnerable and exposed to a high risk of flooding. In our data context, economic vulnerability is related to poverty, inequality, and unemployment conditions. If affected by a disaster, people with these social attributes will experience more significant damage. This information can provide important insights for Indonesian disaster policymakers. In addition, on the left of Figure 44, we can also see the spatial distribution of people who are economically vulnerable and exposed to high-risk flooding. This distribution information can help map high-risk areas for prioritising disaster management policies. The same approach can be applied in other dimensions, as illustrated in Figure 45 to Figure 49.

The next step Is to analyse the flood disaster using social vulnerability index data. This index combines all our dimensions and will be used as a reference for analysing the interactions between flood risk data on the population and an overview of social vulnerability in each region.

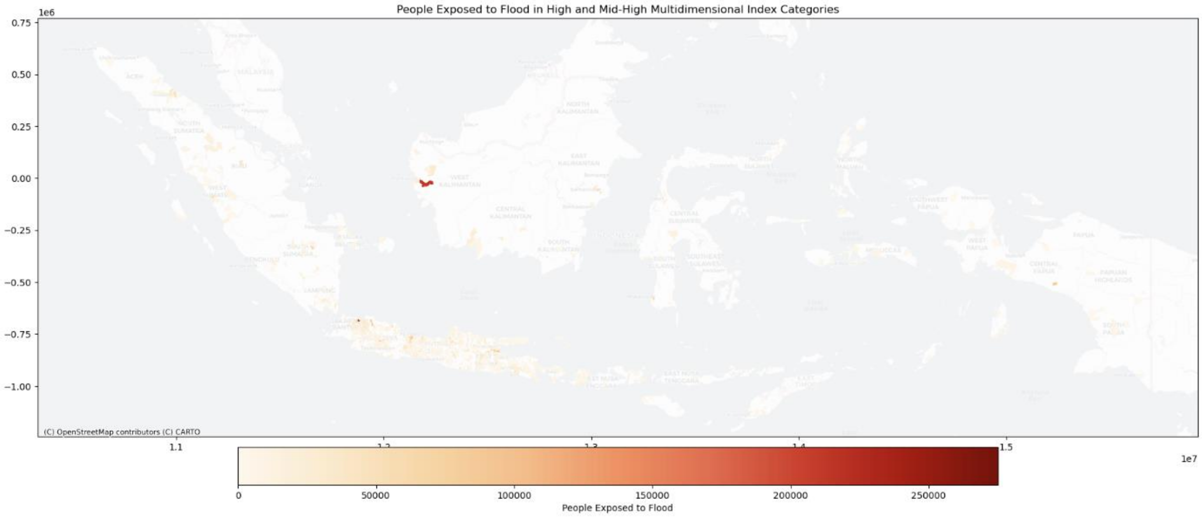


Figure 50 The map of people exposed to flood in high and mid-high Multidimensional Index categories

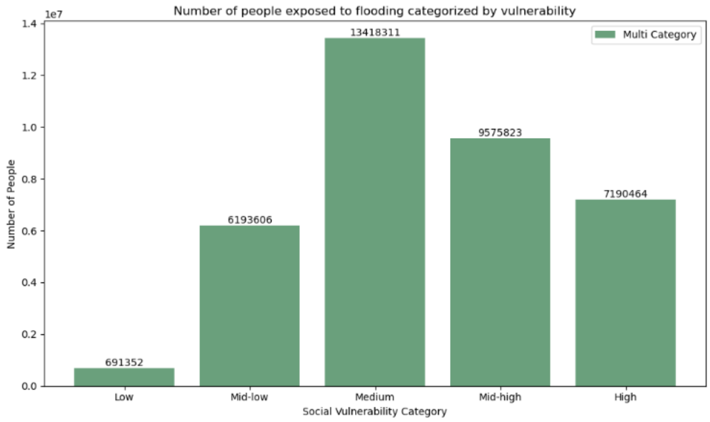


Figure 51 Number of people exposed to flooding categorised by vulnerability level

In Figure 50, we can observe the overlay of flood and social vulnerability data. Figure 51 provides statistics on the number of people exposed to flooding in different categories of social vulnerability. The data shows that 37,069,556 people in Indonesia are exposed to a high risk of flooding, representing 14% of the country's population in

2019. Specifically, within the social vulnerability data, approximately 16 million people, or about 45% of the population, are at a high risk of flooding and high social vulnerability. This is concerning because social vulnerability significantly impacts how people prepare for, respond to, and recover from disasters. Those in a more vulnerable state, whether economically, communally, culturally, etc., tend to suffer more in such situations compared to less vulnerable populations. This presents a significant warning for Indonesia, with nearly half of the population exposed to floods at high risk, potentially facing additional hardships due to weaker social conditions.

We can extract vital insights for shaping disaster management strategies by evaluating the spatial data. Figure 50 showcases regions characterised by high social vulnerability and the extent of exposure to flooding. Darker shades on the map represent areas with a higher concentration of people facing elevated flood risk. For example, the data highlights numerous West Java province areas with high social vulnerability and a significant population exposed to flooding. This correlation is logical since West Java houses Indonesia’s largest population (BPS, 2020). Similar conditions are evident in the Jakarta area, where high vulnerability coincides with a substantial portion of residents facing heightened flood risk. These revelations empower national policymakers to prioritise interventions, while regional stakeholders can devise targeted policies based on their respective vulnerability contexts. Ultimately, this risk data empowers decision-makers to shape policies to mitigate vulnerability and pinpoint key areas for disaster management.

9 Method Implications

The advancement of disaster prevention theory and technology has led to a broader range of measures in the disaster management process. Disaster research contributes to the academic field and influences regulations and policies that aid in developing disaster management techniques. Utilising historical data and evidence, forecasting, qualitative data, and local cultural approaches enriches the array of disaster management measures and helps reduce the impact of disasters on people. Formulating disaster policies based on data and analysis also helps minimise the risk of disaster impacts. Policy developments that stem from academic discussions in the disaster management process will positively impact this field. This research aims to develop new methods for measuring vulnerability in the social realm, contributing to disaster policy development, and assessing the potential implications of disaster policy.

By analysing social vulnerability and flood data in Indonesia, we can evaluate the level of social vulnerability and flooding in the region. With the multidimensional approach method, we can calculate an index to measure vulnerability in each area, considering various dimensions of vulnerability. This index not only indicates the overall vulnerability level but also helps us understand the specific dimensions of vulnerability present in each area. This information is essential for identifying the main vulnerability aspects in each area.

We can gather flood risk data by combining the multidimensional index with flood hazard and exposure data. This data is crucial for assessing the risk of flooding for the population, as it provides an overall vulnerability index as well as a detailed index for each vulnerability dimension. This information is valuable for developing flood management policies tailored to high-risk flooding areas and specific vulnerability dimensions. Furthermore, identifying spatial flood risk helps in mapping flood risk conditions in each region, which is useful for developing targeted policies.

9.1. Policy Implications

In this section, we will explore the policy implications of using a multidimensional index to calculate social vulnerability and flood risk in general disaster management and flood risk management policy.

1. Policy Prioritisation Based on Vulnerability Categories

The process of creating a multidimensional index using social variables is intentionally carried out to capture the actual situation in a population fully. The quality of data for each variable and the use of various variables from each dimension play an important role in creating a more representative index. The level of similarity of the index to the actual conditions of the population will improve the effectiveness of policies created from this index. Using this multidimensional index to assess the level of social vulnerability of the population is useful for understanding the severity and urgency that each region faces in dealing with natural disasters. By applying the index globally to an area and through a categorisation process, we can differentiate one area's vulnerability level from another.

The first policy implication of this assessment method is the prioritised implementation of disaster management measures at all stages. The categorisation index helps institutions in charge of disaster management easily determine an area's level of vulnerability and create a priority list for disaster management.

To illustrate, we will use data from Java Island to demonstrate how the prioritisation process works. Table 9 below are 20 examples of subdistricts on Java Island with multidimensional index values and categorisation. Using this multidimensional index data, we can easily identify areas in the high and mid-high categories as priorities for disaster management, as these areas have high vulnerability. The areas highlighted in red fall into the high and mid-high categories. Using these categories as a reference, policymakers can establish a list of priority areas for implementing disaster management policies.

Table 9 Example of Subdistricts in Java Island

Subdistricts	City	Province	Multidimensional Index	Category
Adimulyo	Kebumen Regency	Jawa Tengah	1,316591	medium
Adipala	Cilacap Regency	Jawa Tengah	1,749972	high
Adiwerna	Tegal	Jawa Tengah	1,81317	high
Agrabinta	Cianjur	Jawa Barat	1,369918	medium
Ajibarang	Banyumas Regency	Jawa Tengah	1,901198	high
Ajung	Jember Regency	Jawa Timur	1,65552	mid-high
Alian	Kebumen Regency	Jawa Tengah	1,448675	medium
Ambal	Kebumen Regency	Jawa Tengah	1,515303	mid-high
Ambarawa	Semarang	Jawa Tengah	1,401934	medium
Ambulu	Jember Regency	Jawa Timur	1,79423	high
Ambunten	Sumenep Regency	Jawa Timur	1,663693	mid-high
Ampel	Boyolali Regency	Jawa Tengah	1,652648	mid-high
Ampelgading	Malang	Jawa Timur	1,520692	mid-high
Ampelgading	Pemalang Regency	Jawa Tengah	1,506652	mid-high
Andir	Bandung	Jawa Barat	1,638999	mid-high
Andong	Boyolali Regency	Jawa Tengah	1,55638	mid-high
Angsana	Pandeglang Regency	Banten	1,075122	mid-low
Anjatan	Indramayu	Jawa Barat	1,404179	medium
Antapani	Bandung	Jawa Barat	1,443767	medium
Anyar	Serang	Banten	1,439871	medium

This method is helpful for prioritising areas as an initial step in the identification process, particularly in the Indonesian context, where there are 7263 subdistricts. By establishing a priority scale for regions with high levels of social vulnerability, policymakers have identified at least 20% of priority areas using our data.

This approach to identification can be applied not only by utilising multidimensional index data but also by conducting an initial screening of high-risk areas in the context of flood risk and social impact indexes across various dimensions. This prioritisation can be phased across other categories, enabling the determination of disaster management policy priority levels for each region. The prioritisation policy could encompass allocations of reduced budget amounts, the timeline for policy implementation, the reduction in quantity or quality of resources, and the prioritisation of emergency actions in high-priority areas.

2. Targeted Policy Development for Vulnerable Hotspots

The next implication of using this methodology in viewing the condition of an area or population in terms of vulnerability or disaster risk is the ability to see the condition of an area spatially. Spatial analysis can be carried out because we have detailed information in each region, specifically if we discuss the context of the data and analysis we carried out in this research at administration level 3 or sub-district level. Policy development can be carried out in a targeted manner by targeting more vulnerable areas, namely areas that are classified as having a high level of vulnerability or, in our multidimensional index categorisation, mid-high and high.

In Figure 52 below, we can see several areas with a high multidimensional index or in the high and mid-high categories (marked in bright yellow and green). These areas are included in the category of socially vulnerable areas and are policy target areas. This implication is similar to the first point, which we can make further priorities by mapping high-index areas.

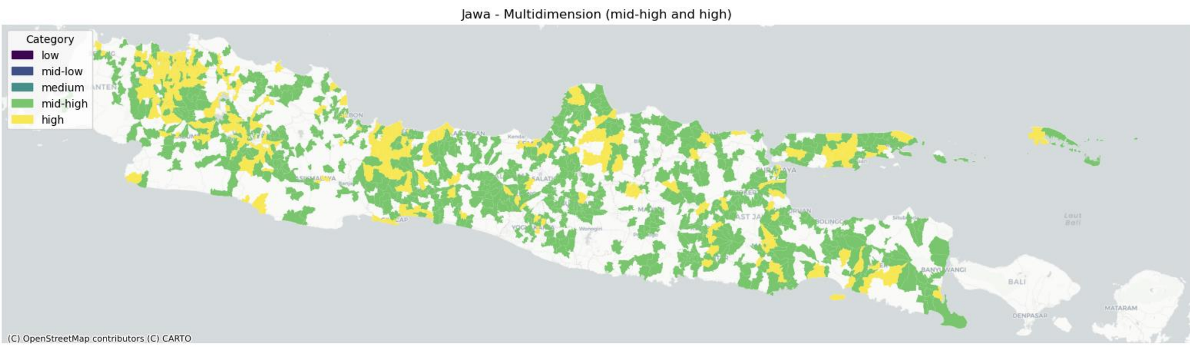


Figure 52 The map of Multidimensional Index in Jawa, with only high and mid-high categories

We can apply the same approach to dimensional index data, similar to the example in Figure 53, which illustrates the built environment dimension index. By concentrating on the mid-high and high categories, we can prioritise specific policies related to built environment dimensions, such as the number of essential infrastructures, based on our data. This spatial analysis allows us to gain insights into our area's geographical situation. Additionally, regarding governance, regions experiencing high levels of vulnerability can be granted greater autonomy to address their regional vulnerability, with the option for tailored localised policies if necessary.

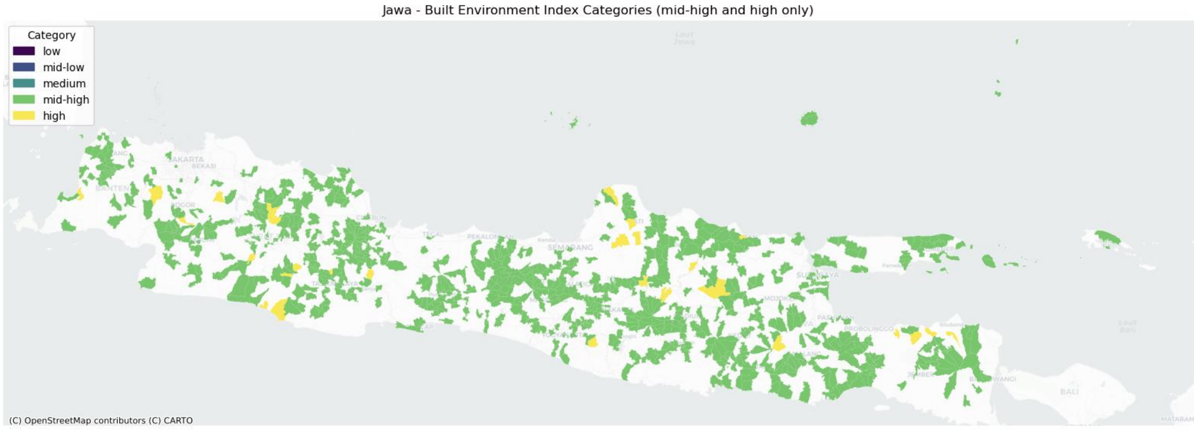


Figure 53 The map of Built Environment Index in Jawa, with only high and mid-high categories

In further analysis of the available data, we can conduct hotspot analysis to pinpoint statistically significant spatial clusters with high or low values within specific geographic areas. This analysis will help us identify areas with particularly high concentrations of social vulnerability. Figure 3 displays the results of the hotspots analysis process using the Gtis Ord Gi* (G-Star) method. The G-star statistics identify clusters of high values (hotspots) and low values (cold spots) based on the spatial proximity of data points. In Figure 54, three dominant colours are visible: red, blue, and white. The red area indicates a significant concentration of high values of the multidimensional index, or what we could call hotspots of social vulnerability. Conversely, blue areas indicate coldspots or areas with a low concentration of the social vulnerability index. The white area indicates no significant clustering of high or low values from the multidimensional index in that area.

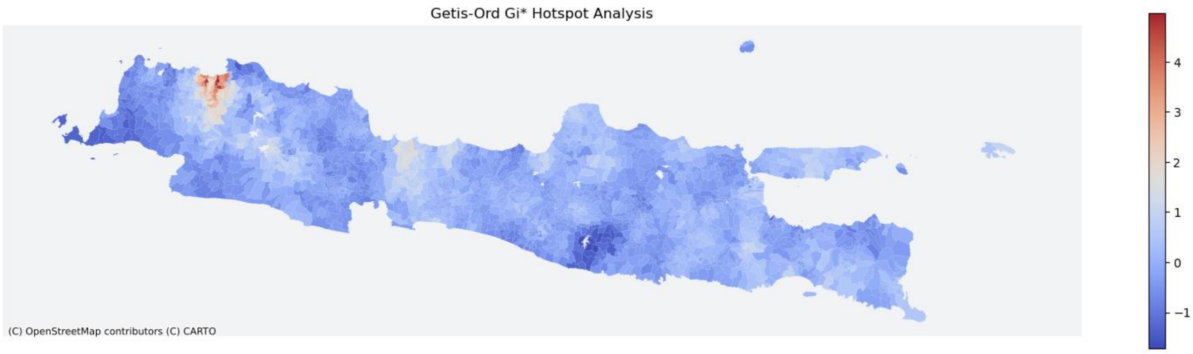


Figure 54 The map of Hotspots Analysis of Jawa

The findings of this analysis suggest that areas with high concentrations of multidimensional indexes are prime candidates for further study. These hotspot areas are likely characterised by high social vulnerability. Using this hotspot analysis to inform targeted policies can help policymakers prioritise areas for social vulnerability reduction and disaster management policy. This analysis can also be developed on the final index and indexes in each dimension and disaster risk analysis. This can be done on various scales, not only on a national or island-wide level but also in smaller areas, by adhering to the responsibilities of each regional disaster response unit (such as BPBD in the Indonesian context).

3. Tailored Disaster Management Policies Based on Dominant Dimensions

In the design methodology section, the multidimensional approach offers the advantage of conducting an in-depth analysis of every aspect of the social impact dimension. This method goes beyond just providing a general assessment of social vulnerability; it also evaluates the specific dimensions of social impacts that contribute to the final index. Recognising the predominant dimensions in each region can aid in identifying and formulating the most appropriate policies for that area. Identifying the dominant vulnerability dimensions can help devise effective policies and allocate resources for specific measures.

Understanding the context of the indicators and variables used in the multidimensional approach is crucial, as these inputs determine the index results for each dimension. Policymakers need to comprehend the variables that constitute the index in each dimension to assess the dominant dimensions contributing to the vulnerability score in each region. The identification process involves using a certain threshold in the dimension index as a reference to determine the dominant number. If a dimension's score exceeds the threshold, it becomes the dominant vulnerability dimension in that area.

For example, the results of the Indonesian data analysis show a heatmap of dimension indices for 20 subdistricts in Figure 55. The subdistrict names and city names constitute the rows, while the columns represent the index values in each dimension. Cell colour indicates the dimension index score, with darker red cells representing higher index values. In this example, a threshold index is determined to identify the dominant dimensions, such as 0.45. Dimensions with index values above the threshold are considered dominant dimensions. For instance, in the Aboy subdistrict in the Bintang Mountains, the dominant dimensions are the economic and built environment dimensions, as their index values exceed the threshold.

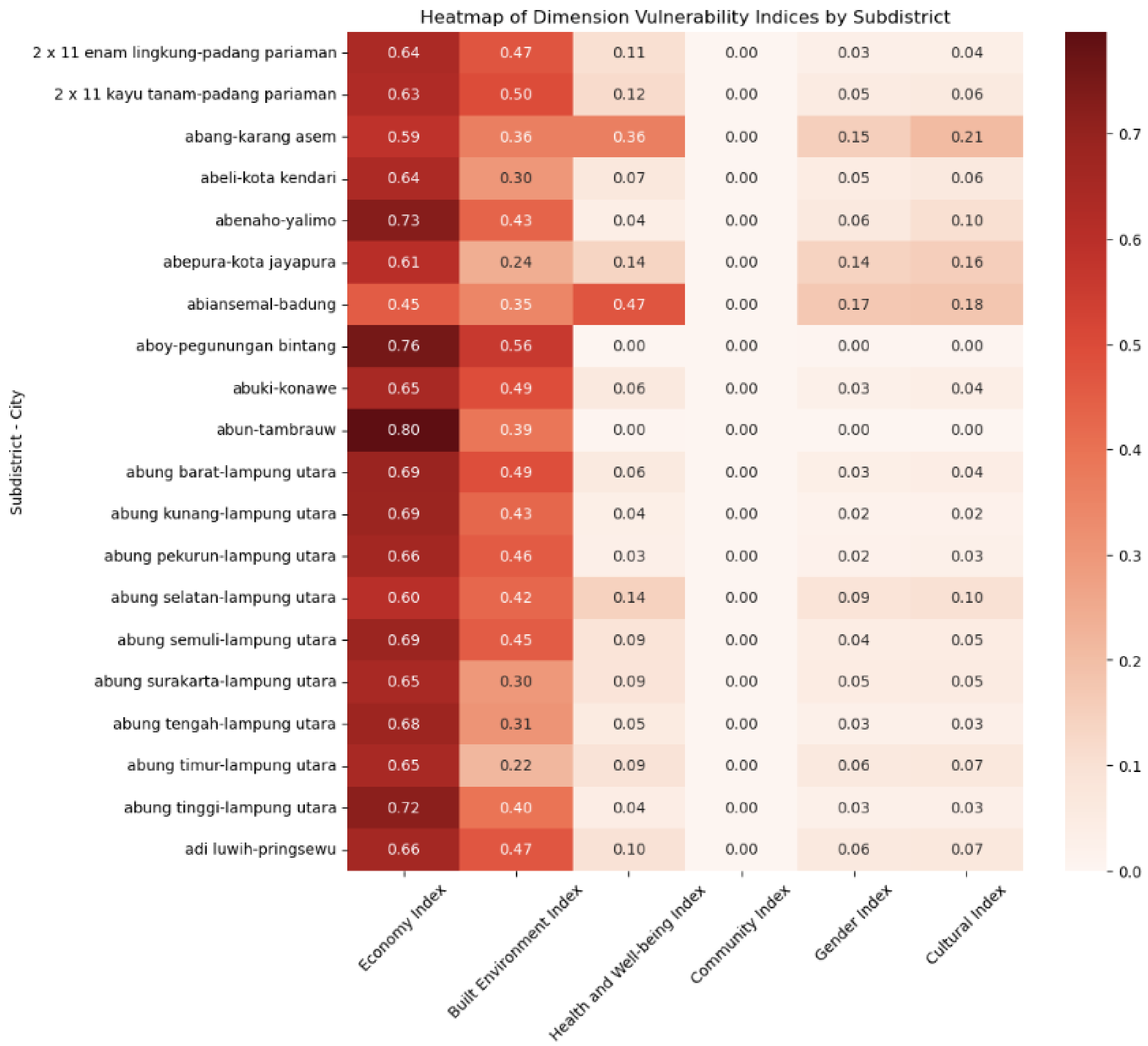


Figure 55 Heatmap of dimension vulnerability indices. The score inside the box describes the value of each dimension index

In the Figure 56 below, we can identify which dimensions of vulnerability are dominant in each subdistrict. With data like the one provided, every level of government and policy formulators can understand the conditions of social vulnerabilities in their respective areas and directly address the most critical vulnerabilities in each location. This will enable the identification and resolution of specific needs as a priority through tailored policies. For example, in areas with a dominant economic dimension, tailored policies could include subsidies for making homes flood-proof to handle floods, or in the built environment dimension, preparing infrastructure and emergency equipment such as rubber boats and emergency communication equipment in vulnerable areas during floods.

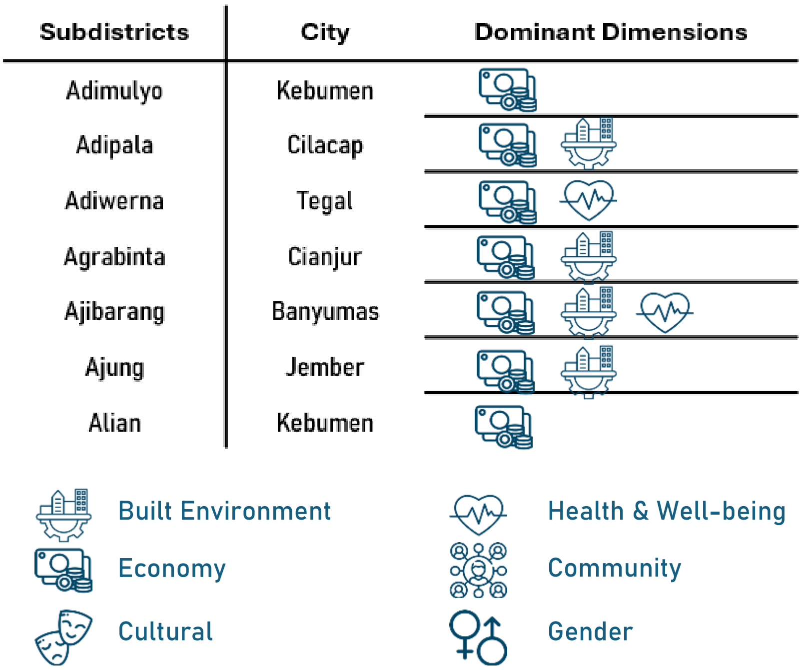


Figure 56 Dominant dimensions of each subdistrict (with threshold 0.4).

Identifying dominant dimensions is not only carried out separately for each dimension. By using intersectionality theory, we can highlight compounded vulnerabilities that occur in areas with more than one dimension of vulnerability. This approach can help identify areas where multiple vulnerabilities intersect, enabling more comprehensive and nuanced policy development. For example, in areas with dominant economic and health & well-being dimensions, policies can be developed to provide social protection for low-income, elderly, and disabled populations in flood-prone areas. With this approach, interventions for vulnerable populations can be formulated holistically. This compounded vulnerability identification approach can address the complex needs of vulnerable populations.

9.2. Practicality of the Method

When applying this multidimensional social vulnerability calculation method, practitioners should consider several essential attributes of this Multidimensional Index. This method was initially developed to incorporate intersectionality and multidimensionality to review a population's vulnerability from a multidimensional perspective. Practitioners interested in conducting an overall vulnerability assessment and assessing vulnerability in each dimension are recommended to use this method. Additionally, those focused on a specific dimension of vulnerability relevant to their field of work can also benefit from the insights and information obtained from this methodology. For example, the Ministry of Infrastructure can use the built environment vulnerability index to assist in planning and development activities, while the Ministry of Health can utilize the health and well-being vulnerability index to formulate policies to reduce health-related vulnerability in a region. For organisations that cover various fields, this method can provide insights about the dominant vulnerabilities in an area and help assess the urgency of addressing the highest dimensions of vulnerability, creating a priority scale for reducing social vulnerability.

The steps for calculating social vulnerability using the multidimensional index are as follows:

a) Determine the appropriate variables

When determining social variables for calculating social vulnerability using a multidimensional index, one can consider a variety of social indicators, as outlined in Table 2. These indicators have been adapted for the social impact assessment framework based on a literature review aimed at capturing conditions of vulnerability in a social context. It is important to note that data availability and the suitability of variables with indicators may not always be consistent across all locations, particularly in countries or regions lacking comprehensive data recording systems and surveys for social vulnerability indicators. Therefore, modellers must carefully search for and select appropriate variables that align with the existing indicators. The index results will heavily rely on the completeness of the input data, the diversity of variables, and the data quality. Hence, this process is crucial in determining the final index results using this method.

b) Grouping variables based on their related dimensions

Variables collected based on social vulnerability indicators are grouped according to dimensions of social vulnerability (refer to Table 2). The associated variables will be processed to generate a social vulnerability index for each dimension. As a significant output of this method, the results of the vulnerability dimension index will rely on the quality, completeness, and indicators that represent the vulnerability dimension index.

c) Performing multidimensional index calculations

Multidimensional index calculations can be performed after collecting the input data and grouping them based on their respective dimensions. Before using the model to calculate, it is important to ensure that the scale of the input data and the expected output are aligned, making adjustments if necessary. The steps for calculating this multidimensional index can be followed based on the model in Figure 8. The final results obtained from this method include the final social vulnerability index, the vulnerability index for each dimension, and the identification of the dominant vulnerability dimensions in each area.

d) Determine the point of interest

It is crucial to identify the points of interest and the needs of the users of this method as reference material for obtaining the output and processed data from vulnerability calculations using the multidimensional index. As mentioned, this index is designed for practitioners requiring vulnerability calculations using a multidimensional approach. The specific point of interest of the practitioner will determine the data that needs to be extracted. This can be categorised into: a) Practitioners needing final calculations of social vulnerability, b) Practitioners needing specific vulnerability dimensions, c) Practitioners needing to identify the dominant vulnerability dimensions in an area, and d) Practitioners needing combined data. However, the capabilities of the method and the output obtained from this multidimensional index model allow for a broader and more varied range of needs to be addressed.

e) Extract the appropriate output

The needs study has identified particular interests, and the results are used to create model outputs that align with these initial needs. In disaster management policy, practitioners in coordinating positions can access the final social vulnerability value. These practitioners can obtain results specific to the dimensions they need using this multidimensional index. Additionally, practitioners looking to identify predominant vulnerabilities in specific areas can conduct advanced calculations by setting a vulnerability index threshold for each dimension. This allows them to filter out dimensions exceeding the threshold, establishing them as dominant. Lastly, practitioners who require comprehensive data can obtain the entire model output and use it as needed.

The multidimensional index was created to address the need to evaluate social vulnerability, focusing on intersectionality and multidimensionality. This calculation can be utilised for various purposes, such as mapping vulnerable areas, identifying vulnerabilities in specific regions, and comparing vulnerability conditions across different areas. Practically, this index suits practitioners requiring a multidimensional social vulnerability calculation. It not only provides a final social vulnerability index value but also calculates a dimensional vulnerability index while identifying the primary dimensions of social vulnerability. As a valuable source of information and insights for formulating disaster management policies, particularly regarding vulnerability, the multidimensional index presents alternative calculation models and perspectives that benefit practitioners needing this model. It is important to emphasise that the development of any social vulnerability calculation model is not intended to determine superiority; instead, it aims to find the model that best aligns with user needs. The multidimensional index was also developed with this goal in mind.

9.3. Reflection on Disaster Management in Indonesia

The institution responsible for coordinating all disaster-related matters in Indonesia is the National Disaster Management Agency (BNPB). At the regional level, the Regional Disaster Management Agency (BPBD) oversees disaster affairs and implements policies derived from the BNPB. The primary reference for Indonesian disaster guidance is the Indonesian Disaster Risk Book 2023 (BNPB, 2023), which defines risk using three primary parameters: hazard, vulnerability, and disaster-related capacity. BNPB utilises field data, hazard event probability analysis, and risk studies to develop general policies for disaster risk reduction.

BNPB's vulnerability assessment for risk calculations uses four categories: social, economic, physical, and environmental vulnerability. Social vulnerability is determined using population density and the ratio of vulnerable groups, including gender ratio, vulnerable age groups, disabled population ratio, and poor population ratio. Physical vulnerability is assessed based on houses, public facilities, and critical facilities. Economic vulnerability is calculated from the gross regional domestic product contribution and productive land. Meanwhile, environmental vulnerability is determined by examining protected forests, natural forests, mangrove forests, shrubs, and swamps. Each existing disaster has a different vulnerability index based on these four categories.

This multidimensional index method we have developed can be used as an alternative for calculating social vulnerability in the Indonesian context. It focuses on the dimension of vulnerability, which differs from the economic and environmental vulnerability parameters BNPB uses. Using our method, BNPB can replace its social vulnerability parameters with a more comprehensive approach, as our multidimensional method considers six dimensions: economy, built environment, health & well-being, community, gender, and culture, using 23 input variables. This can help BNPB better understand the complexity of social vulnerability in different populations. Furthermore, our research suggests policy implications such as identifying regional priorities, analysing social vulnerability hotspots, and understanding the dominant vulnerability dimensions in each region, which can provide a new perspective for formulating the Indonesian disaster policy.

This research also reveals the complexity of social vulnerability in Indonesia despite the BNPB's significant role in disaster management. It emphasises the need for well-coordinated efforts by various institutions in disaster management. BNPB should ensure the active involvement of other institutions in reducing social vulnerability and handling disaster-related matters, such as coordinating with Bappenas (Ministry of National Development Planning of the Republic of Indonesia) and the Ministry of Public Works and Housing to reduce vulnerability in the built environment. BNPB should also collaborate with the Ministry of Health to address health and well-being vulnerability. It also applies to other dimensions of all ministries and institutions that are related to it.

Due to limited processing time and BNPB's hazard and capabilities data in this research, direct implementation of the multidimensional index results in disaster risk calculations in Indonesia cannot yet be carried out. Further research is recommended to directly implement the results of the multidimensional index on BNPB's disaster risk data to observe real results from developing this alternative method.

10 Discussion

The main contribution of this research is the development of an alternative method for calculating social vulnerability. This method takes into account the various dimensions of social impacts to create a social vulnerability index. The research is based on the concept of intersectionality, which suggests that social vulnerability can be better assessed by understanding the different vulnerability dimensions that contribute to it and the interlinked relation of vulnerability dimensions. The alternative method, referred to as a multidimensional index, aims to provide a more comprehensive measurement of social vulnerability in a population. By incorporating different social variables and calculation processes, the multidimensional index could offer a new approach to developing policies related to population vulnerability, particularly in disaster risk management.

In applying this research, social data from Indonesia serves as the testing ground for the multidimensional index. This index is derived by considering various dimensions, resulting in a final multidimensional index and indexes for each dimension of vulnerability. Unlike other measurements of social vulnerability in Indonesia, this method provides indexes for each dimension, offering a detailed understanding of social vulnerability in the country. Identifying dominant dimensions in each area can provide valuable insights for understanding a population's vulnerability. This approach allows for a more nuanced analysis of compounded vulnerability, considering the complexity of the issue rather than viewing each dimension in isolation.

Comparison to the existing methodology

The methodology development section thoroughly explains the creation of this alternative method. It outlines the design choices and thought process at each stage, detailing how the index is formed in each dimension and the final index. A comparison is drawn between the results of the multidimensional method and the existing approach, SoVI. The comparison seeks to understand the differences between the two approaches rather than determine the superior method. It emphasizes that the choice of tools or theoretical approach in defining social vulnerability depends on which best suits the intended purpose of the measurement for that study (Cutter, 2024).

The first comparison involves a theoretical comparison between the two methods. SoVI, known for calculating social vulnerability using an inductive method, processes social variable data into an index. On the other hand, the multidimensional method enhances more to the dimensions of vulnerability that contribute to vulnerability. It uses Principal Component Analysis (PCA) to isolate important variables within each dimension, ensuring that the weights of variables in the final index are specific to each dimension. The multidimensional method also recognises the interconnected relationship between vulnerability dimensions.

A visual comparison, as the second comparison, reveals several differences between the two methods. For instance, some regions with a high social vulnerability index in the multidimensional method do not appear in SoVI, and vice versa. The differences in distribution highlight the deviations between the two methods. Despite showing similar patterns to normal distribution graphs, the methods display deviations in each category of social vulnerability. However, these deviations are not significant when considering the entire study area. This difference in distribution is essential as it can provide varied definitions and analysis results for each region.

The analysis of class change also reveals that 3000 out of 6446 subdistricts in our data have experienced class change. This shows discrepancies in the results of the social vulnerability assessment from the two methods. These differences can lead to variations in policy decisions, considering that the vulnerability factor plays a crucial role in determining disaster management policies.

The last comparison looks at the contribution of the indicator variables in our model to the output values in each method. This comparison is crucial because the development of the multidimensional index aimed to ensure that the vulnerability dimensions taken from the social impacts dimension are evenly represented in our model. With this balanced representation, we can analyse the dominant dimensions to assess the potential for compounded vulnerability in each region without inequality in the contribution values of the variables. Based on the available data, we observe that each vulnerability dimension contributes evenly to the final multidimensional index. In contrast, the SoVI method appears to give a significant weight to one dimension and a smaller weight to the other dimensions, resulting in notable disparities. Through this comparative analysis, we can ensure that the main objective of the multidimensional index as a method for calculating social vulnerability, which emphasises the representation of each dimension of vulnerability, has been empirically fulfilled.

Practical applications to flood risk analysis

Moreover, this research demonstrates the practical application of the multidimensional approach in Indonesia's flood data context. Using 1-in-100-year flood data illustrates how flood risk analysis can be effectively conducted using a multidimensional approach. By combining flood hazard data and Indonesian population data, the research identifies the population exposed to high-risk flood areas and conducts a social vulnerability analysis. The results of using SoVI and Multidimensional vulnerability data provide intriguing insights, highlighting the potential of disaster data, such as floods, when combined with social vulnerability data, to enhance flood risk analysis for each study area in Indonesia.

The research shows how to calculate flood risk by identifying high-risk flood areas in each subdistrict. It provides a ranking list of regions with the highest number of exposed people, the percentage of the population exposed to flooding, and the total population. This information can help formulate disaster policies. The research also highlights the ability to analyse flood risk in each dimension of vulnerability through a multidimensional index approach. It explains the additional information the dimensions of social vulnerability can provide regarding flood risk analysis. Detailed information about risk conditions in each dimension can help resolve population problems in the context of disasters. The analysis of counts in each category of the index dimension of exposed population in floods can be used in evaluating disaster-prone areas and formulating disaster management policies. Furthermore, the distribution data of areas with high levels of vulnerability in each dimension can also be used as useful analytical material in formulating disaster management policies.

Policy implications

In the final part, this research explores the implications of method development and implementation of disaster data in the context of disaster risk management policy. Three main policy implications were identified for using multidimensional indexes in formulating disaster risk management. The first policy implication involves prioritising policies based on vulnerability categories. This method can identify the level of social vulnerability in a population and categorise it based on the level of vulnerability in the study area. The indexes and categorisations representing social vulnerability conditions can be used as a reference for policymakers to determine priority areas for implementing disaster management policies. This research identifies the high vulnerability category as a priority area, allowing for the prioritisation of limited resources and finances in vulnerable areas.

The next policy implication involves developing targeted policies for vulnerable hotspots. The analysis in this research provides the ability to create a spatial analysis for socially vulnerable areas, allowing policy formulators to make geographic analyses of factors causing or worsening vulnerabilities. Targeted areas for policy implementation can be identified, and hotspot analysis can reveal spatial clusters with high levels of vulnerability, which become prime candidates for further study by policy formulators. The final implication is that by utilising this multidimensional method, tailored policies can be formulated based on the dominant dimensions in each population to reduce the level of vulnerability and disaster risk. In-depth analysis using this method provides a detailed understanding of the population's condition, allowing policy proposals to focus on the dominant dimensions and important aspects of a population. Tailored policies can utilise the list of dominant dimensions, and further analysis can identify compounded and interlinked vulnerabilities using the results of the multidimensional index.

10.1. The Value of the Method

The main focus of this research is the development of an alternative multidimensional index method for measuring the level of social vulnerability. The methodology is based on social vulnerability and intersectionality theory, providing insight into why and how this approach was developed. By comparing existing methods, the research demonstrates notable differences. Rather than determining the best method, the goal is to introduce new social vulnerability measurement methods, accompanied by theoretical considerations and measurement techniques, to provide alternative measurement methods that adhere to an even distribution of vulnerability dimensions.

The implication of the alternative method developed in this research is that intersectionality analysis in the calculation of social vulnerability enhances the dimensions of social vulnerability not well recognized in the previous method due to data and statistical considerations. The vulnerability index obtained is produced from a calculation process that is more proportional to all existing dimensions of vulnerability. This method is useful for policymakers, researchers, governments, and other parties who need and are interested in seeing the results of proportional vulnerability assessments in all dimensions that form social vulnerability.

The variations observed in comparing the two methods also demonstrate the need for careful consideration of the method used by policymakers intending to utilize social vulnerability measurement methods, because discrepancies in social vulnerability results can significantly impact the identification of vulnerable categories that are crucial for disaster management policy formulation.

10.2. Limitations

In this research, several limitations should be considered when interpreting the results. Firstly, the selection and categorisation of indicators used to calculate social vulnerability were determined based solely on the suitability of indicators found in the existing literature. The choice of variables was limited to those referenced in the SoVI (Cutter et al., 2003) and the methodology development section. This was due to the availability of social variables at the commencement of this research and their applicability to the measurement method's indicator requirements. Another limitation regarding variable selection is the potential variation between the use of social variables in the literature and the practical data used in this research. The majority of social vulnerability indicator literature relies on data from the US census, both as a foundational basis for preliminary research on the SoVI method and as a common source among other research in this field. The potential for differences in the contextual data used for variable selection is a limitation of this research. Addressing these limitations, careful consideration was given to the issues related to variable selection, including their suitability with indicators, the context of the study area, and the validity of variables in representing social vulnerability.

The next limitation pertains to the data used in our research. We utilised various Indonesian social data from different sources and different years. This limitation arose due to the challenge of accessing the required data, as updated social data in Indonesia is not readily available publicly. The discrepancy in years increases the likelihood of data inaccuracy over time. Since the social data used dates back to 2015, it is highly probable that the conditions in the study area have changed. Additionally, the annual changes in administrative boundaries in Indonesia lead to differences in the analysis. Although we employed aggregation and other methods to obtain representative values, this limitation will likely result in disparities between the analysis results and real conditions. Therefore, it is advisable for future research to use consistent data across time and sources to achieve more accurate and representative results.

In developing this multidimensional index, the validation phase of the analysis results with real conditions is another limitation of this research. Time limitations and the need for comprehensive validation with various stakeholders in the Indonesian context are limitations that make it impossible to carry out the final step of compiling a multidimensional index. This final phase is crucial to see how the index we have compiled can be used as a basis for analysis for policy formulators. In the comparison analysis stage, there are also validation limitations, where the SoVI calculation with the variables used has not been validated in the local area. This makes the comparison between SoVI and the Multidimensional Index only exist at the level of theory, concepts and quantitative calculations, which cannot be used as the main reference in the context of actual results. The continued validation process in future research will help increase the level of confidence in the analysis we carry out on real data.

At the policy implication stage, there are some methodological limitations in seeing the potential implications that exist with the use of multidimensional methods in disaster risk management. The formulation of policy implications was not preceded by interviews and discussions with vulnerability data users or, in this context, disaster risk management decision-makers. This results in the potential for not including other policy implications that could occur due to the development of this alternative method. Another limitation is that this research's formulation of policy implications does not consider the institutions and authority held by each person responsible for disaster risk management. So, the existing policy implications are only general and holistic without paying attention to the detailed responsibilities of the institutions with an interest in disaster management.

11 Conclusion

11.1. Answering Research Questions

Main Research Question:

“*How can developing and applying a multidimensional approach to social vulnerability measurement enhance and support the disaster risk assessment process and policies?*”

Five sub-questions were formulated to assist in answering this study's main research question.

- Sub-question 1: *What are the needs and implications of applying a multidimensional approach to social vulnerability measurement?*

This research uses a multidimensional approach to explore other methods of measuring social vulnerability. Our focus is on applying intersectionality thinking to the context of social vulnerability, along with using the social impact dimensions from the SIA framework. This will help us gain insight into analysing compounded vulnerability within populations. The analysis revealed that a disaster could more heavily impact individuals or populations with multiple vulnerabilities. This understanding will provide valuable information for analysing vulnerabilities and forming disaster risk management policies.

We obtained the constituent dimensions for this multidimensional approach from a literature review using the SIA framework as our reference. The dimensions that make up this multidimensional index include economic, built-environment, health and well-being, institutional, community, gender, and cultural dimensions. These dimensions are essential components in understanding a population's vulnerability.

- Sub-question 2: *How can we design a multidimensional approach to measure social vulnerabilities?*

The multidimensional index was designed using a composite index construction approach structure inspired by the literature on methodological choices in the construction of composite indices from Salzman (2003) and an article on a systematic review of flood vulnerability indices from Moreira et al. (2021)This structured methodology design takes into account a number of design choices, both conceptual-theoretical and statistical techniques. The methodological design for this multidimensional approach involves index construction, determining social dimensions, preparing dimensional indexes, aggregation to produce a composite index, sensitivity analysis, and validation methods. Due to time and data limitations, only sensitivity analysis was conducted in this research.

- Sub-question 3: *How can we apply the multidimensional approach to measure social vulnerability, and what are the comparison results with the existing method?*

After finalising the methodological framework with a series of design decisions, the multidimensional index is calculated. The Social Vulnerability Index (SoVI) is also calculated as a benchmark for comparison with the alternative methodology under development. Indonesian socioeconomic and demographic data are used as inputs to measure social vulnerability using both SoVI and the Multidimensional Approach. The results of these calculations produce a social vulnerability index for all regions of Indonesia at the subdistrict level. These values are then divided into five categories based on the standard deviation distance from the mean data: low, mid-low, medium, mid-high, and high. In addition to the final index data, other output data from the multidimensional index is used for analysis, including index data in each dimension. Using Indonesian data, we obtain information on six dimensions, each categorised into the same groups.

After obtaining the multidimensional index and SoVI results, we compare them to identify differences and deviations. Various methods are used for the comparison. In the theoretical aspect of SoVI, PCA results in different loadings for each variable, where variables with high variance receive more significant loadings. The multidimensional method also uses PCA to calculate each dimension, but the difference lies in the loadings being based on the variance in index preparation, specifically within each dimension. This minimises the potential for significant differences in loadings on variables with different dimensions, ensuring a more equitable index calculation for each dimension. Generating an index for each dimension allows for a deeper exploration of the interconnected relationship between vulnerability dimensions, aligning with the notion of compounded vulnerability in a population.

In terms of visual comparison and category distribution, the two indices exhibit significant differences. Differences in category distribution are noticeable in several areas where visually evident disparities are apparent. Statistically, both methods demonstrate a normal distribution pattern for category distribution. The distinctions lie in the specific number of regions within each social vulnerability category.

One crucial aspect tested at this stage is to compare the contribution of each variable to the social vulnerability index. By using information on variable loadings and variance for each factor, we calculate the contribution of each input variable to the final SoVI index results. We also adjust the calculation process to calculate variable contribution on the multidimensional index. The results of the variable contributions are then grouped and aggregated according to their respective dimensions to observe how evenly the contribution of all vulnerability dimensions is in the two indices. The test results indicate that the Multidimensional Index has an even contribution in each vulnerability dimension, while the SoVI shows inequality in the contribution of the vulnerability dimensions that form it.

- Sub-question 4: *What are the processes and results of implementing the multidimensional index in a disaster risk assessment?*

The next phase of our research on vulnerability involves implementing the method to assess disaster risk by integrating vulnerability findings with disaster hazard and exposure data. For our study, we are focusing on flood as a natural hazard case, with Indonesia as our specific area of study. We are utilising data from the Global Flood Map (GFM) to analyse flood hazard conditions in Indonesia. The GFM provides data on both riverine and rainfall-induced floods for a 1-in-100-year period. We are combining this information with population data from WorldPop to identify the population at risk of high-risk floods. Both the GFM and population data are in raster format with a resolution of 90 x 90 meters, enabling us to evaluate the number of people impacted by high-risk flooding (exceeding 0.5 meters) in each pixel. Subsequently, we aggregate the raster data to align with the scale used for vulnerability data, particularly at the subdistrict level. The statistical data on the population exposed to flood hazards in each subdistrict serves as a reference for our flood hazard analysis. This data highlights areas with differing levels of exposure to flood hazards based on the population in each subdistrict.

The data obtained on people exposed to high-risk flooding is further analysed together with social vulnerability data to assess the risk of flooding in the population. By incorporating this data, we can determine the number of people in different social vulnerability categories exposed to high-risk flooding using the multidimensional index. The statistical distribution data on exposed people was further analysed to examine the results of flood risk analysis based on a multidimensional index. In addition to assessing general risk conditions, the multidimensional index will also help us understand the risk of flooding based on the level of vulnerability in each dimension of social vulnerability.

- Sub-question 5: *What are the implications of using a multidimensional approach in measuring social vulnerability for disaster risk management policymaking?*

The analysis conducted during the multidimensional method's development stage using Indonesian data, comparison with SoVI, and flood risk analysis yielded valuable insights for formulating disaster management policies. The social vulnerability index not only helps identify an area's vulnerability level and population but also provides additional analysis to assist policymakers in creating appropriate policies.

The first important implication of this analysis is the ability to prioritise policies based on vulnerability categories. Identifying vulnerabilities using a multidimensional index at an overall index level and for each dimension offers valuable insights for policymakers to identify high-vulnerability areas. These areas can then be given priority in disaster risk policy intervention efforts, both in reducing vulnerabilities and managing disasters.

The second implication involves the ability to create targeted policies for vulnerable hotspots. This method's spatial analysis capabilities enable policymakers to identify areas with a high concentration of high vulnerability index clusters. These hotspots can serve as references for further study and primary policy targets in formulating disaster management policies.

The third implication is the ability to tailor disaster management policies based on the dominant dimensions contributing to a region's vulnerability. The method's capacity to identify a region's dominant dimensions provides crucial insights for policymakers, assisting in creating tailored disaster management policies. Further analysis can also help identify the interlinked relationship between dominant vulnerabilities, providing important information for policymakers to develop appropriate policies according to population conditions.

After understanding how disaster management policy could be affected, the explanation of how practitioners can practically use this method is provided. This explanation includes details about the variables that correspond to the indicators, the process of calculating dimensional and final indices, and the outputs that align with the interests and needs of practitioners. This clarity helps in understanding how the method can be used in practice.

11.2. Reflection

The research delves into innovative approaches for assessing social vulnerability, focusing on the dimensions of vulnerability. By drawing insights from intersectionality theory, which examines discrimination against black women in the US, the study offers a comprehensive understanding of social vulnerability. One of the central challenges is integrating this perspective into calculating social vulnerability, which is addressed by developing a multidimensional index method. Using statistical tools, such as Principal Component Analysis in index calculations, facilitates a deeper comprehension of compiling a composite index using multiple variables.

The research's notable findings, which have direct implications, include the identification of predominant vulnerability dimensions in each region, disparities observed in comparison with SoVI results, and the practical application of these findings in flood risk analysis in Indonesia.

Another important finding is the ability of this alternative social vulnerability calculation to recognise multiple dominant vulnerability dimensions. This information can be used for social vulnerability analysis and insight into formulating disaster management policies. It is critical to highlight this because discussions about compounded vulnerability in a person or a population show the potential for worse impacts during a disaster. Recognising these characteristics can assist policymakers in creating comprehensive and appropriate disaster management policies based on a person's complex vulnerability characteristics.

While the research uses Indonesia as the study case and has yet to explore localised analysis approaches, it aspires to stimulate new conversations within social vulnerability indexing.

11.3. Societal Contribution

This research was initiated to add value to society through scientific methods. The practical significance of this research lies in offering an alternative method and analysis using real data to assess how this approach can be applied to real-life scenarios. This could provide Indonesia's national disaster management agency and other disaster policy formulators with scientific insights into using alternative multidimensional-based social vulnerability calculation methods. The policy implications discussed in the research aim to help society understand the analytical and practical potential of the research results. Additionally, the research provides guidance on applying multidimensional methods and utilising various types of analysis results as a reference for real-life scenarios. It is hoped that this research can significantly contribute to enhancing the understanding of social vulnerability and increasing disaster resilience by offering a comprehensive assessment tool for policymakers.

11.4. Scientific Contributions

The alternative method presented in this research aims to measure social vulnerability differently compared to the existing method. This contributes to the advancement of scientific knowledge in the field of disaster risk management and social vulnerability measurement. By providing an index of social vulnerability dimensions, this innovative approach is expected to enrich academic discussions in the field of disaster management.

This research introduces a methodological advancement by integrating intersectionality theory into vulnerability assessment using statistical tools such as Principal Component Analysis (PCA) and accommodating the vulnerability dimensions as the main steps of measuring social vulnerability. By utilising real data on social variables in Indonesia, the research not only aims to present the concept of a multidimensional index but also provides examples of its application in real-world scenarios. The comparative analysis conducted in this research seeks to offer a clearer understanding of how this method assesses social vulnerability compared to existing methods and their results. It is important to note that while this research includes several comparative analyses, its purpose is not to determine the best method or the most representative results. Instead, it sheds light on the insights for the users who need a different way to measure social vulnerability and presents the limitations of this alternative, multidimensional approach.

11.5. Recommendation for Future Works

The use of a multidimensional index in the social vulnerability analysis process can offer additional insights into disaster risk analysis. This approach allows for a detailed analysis of vulnerability dimensions and interlinked relations within each dominant vulnerability dimension. It is also important to consider the policy implications of this research, as using a multidimensional index can contribute to the formulation of more nuanced disaster risk policies.

In addressing the limitations of this research, several recommendations for future work can be made to enhance the development of this method. Firstly, this multidimensional research needs further analysis regarding variable selection and categorisation. The research will better reflect real conditions by evaluating the suitability of more representative and validated variables for measuring social vulnerability. Additionally, utilising up-to-date data from consistent sources and years will produce clearer and more reliable research output. Overcoming differences in the data used in this research can be achieved by incorporating more complete and consistent data input.

In future work, the validation stage should be emphasised to test the validity of this method. This can be done through statistical methods or by conducting interviews with policymakers in relevant fields. The validation process will enable the practical use of methods in formulating disaster risk management policies with high confidence, provided that the results are positive. Furthermore, validation can be performed on SoVI calculations to compare the results and justify their validity as representative data for real conditions.

The research can further explore the policy implications by involving authorised institutions. This is important because the practical application of this method depends on the institutions that develop disaster risk management policies. Discussing the practical challenges during the analysis stage and the potential impacts of using a multidimensional index in social vulnerability analysis can provide valuable insights for policymakers in the field. Further analysis of compounded vulnerability and its implications for policy formulation can also be explored in more detail. Considering that the dimensions of social vulnerability are not isolated but interconnected within a population, the combination of vulnerability dimensions in a population gives it a unique character.

References

Adger, W. N. (1999). *Social Vulnerability to Climate Change and Extremes in Coastal Vietnam*.

Andrade, M. M. N. de, & Szlafsztein, C. F. (2018). Vulnerability assessment including tangible and intangible components in the index composition: An Amazon case study of flooding and flash flooding. *Science of The Total Environment*, *630*, 903–912. https://doi.org/10.1016/J.SCITOTENV.2018.02.271

Arif, S., Syukri, M., Holmes, R., & Febriany, V. (2010). *Gendered risks, poverty and vulnerability in Indonesia - ; Gendered risks, poverty and vulnerability in Indonesia* -. www.odi.org.uk

Birkmann, J. (2006). *Measuring vulnerability to natural hazards*.

BNPB. (2024). *Data Informasi Bencana Indonesia (DIBI)*. https://dibi.bnpb.go.id/kwaktu2

BNPB; UNPFA; BPS. (2015). *Population Exposed to Natural Hazard*.

Booysen, F. (2002). Canadian Journal of Disability Studies. *Social Indicator Research*, *59*, 115–151. www.cjds.uwaterloo.ca

Boruff, B. J., Emrich, C., & Cutter, S. L. (2005). Erosion hazard vulnerability of US coastal counties. *Journal of Coastal Research*, *21*(5), 932–942. https://doi.org/10.2112/04-0172.1

BPS. (2014). *Statistik Potensi Desa Indonesia 2014*.

BPS. (2020). *Jumlah Penduduk Hasil Proyeksi Menurut Provinsi dan Jenis Kelamin*. https://www.bps.go.id/id/statistics-table/2/MTg4NiMy/jumlah-penduduk-hasil-proyeksi-menurut-provinsi-dan-jenis-kelamin--ribu-jiwa-.html

BPS. (2023). *LAPORAN PEREKONOMIAN INDONESIA 2023 BADAN PUSAT STATISTIK*. www.freepik.com

BPS. (2024, April 22). *Tingkat Penyelesaian Pendidikan Menurut Jenjang Pendidikan dan Provinsi, 2021-2023.* Badan Pusat Statistika Indonesia. https://www.bps.go.id/id/statistics-table/2/MTk4MCMy/tingkat-penyelesaian-pendidikan-menurut-jenjang-pendidikan-dan-provinsi.html

Climent-Gil, E., Aledo, A., & Vallejos-Romero, A. (2018). The social vulnerability approach for social impact assessment. *Environmental Impact Assessment Review*, *73*, 70–79. https://doi.org/10.1016/j.eiar.2018.07.005

Collins, P. H., & Bilge, S. (2016). *Intersectionality* (1st ed.). MA: Polity.

Crenshaw, K. (1989). Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics. *University of Chicago Legal Forum*, *1989*(1). http://chicagounbound.uchicago.edu/uclfhttp://chicagounbound.uchicago.edu/uclf/vol1989/iss1/8

Cutter, S. L. (1996). *Vulnerability to environmental hazards*.

Cutter, S. L. (2024). The origin and diffusion of the social vulnerability index (SoVI). *International Journal of Disaster Risk Reduction*, *109*. https://doi.org/10.1016/j.ijdrr.2024.104576

Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, *84*(2), 242–261. https://doi.org/10.1111/1540-6237.8402002

Cutter, S. L., & Finch, C. (2008). Temporal and spatial changes in social vulnerability to natural hazards. *Proceedings of the National Academy of Sciences of the United States of America*, *105*(7), 2301–2306. https://doi.org/10.1073/pnas.0710375105

Eisenman, D. P., Wilhalme, H., Tseng, C. H., Chester, M., English, P., Pincetl, S., Fraser, A., Vangala, S., & Dhaliwal, S. K. (2016). Heat Death Associations with the built environment, social vulnerability and their interactions with rising temperature. *Health & Place*, *41*, 89–99. https://doi.org/10.1016/J.HEALTHPLACE.2016.08.007

English, P. B., Sinclair, A. H., Ross, Z., Anderson, H., Boothe, V., Davis, C., Ebi, K., Kagey, B., Malecki, K., Shultz, R., & Simms, E. (2009). Environmental health indicators of climate change for the United States: Findings from the state environmental health indicator collaborative. In *Environmental Health Perspectives* (Vol. 117, Issue 11, pp. 1673–1681). https://doi.org/10.1289/ehp.0900708

Filatova, T. (2014). Market-based instruments for flood risk management: A review of theory, practice and perspectives for climate adaptation policy. *Environmental Science & Policy*, *37*, 227–242. https://doi.org/10.1016/J.ENVSCI.2013.09.005

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2020). A Social Vulnerability Index for Disaster Management. *Journal of Homeland Security and Emergency Management*, *8*(1). https://doi.org/10.2202/1547-7355.1792

Fordham, M., Lovekamp, W. E., Thomas, D. S. K., & Phillips, B. D. (2013). Understanding Social Vulnerability. In *Social Vulnerability to Disasters* (2nd ed., pp. 1–32). CRC Press. https://books.google.nl/books?hl=id&lr=&id=onAWhiaVsuIC&oi=fnd&pg=PA1&dq=Understanding+social+vulnerability.+Social+vulnerability+to+disasters&ots=XH5uQfZfpF&sig=zpgSXlauGDdAGw9IfsFSj6kAgP8#v=onepage&q=Understanding%20social%20vulnerability.%20Social%20vulnerability%20to%20disasters&f=false

Garbutt, K., Ellul, C., & Fujiyama, T. (2015). Mapping social vulnerability to flood hazard in Norfolk, England. *Environmental Hazards*, *14*(2), 156–186. https://doi.org/10.1080/17477891.2015.1028018

Gerrard, R. E. C. (2018). Developing an index of community competence in flood response for flood-affected rural parishes on the Somerset Levels and Moors using composite and spatial datasets. *Area*, *50*(3), 344–352. https://doi.org/10.1111/AREA.12416

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: a Review of the Literature. *Economics of Disasters and Climate Change 2020 4:1*, *4*(1), 223–247. https://doi.org/10.1007/S41885-020-00060-5

Hazards & Vulnerability Research Institute. (2016). *The SoVI Recipe (September 2016)*.

Intani, N. P., Nadzifah, S., Hakim, A. L., & Hasan Asy'ari, M. (2022). PERANG SAMPIT (KONFLIK SUKU DAYAK DENGAN SUKU MADURA) PADA TAHUN 2001. *Jurnal Penelitian Ilmu Sosial*. http://sosial.unmermadiun.ac.id/index.php/sosial

Intergovernmental Panel on Climate Change. (2014). *Climate change 2014 : synthesis report : longer report*.

Jamshed, A., Rana, I. A., Mirza, U. M., & Birkmann, J. (2019). Assessing relationship between vulnerability and capacity: An empirical study on rural flooding in Pakistan. *International Journal of Disaster Risk Reduction*, *36*, 101109. https://doi.org/10.1016/J.IJDRR.2019.101109

Jha, R. K., & Gundimeda, H. (2019). An integrated assessment of vulnerability to floods using composite index – A district level analysis for Bihar, India. *International Journal of Disaster Risk Reduction*, *35*, 101074. https://doi.org/10.1016/J.IJDRR.2019.101074

Kienberger, S., & Steinbruch, F. (2014). *P-GIS and disaster risk management: Assessing vulnerability with P-GIS methods-Experiences from Búzi, Mozambique*. https://www.researchgate.net/publication/228917329

Koks, E. E., Jongman, B., Husby, T. G., & Botzen, W. J. W. (2015). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. *Environmental Science and Policy*, *47*, 42–52. https://doi.org/10.1016/j.envsci.2014.10.013

Ministry of Health. (2013). *BASIC HEALTH RESEARCH RISKESDAS 2013*. www.litbang.depkes.go.id

Ministry of Internal Affairs. (2019). *Visualisasi Data Kependudukan*.

Moreira, L. L., De Brito, M. M., & Kobiyama, M. (2021). Review article: A systematic review and future prospects of flood vulnerability indices. In *Natural Hazards and Earth System Sciences* (Vol. 21, Issue 5, pp. 1513–1530). Copernicus GmbH. https://doi.org/10.5194/nhess-21-1513-2021

Morgan, M. R. (2013). *The Eruption of Krakatoa in 1883*. Branchcollective.

Munyai, R. B., Musyoki, A., & Nethengwe, N. S. (2019). An assessment of flood vulnerability and adaptation: A case study of Hamutsha-Muungamunwe village, Makhado municipality. *Jàmbá: Journal of Disaster Risk Studies*, *11*(2), 8. https://doi.org/10.4102/JAMBA.V11I2.692

Otto, I. M., Reckien, D., Reyer, C. P. O., Marcus, R., Le Masson, V., Jones, L., Norton, A., & Serdeczny, O. (2017). Social vulnerability to climate change: a review of concepts and evidence. *Regional Environmental Change*, *17*(6), 1651–1662. https://doi.org/10.1007/s10113-017-1105-9

Painter, M. A., Shah, S. H., Damestoit, G. C., Khalid, F., Prudencio, W., Chisty, M. A., Tormos-Aponte, F., & Wilhelmi, O. (2024). A systematic scoping review of the Social Vulnerability Index as applied to natural hazards. *Natural Hazards*. https://doi.org/10.1007/s11069-023-06378-z

Pearse, R. (2017). Gender and climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *8*(2). https://doi.org/10.1002/wcc.451

Pelling, M. (2003). *The Vulnerability of Cities: Natural Disasters and Social Resilience* (1st ed.). Earthscan Publications.

Phillips, D. (2023). *Hidden and Persistent Unemployment Among Older Workers*.

Phraknoi, N., Sutanto, J., Hu, Y., Goh, Y. S., & Lee, C. E. C. (2023). Older people's needs in urban disaster response: A systematic literature review. In *International Journal of Disaster Risk Reduction* (Vol. 96). Elsevier Ltd. https://doi.org/10.1016/j.ijdrr.2023.103809

Rabinovich, A. B., Geist, E. L., Fritz, H. M., & Borrero, J. C. (2015). Introduction to "Tsunami Science: Ten Years After the 2004 Indian Ocean Tsunami. Volume

I." In *Pure and Applied Geophysics* (Vol. 172, Issues 3–4, pp. 615–619). Birkhauser Verlag AG. https://doi.org/10.1007/s00024-015-1038-5

Reckien, D., Creutzig, F., Fernandez, B., Lwasa, S., Tovar-Restrepo, M., Mcevoy, D., & Satterthwaite, D. (2017). Climate change, equity and the Sustainable Development Goals: an urban perspective. *Environment and Urbanization*, *29*(1), 159–182. https://doi.org/10.1177/0956247816677778/ASSET/IMAGES/LARGE/10.1177_0956247816677778-IMG1.JPEG

Rentschler, J., & Salhab, M. (2020). *People in Harm's Way Flood Exposure and Poverty in 189 Countries Poverty and Shared Prosperity 2020 Background Paper*. http://www.worldbank.org/prwp.

Robinson, C., Lindley, S., & Bouzarovski, S. (2019). The Spatially Varying Components of Vulnerability to Energy Poverty. *Annals of the American Association of Geographers*. https://doi.org/10.1080/24694452.2018.1562872

Rygel, L., O'Sullivan, D., & Yarnal, B. (2006). A method for constructing a social vulnerability index: An application to hurricane storm surges in a developed country. *Mitigation and Adaptation Strategies for Global Change*, *11*(3), 741–764. https://doi.org/10.1007/s11027-006-0265-6

Salzman, J. (2003). *A Summary of methodological issues associated with the construction of indices of economic and social well being*.

Santamouris, M. (2020). Recent progress on urban overheating and heat island research. Integrated assessment of the energy, environmental, vulnerability and health impact. Synergies with the global climate change. In *Energy and Buildings* (Vol. 207). Elsevier Ltd. https://doi.org/10.1016/j.enbuild.2019.109482

Schellekens, P. (2001). *English Language As A Barrier To Employment, Education And Training ACKNOWLEDGEMENTS*.

Schmidtlein, M. C., Shafer, J. M., Berry, M., & Cutter, S. L. (2011). Modeled earthquake losses and social vulnerability in Charleston, South Carolina. *Applied Geography*, *31*(1), 269–281.

Siagian, T. H., Purhadi, P., Suhartono, S., & Ritonga, H. (2014). Social vulnerability to natural hazards in Indonesia: Driving factors and policy implications. *Natural Hazards*, *70*(2), 1603–1617. https://doi.org/10.1007/s11069-013-0888-3

SMERU Insititute. (2015). *PRESS RELEASE THE LAUNCHING OF THE 2015 POVERTY AND LIVELIHOOD MAP OF INDONESIA Challenges for Poverty Reduction Policies*. www.indonesiapovertymap.org.

Sufa, T. (2019, July 12). *Greater Jakarta braces for harsher dry season as El Nino looms over Indonesia*. The Jakarta Post. https://www.thejakartapost.com/news/2019/07/12/greater-jakarta-braces-for-harsher-dry-season-as-el-nino-looms-over-indonesia.html

Tapia, C., Abajo, B., Feliu, E., Mendizabal, M., Martinez, J. A., Fernández, J. G., Laburu, T., & Lejarazu, A. (2017). Profiling urban vulnerabilities to climate change: An indicator-based vulnerability assessment for European cities. *Ecological Indicators*, *78*, 142–155. https://doi.org/10.1016/j.ecolind.2017.02.040

Tate, E. (2012). Social vulnerability indices: A comparative assessment using uncertainty and sensitivity analysis. *Natural Hazards*, *63*(2), 325–347. https://doi.org/10.1007/s11069-012-0152-2

Teo, M., Goonetilleke, A., Deilami, K., Ahankoob, A., & Lawie, M. (2019). Engaging residents from different ethnic and language backgrounds in disaster preparedness. *International Journal of Disaster Risk Reduction*, *39*. https://doi.org/10.1016/j.ijdrr.2019.101245

Thomas, K., Hardy, R. D., Lazrus, H., Mendez, M., Orlove, B., Rivera-Collazo, I., Roberts, J. T., Rockman, M., Warner, B. P., & Winthrop, R. (2019). Explaining differential vulnerability to climate change: A social science review. *Wiley Interdisciplinary Reviews. Climate Change*, *10*(2). https://doi.org/10.1002/WCC.565

Transparency International. (2023). *2023 Corruption Perceptions Index*. https://www.transparency.org/en/cpi/2023?gad_source=1&gclid=CjwKCAjw1K-zBhBIEiwAWeCOF96_a2GM-6g26ZneugqlgOguKR_NDnDajZypb9GrSM-rsAI70BnUhxoCtw4QAvD_BwE

Uejio, C. K., Wilhelmi, O. V., Golden, J. S., Mills, D. M., Gulino, S. P., & Samenow, J. P. (2011). Intra-urban societal vulnerability to extreme heat: The role of heat exposure and the built environment, socioeconomics, and neighborhood stability. *Health and Place*, *17*(2), 498–507. https://doi.org/10.1016/j.healthplace.2010.12.005

UNDRR. (2024a). *Hazard | UNDRR*. https://www.undrr.org/terminology/hazard

UNDRR. (2024b). *Vulnerability | UNDRR*. https://www.undrr.org/terminology/vulnerability

USAID. (2017). *Climate Risk Profile: Indonesia*.

Vanclay, F. (2002). Conceptualising social impacts. *Environmental Impact Assessment Review*, *22*, 18–211. www.elsevier.com/locate/eiar

Vincent, K. (2004). *Creating an Index of Social Vulnerability to Climate Change in Africa*. https://www.researchgate.net/publication/228809913

Weber, S., Sadoff, N., Zell, E., & de Sherbinin, A. (2015). Policy-relevant indicators for mapping the vulnerability of urban populations to extreme heat events: A case study of Philadelphia. *Applied Geography*, *63*, 231–243. https://doi.org/10.1016/j.apgeog.2015.07.006

White, G. F. (1974). *Natural Hazards, Local, National, Global*. Oxford University Press.

Wisner, C., & Nivaran, D. (2004). *At Risk: natural hazards, people's vulnerability and disasters Second edition 2003*.

Wold, S., Esbensen, K., & Geladi, P. (1987). *Principal Component Analysis*.

YEU. (2013, January 22). *Jakarta Flood Response 2013*. Reliefweb.

Appendices

This section presents additional information on the process of measuring and analysing the multidimensional method used previously. Table 10 displays the data layers and sources utilised in this project.

Table 10 Data Layer

Data Layer	Data Set	Data Source
Poverty data	SMERU Poverty Map 2015	SMERU
Village data	PODES 2014	National Statistics Bureau
Demographic data	Indonesia Demographic data	Ministry of Internal Affairs of Indonesia
Administration level 3 boundaries	Administration level 3 boundaries	National Statistics Bureau (from humdata.org)
Pluvial Flood data	Global Flood Map v.2	Fathom
Fluvial Flood data	Global Flood Map v.2	Fathom
Indonesia Population	Indonesia Population Data	WorldPop

Furthermore, in Figure 57, you can find the correlation matrix for all social variables utilised in this analysis. This correlation matrix is employed at the outset of the PCA calculation to assess the correlation between variables and to discern its impact on the loadings dynamics during the components calculation stage.

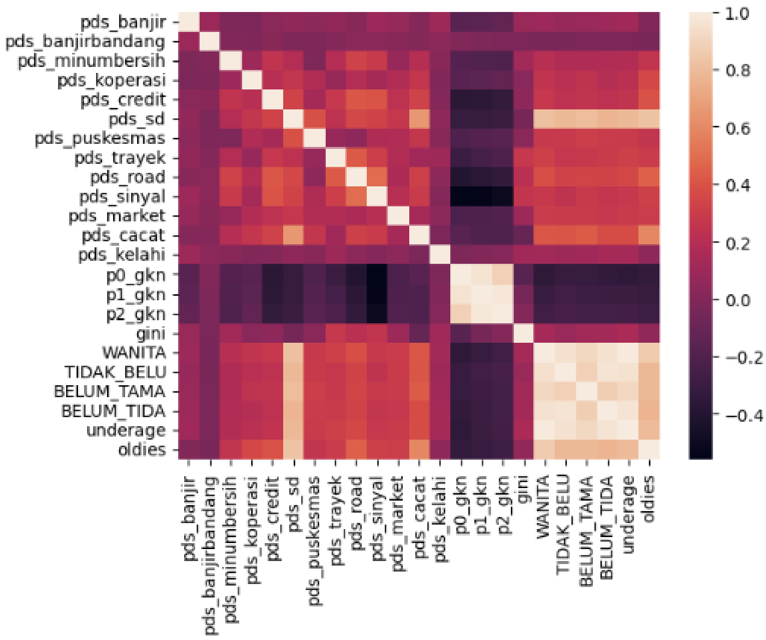


Figure 57 Correlation matrix of all variables in the social vulnerability measurement

In determining the number of PCA components in the SoVI calculation, the scree plot is used as a reference to decide the appropriate number of components based on the Kaiser Criterion or an eigenvalue above 1. Figure 58 shows the Scree Plot used in the SoVI calculation process.

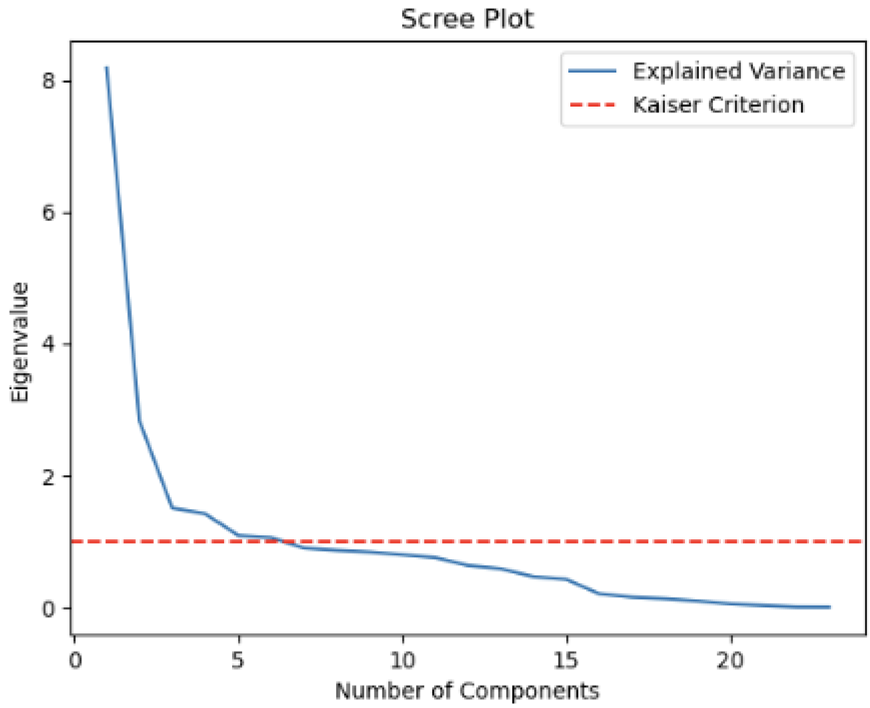
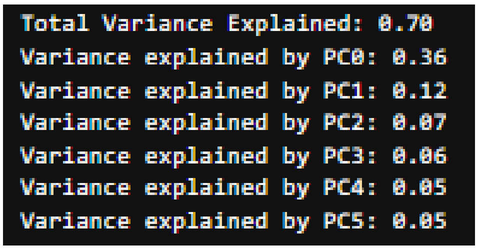


Figure 58 Scree plot of SoVI

The SoVI calculation process determined six components based on the Kaiser Criterion. Following this, a PCA model was constructed and the Varimax rotator was used for rotation. Figure 59 displays the variance value for each PCA component while

Table 11 SoVI variables loadings shows the loadings of each input variable for this SoVI model.



```
Total Variance Explained: 0.70
Variance explained by PC0: 0.36
Variance explained by PC1: 0.12
Variance explained by PC2: 0.07
Variance explained by PC3: 0.06
Variance explained by PC4: 0.05
Variance explained by PC5: 0.05
```

Figure 59 SoVI variance explained per component.

Table 11 SoVI variables loadings

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
pds_banjir	0,042111	-0,078626	-0,1443	-0,379053	0,366515	-0,178888
pds_banjirbandang	-0,005945	-0,044151	-0,02434	-0,057409	0,611783	-0,500468
pds_minumbersih	0,109091	-0,119127	-0,145389	0,379879	-0,133078	-0,263992
pds_koperasi	0,116541	-0,000315	0,185878	0,237128	0,269888	0,373309
pds_credit	0,163534	-0,18986	0,051742	0,32083	0,187913	0,002609
pds_sd	0,297394	0,150894	0,181537	0,040746	0,036397	-0,069322
pds_puskesmas	0,128978	0,031741	0,228192	-0,12864	0,272523	0,427418
pds_trayek	0,147069	-0,119406	-0,392035	0,158565	0,020915	0,059202
pds_road	0,192364	-0,181186	-0,200155	0,345614	-0,003598	-0,114342
pds_sinyal	0,181783	-0,311005	-0,081978	0,134673	0,042749	0,02251
pds_market	0,134553	-0,034137	-0,029072	-0,021688	0,321594	0,400714
pds_cacat	0,192417	0,052945	0,321422	0,303198	0,174904	-0,129209
pds_kelahi	0,03582	0,04644	-0,331426	-0,181261	0,271266	-0,052824
p0_gkn	-0,208336	0,411593	-0,056992	0,227548	0,108389	-0,041731
p1_gkn	-0,200096	0,432365	-0,145262	0,226033	0,121847	0,026143
p2_gkn	-0,185326	0,424916	-0,181214	0,221492	0,129688	0,058936
gini	0,054517	-0,081219	-0,580542	0,028397	0,007124	0,328442
WANITA	0,319461	0,196555	-0,066295	-0,087341	-0,085016	-0,046802
TIDAK_BELU	0,305999	0,219494	-0,033116	-0,118356	-0,095922	-0,053182
BELUM_TAMA	0,303843	0,194709	-0,030641	-0,088889	-0,046056	-0,021242
BELUM_TIDA	0,30628	0,203348	-0,073696	-0,144228	-0,10178	-0,045853
underage	0,31364	0,19911	-0,094059	-0,134832	-0,087233	-0,036684
oldies	0,303066	0,136754	0,076111	0,148688	-0,00854	-0,03389

The value of each factor is totalled by first determining the cardinality of each factor using an additive model. The additive model formula and the cardinality used in the SoVI model are below.

Total SoVI = Factor 1 + Factor 2 – Factor 3 + Factor 4 + Factor 5 – Factor 6

From the obtained SoVI total, the final index results are categorised based on the standard deviation value. Table 12 Social Vulnerability categorisation below explains the categorisation using this standardisation:

Table 12 Social Vulnerability categorisation

Category	Criteria
High	>1,5 std
Mid-high	0.5 – 1.5 std
Medium	-0.5 – 0.5 std
Mid-low	-1.5 – -0.5 std
Low	<1.5 std

Based on the categorisation calculations explained above, we obtained the SoVI map presented in Section 7.2.

The next step is calculating the multidimensional index. This process starts with determining the index value in each vulnerability dimension. The first step involves categorising the input variables in each dimension and grouping them accordingly. Table 13 illustrates the division of variables based on vulnerability dimensions.

Table 13 Variables categorisation based on its dimension

Dimension	Variables
Economy	'p0_gkn', 'p1_gkn', 'p2_gkn', 'gini', 'pds_koperasi', 'pds_credit', 'BELUM_TIDA'
Cultural	'TIDAK_BELU', 'BELUM_TAMA'
Gender	'WANITA'
Community	'pds_kelahi'
Health and Wellbeing	'underage', 'oldies', 'pds_cacat'
Built Environment	'pds_trayek', 'pds_road', 'pds_sinyal', 'pds_sd', 'pds_banjir', 'pds_banjirbandang', 'pds_minumbersih', 'pds_puskesmas'

The process starts with calculating dimensions based on each existing variable, as explained in Chapter 5The calculation of the dimension index depends on the number of variables in each index. For dimensions with more than three variables, we use

PCA. For dimensions with two variables, we use the geometric mean, and for dimensions with only one variable, we use the normalised value for that variable.

In the economic dimension, PCA is used for calculations. Figure 60 displays a scree plot illustrating the economic dimensions and helping determine the number of components. In this calculation, three components are utilised, as shown in Table 14 with the variable loadings for each factor. The final economic index and the cardinality of each factor can be calculated using the formula provided.

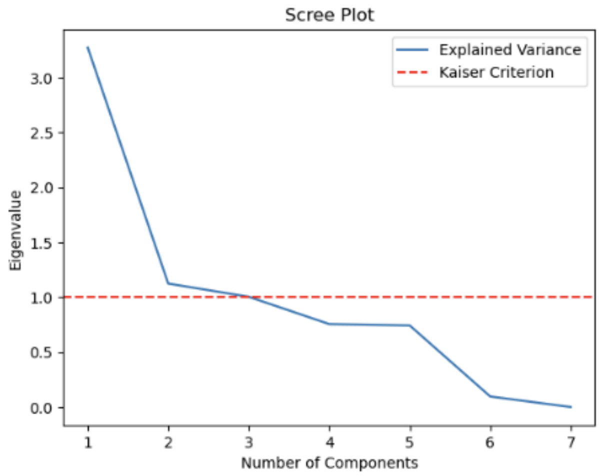


Figure 60 Scree plot of Economy Index

Table 14 Economy Index variables loadings

	Factor 1	Factor 2	Factor 3
p0_gkn	0,525736	0,125398	0,123001
p1_gkn	0,53	0,227678	0,031255
p2_gkn	0,513747	0,274841	-0,008598
gini	-0,071619	0,438341	-0,830971
pds_koperasi	-0,153707	0,58689	0,487524
pds_credit	-0,287582	0,29571	0,23466
BELUM_TIDA	-0,252607	0,482569	-0,023712

Economy Index = Factor 1 – Factor 2 – Factor 3

The same categorisation is carried out on the economic index to be used as a category reference in the economic index map, which can be seen in Figure 9The Built Environment Index calculation also uses the PCA method. The scree plots, loadings tables, and formulas are in the data below.

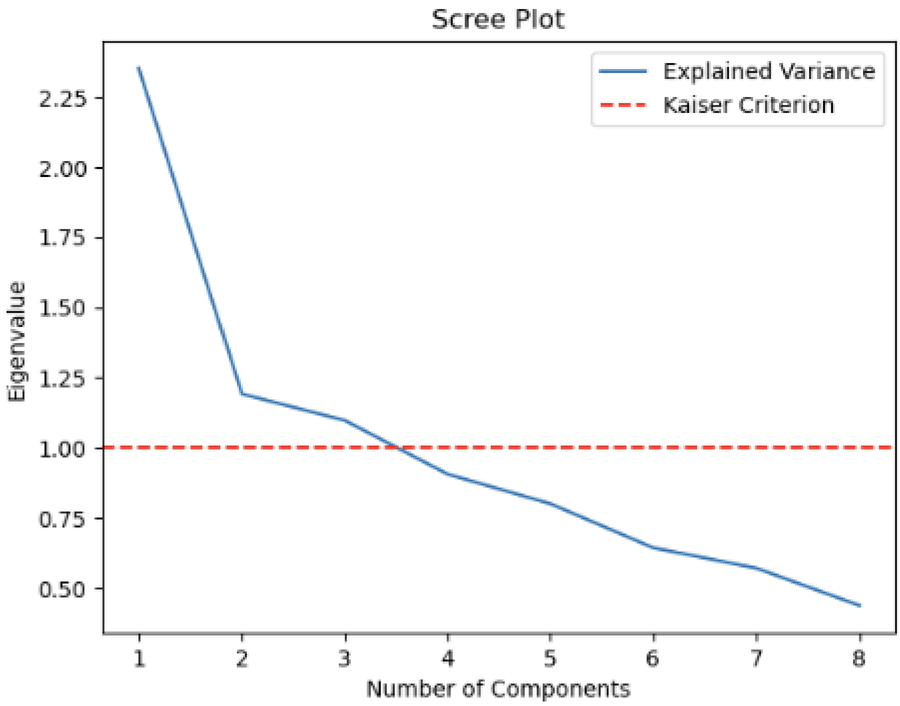


Figure 61 Scree plot of Built Environment Index

Table 15 Built Environment Index variables loadings

	1	2	3	4
pds_trayek	-0,403851	-0,19307	0,048072	-0,16317
pds_road	-0,503159	-0,250448	-0,006682	0,016871
pds_sinyal	-0,483017	-0,038381	0,066516	-0,035817
pds_sd	-0,429518	0,408197	-0,114175	0,102045
pds_banjir	-0,076387	0,182471	0,678844	-0,654409
pds_banjirbandang	-0,01773	-0,04572	0,70249	0,705286
pds_minumbersih	-0,33495	-0,381721	-0,118894	0,099396
pds_puskesmas	-0,218182	0,742163	-0,10829	0,160735

Built Environment Index = Factor 1 – Factor 2 + Factor 3 + Factor 4

The Health and Wellbeing Index is calculated using the PCA method. The screen plot is used to determine the number of components, loadings factor for each variable, and the index formula, which can be seen in the data below.

Table 16 Scree plot of health and well-being index

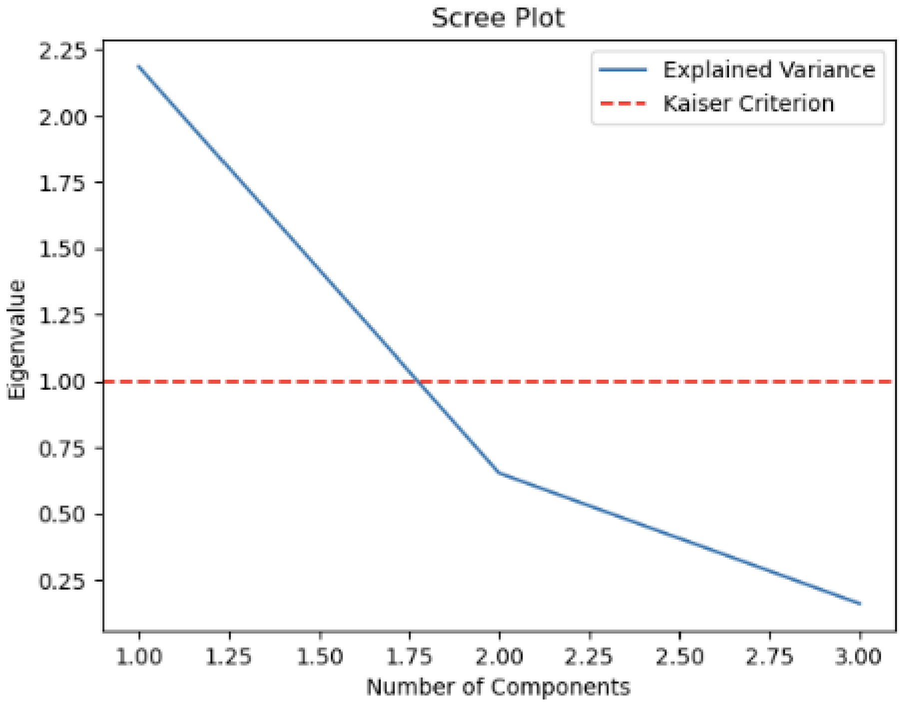


Table 17 Health and well-being Index variables loadings

	Factor 1
underage	0.584624
oldies	0.639812
pds_cacat	0.498854

Health and well-being Index = Factor 1

To calculate the cultural index with two variables, we use the geometric mean, the formula of which is found in Chapter 5. Prior to applying the geometric mean to the cultural variables, we use the min-max normalisation method. The resulting geometric mean is then used as a map index based on the categories in Table 12.

For the gender and community index, which has only one variable, we use the value of that variable as the dimension index value. Before categorisation, the value index is normalised using the min-max method to produce a value between 0 and 1.

Finally, we use an additive model to obtain the multidimensional index value, adding all the dimensional indexes obtained. We use the same categorisation technique as the previous index map to map the multidimensional index. The results of the multidimensional index mapping, along with the distribution of each category, can be found in Chapter 6.

The sensitivity analysis calculation process in this research was carried out by testing other aggregation methods in forming a composite index from the dimension's index. We performed geometric mean and PCA to understand the differences that arise when these two methods are applied to the existing dimension index data. The PCA calculation followed the same method for calculating the previous indices. The results include a scree plot, loadings for each variable, and the composite index formula applied in the sensitivity testing model with PCA.

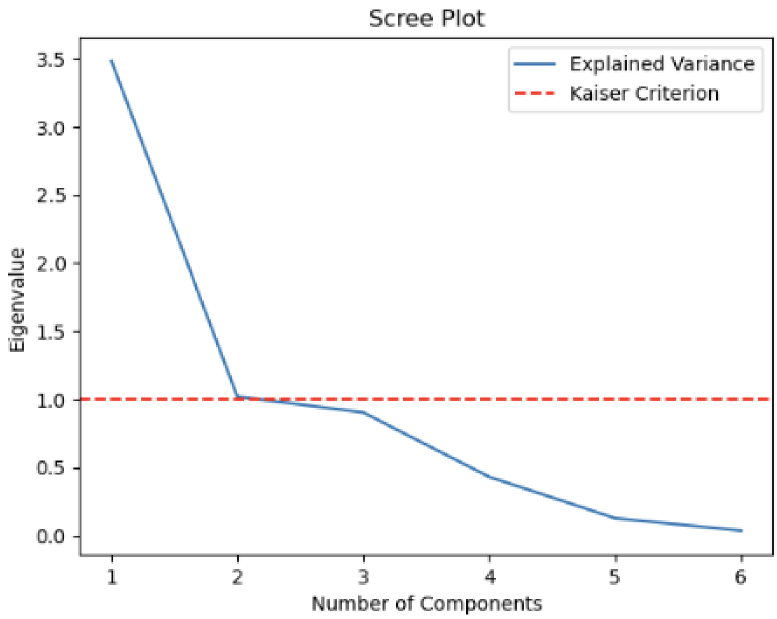


Figure 62 Scree plot for sensitivity analysis

Table 18 Sensitivity analysis variable loadings

	Factor 1	Factor 2
Economy index	-0,43197	0,083207
Built environment index	-0,16348	-0,50471
Health and wellbein index	0,503251	-0,12486
Community index	0,078214	0,847354
Gender index	0,516812	-0,04881
Cultural index	0,510097	-0,04859

Sensitivity analysis factors total = Factor 1 + Factor 2

In another process, we calculate the geometric mean of the dimensional indices. The results of these calculations are then added to a table alongside the multidimensional index results from the original additive model. We conduct sensitivity analysis by examining the results of correlation analysis, rank correlation analysis, and visual analysis.

All the data processing steps for SoVI and Multidimensional Index can be accessed at https://github.com/HaekalAkbar/multidimensionalindex.