

Article

Spatial Inequalities and the Sensitivity of Social Vulnerability in Ecuador

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Abstract

Vulnerability to hazards is a critical global issue, as it not only depends on the magnitude of natural hazards but also on the underlying social and economic conditions of communities. Understanding these factors is essential for designing effective risk reduction strategies and informed policy decisions. The objective of this research is to define a social vulnerability index (SoVI) and to analyse its distribution at the provincial and urban levels by applying different aggregation methods. This study provides a novel approach by examining the sensitivity of the index to different weighting methodologies, addressing a gap in the literature regarding the robustness of social vulnerability measures. An alternative approach is provided to determine the sensitivity of the SoVI in regions, in addition to understanding the dynamics of the socioeconomic characteristics considered in the territory and contributing to the theoretical and normative discussion of the construction of the index. To meet the objective, a sensitivity analysis is provided through different methods of weighting the vulnerability dimensions. The results indicate that the distribution of the SoVI in the provinces of Ecuador is heterogeneous, highlighting the importance of considering local socioeconomic contexts in vulnerability assessments. Additionally, the study shows that the values of the constructed index are sensitive to the weighting methods of the dimensions, which underscores the need for a careful selection of aggregation techniques to ensure reliable policy implications. It was also possible to identify that when social vulnerability is analysed at the city level, these show higher values than the corresponding provinces, challenging the common assumption that urban areas inherently provide better living conditions. This finding contributes to the ongoing debate on the impacts of rapid urbanization on social vulnerability.

Keywords: social vulnerability; social vulnerability index; living conditions; sensitivity analysis



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1. Introduction

In recent years, the increasing frequency and intensity of both natural and human-induced hazards have highlighted the urgent need to assess social vulnerability as a key factor in disaster risk management. Despite significant advancements in disaster risk reduction strategies, many societies remain disproportionately affected by hazards due to pre-existing social and economic disparities. The COVID-19 pandemic, in particular, has underscored how pre-existing social and economic disparities can exacerbate the impacts of crises, ultimately threatening sustainable development [1].

Social vulnerability results from natural hazards and human factors, including climate change, famine, droughts, earthquakes, pandemics, rapid urbanization, and environmental pollution. These elements contribute to disasters and risks that are anticipated to grow more complex and systematic in the future [2,3]. Vulnerability, owing to its interdisciplinary nature, has been applied in various research contexts, including natural hazards, disaster risk management, food security, public health, and climate change adaptation [4–6]. A significant limitation in the current literature is the absence of standardized methods for assessing social vulnerability across various geographical and socio-economic contexts, which complicates the comparison of findings across regions.

In broad terms, vulnerability is typically classified into physical and social dimensions [7,8]. Physical vulnerability pertains to the attributes of infrastructure and spatial arrangements, whereas social vulnerability includes socio-demographic factors such as age, gender, education, income, housing conditions, economic capacity, and family structure [9]. The literature highlights that social vulnerability is particularly significant in disaster risk studies, as it influences how various groups experience, respond to, and recover from hazardous events [10]. This perspective integrates previous definitions, including Cutter's view of susceptibility to losses [11], Bankoff's emphasis on structural inequalities [12], and Kuhlicke et al.'s focus on the conditions that convert threats into disasters [13].

In the last decade, the issue on social vulnerability has been a hot topic among researchers [14], with research conducted on different aspects of vulnerability: (1) how to resist the impacts of hazards, (2) how to improve the response capacity of the system, and (3) how to reduce the vulnerability of social systems [3,15]. These studies consistently highlight the significance of socio-economic disparities. Spielman et al. [16] highlight that income, education, and ethnicity serve as obstacles to recovery, whereas Cannon [17] and Cutter et al. [10] contend that pre-existing social inequalities predominantly account for varying disaster impacts.

To effectively address these concerns, it is crucial to develop a reliable mechanism for measuring social vulnerability. Several researchers have focused on building index systems for this purpose [1,18–20], as well as analyzing spatial–temporal variations and identifying vulnerable groups [14,21]. Additionally, other studies have investigated the underlying mechanisms of vulnerability formation and adaptation strategies [22–25].

Several empirical studies have developed social vulnerability indices at national and subnational levels, particularly in the context of climate change impacts, natural hazard responses, and disaster risk reduction [26–29]. Research has been conducted in various territories, including Australia [30,31], the United Kingdom [32–34], the United States [35–37], Latin America and the Caribbean [5,38], Spain [39], Sweden [40,41], Italy [42], Israel [43], Germany [44], and Indonesia [45]. These studies highlight the multidimensional nature of social vulnerability and the importance of integrating various socioeconomic factors into vulnerability assessments.

Among the various approaches to vulnerability measurement, one of the most widely used is the Social Vulnerability Index (SoVI), developed by Cutter et al. [10]. The SoVI provides a standardized metric for comparing relative social vulnerability across regions

by aggregating socioeconomic and demographic variables. This index has been applied in different geographical contexts to assess vulnerability levels, track changes over time, and inform disaster risk reduction policies [7,46]. However, a critical challenge in its application lies in the sensitivity of the index to different weighting and aggregation methods, which can influence the final vulnerability rankings of regions. A comprehensive systematic evaluation of SoVI, conducted by Painter et al. [47], found that Social Vulnerability Indices have been used in at least 20 different hazard and disaster contexts across 91 countries since the year 2000, highlighting the importance of methodological consistency in vulnerability assessments. This underscores the need for further research on how different weighting and aggregation techniques affect the robustness and comparability of results.

In the context of Ecuador, where socio-economic disparities are highly pronounced, understanding social vulnerability is particularly relevant for disaster risk reduction and policy planning. Previous studies have largely focused on individual hazards, such as floods, pollution, and volcanic eruptions [48–52]. Nevertheless, there is currently no official index that fully incorporates the various facets of social vulnerability in the nation. The inability to develop evidence-based policies that target the most vulnerable groups and the inability to capture current socioeconomic dynamics are restricted by the absence of an updated, standardized SoVI.

One of the major challenges in disaster risk management in Ecuador is the reliance on outdated and highly aggregated data sources, such as the 2010 Population and Housing Census. This data gap hinders efforts to develop proactive strategies that address evolving vulnerability patterns, leaving communities at greater risk of exposure to hazards. Therefore, this study seeks to fill this gap by constructing a Social Vulnerability Index (SoVI) in Ecuador, analyzing spatial patterns, and evaluating the impact of different aggregation methods on vulnerability assessments. In doing so, it contributes (1) conceptually, by offering the first multidimensional and spatially explicit SoVI for Ecuador, and (2) methodologically, by testing the robustness of vulnerability rankings under different aggregation schemes, thus enhancing the reliability of results for disaster risk reduction and policy planning.

Given these limitations, this study seeks to bridge this gap by developing a more comprehensive and context-specific assessment of social vulnerability in Ecuador. By incorporating security-related variables, it aims to provide an updated and multidimensional understanding of vulnerability patterns, ensuring greater applicability for disaster risk reduction and policy planning.

Given the above context, this study aims to (1) construct a Social Vulnerability Index (SoVI) for Ecuador at both provincial and urban levels, (2) analyze the spatial distribution of vulnerability across different regions, and (3) assess the sensitivity of the index to different aggregation methods and weighting techniques. Unlike previous studies that focus on specific hazards or dimensions of vulnerability, this research integrates a more comprehensive set of socioeconomic and security-related variables, allowing for a more nuanced and holistic assessment of social vulnerability in Ecuador. These objectives lead to the following key research questions:

1. Which households and regions exhibit the highest levels of social vulnerability in Ecuador at the provincial and urban levels?
2. How do urban and provincial vulnerability levels compare?
3. How sensitive is the SoVI to variations in aggregation and weighting methods?

This study contributes to the field by: (1) integrating a broader range of socio-economic variables, including security-related factors, which have been largely overlooked in previous vulnerability assessments; (2) assessing the sensitivity of the SoVI to different aggregation methods, thus providing a methodological advancement in the evaluation of vulnerability indices; and (3) providing a comparative analysis of vulnerability across

Ecuadorian provinces and cities, which will generate insights into territorial disparities that can inform more effective disaster risk management and social policies.

By addressing these issues, this research not only enhances the understanding of social vulnerability in Ecuador but also provides policymakers with an improved tool for identifying high-risk populations, designing targeted interventions, and optimizing resource allocation for disaster risk reduction and social protection programs.

The document is organized into five sections. Section 2 presents a comprehensive literature review, summarizing theoretical perspectives on vulnerability and different measurement approaches. Section 3 describes the study area, data sources, and methodology, detailing the aggregation methods applied. Section 4 discusses the results at both provincial and urban levels, highlighting key spatial patterns and disparities. Finally, Section 5 presents the conclusions and policy implications, along with recommendations for future research.

2. Literature Review

Vulnerability is a complex and multidimensional concept that has been widely studied across different disciplines. However, there is no universally accepted theoretical construct for its definition [11,53]. It is primarily applied in disaster risk management and related fields to understand disaster risks [54,55]. According to these authors, vulnerability includes both direct disaster damage and indirect factors such as exposure, susceptibility, and adaptation. Although extensive research has been conducted on vulnerability, there is still debate about how to best conceptualize and measure it. One of the main challenges is bridging the gap between theoretical definitions and practical applications in different socio-economic and geographic contexts.

Different disciplines have approached the concept from various perspectives. Adger [56] defines vulnerability as the exposure of a group or individual to stress caused by social and environmental changes that alter livelihoods. Meanwhile, Cutter et al. [57] conceptualize social vulnerability as the set of social, political, cultural, economic, and institutional characteristics of a place and its population that influence how communities prepare for, experience, and recover from hazards. A key limitation in the literature is the inconsistency in how these dimensions are integrated into vulnerability assessments, making cross-regional comparisons difficult.

From a gender perspective, recent studies have demonstrated that vulnerability is not gender-neutral but rather shaped by structural inequalities that determine the differentiated exposure, sensitivity, and adaptive capacity of men and women [58]. Women often face higher vulnerability to disasters due to socio-economic disadvantages, cultural norms that restrict their mobility or decision-making power, and unequal access to resources and information [59–62]. These gendered patterns are particularly pronounced in low- and middle-income countries, where the feminization of poverty and the predominance of care responsibilities limit women's ability to anticipate, respond to, and recover from disasters [63]. Integrating gender as an analytical dimension of vulnerability thus provides a more comprehensive understanding of the social processes that underlie risk and resilience.

In the context of climate change, the Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as the susceptibility of human and ecological systems to damage and their capacity to respond to the pressures exerted by climate change [64]. Likewise, the World Health Organization [65] recognizes vulnerability and hazards as key factors influencing disaster risk levels and their impact on human health.

To better understand the complexity of vulnerability, Hufschmidt [54] categorizes existing theories into two main schools of thought: the “human ecologist school” and the “structural view”. The human ecologist school defines vulnerability as a consequence of human adaptation to natural hazards, emphasizing proactive strategies to reduce risk [54,66]. In contrast, the structural view attributes vulnerability to socioeconomic conditions and

political systems that influence exposure and response capacities [54,55] further classify vulnerability into three conceptual frameworks: (1) vulnerability as adaptation [8], focusing on the capacity of societies to adjust to changing environmental and social conditions, (2) disaster proneness as susceptibility and exposure [67–69], emphasizing pre-existing conditions that make populations more prone to disasters, (3) an integrated approach combining susceptibility and adaptation [56,65,70], which examines how individuals and communities respond and recover from hazards.

Social vulnerability is a key component of disaster risk studies, as it focuses on the differential ability of populations to cope with hazards based on social inequalities [10]. Cutter [11] describes it as “the susceptibility of social groups or society in general to potential losses (structural and non-structural) due to hazardous events and disasters”. Similarly, Bankoff et al. [12] emphasize that social vulnerability is the result of historical and social processes that create unequal exposure to risks.

Studies indicate that social vulnerability manifests across different scales and dimensions [48,71], which highlights their complexity and the need for nuanced assessments. This variability is evident in different spatial contexts, influencing how vulnerability is perceived and addressed. Assessments of social vulnerability, such as the Social Vulnerability Index in Sweden, demonstrate that results can vary significantly depending on the scale of analysis, affecting the identification of vulnerable groups [41]. Similarly, frameworks evaluating urban social vulnerability reveal clear socioeconomic disparities, emphasizing the importance of localized data for effective interventions [72]. These findings suggest that a one-size-fits-all approach may not be suitable for measuring social vulnerability and that methodologies should be adapted to specific territorial contexts.

Social vulnerability is inherently multidimensional, shaped by a range of factors that influence the ability of individuals and communities to withstand and recover from adverse events. Factors such as economic status, age, and disability play a fundamental role in understanding social vulnerability, as demonstrated by studies employing machine learning techniques to construct vulnerability indices [29]. Additionally, social vulnerability is not static but evolves over time and space, as various interacting factors contribute to its dynamic nature [73].

This multifaceted nature is evident in different contexts, from urban settings to broader geographic analyses. Spielman et al. [16] argue that vulnerability is shaped by a combination of social, cultural, economic, political, and institutional processes, which determine how different groups experience and recover from disasters. For instance, age plays a significant role in shaping vulnerability, as children and the elderly often face greater difficulties in responding to hazards [74,75]. Similarly, income levels influence vulnerability, with lower-income households more likely to reside in high-risk areas with inadequate infrastructure, exacerbating their exposure to hazards [76,77]. Furthermore, race and ethnicity can impact access to resources and recovery opportunities, leading to disparities in disaster preparedness and response effort.

Measurement of Social Vulnerability

Given the complexity of social vulnerability, various methodologies have been developed to quantify it using composite indices. These indices integrate different socioeconomic indicators to estimate relative vulnerability across geographical areas. However, the selection of variables and weighting methods significantly influences the final results [78]. Each index employs distinct methodologies to assess vulnerability and performance across different contexts, highlighting the need for careful selection based on specific analytical goals.

Among the most recognized indices are the Social Vulnerability Index (SoVI), the Climate Vulnerability Index (CVI), and the Environmental Performance Index (EPI), each offering unique approaches to measuring vulnerability. The SoVI, developed by Cutter [7], incorporates 42 socio-demographic variables to evaluate community vulnerability to hazards. Recent studies emphasize the importance of wealth-related factors in explaining variance in social vulnerability, further underscoring the multidimensional nature of the index [29].

Similarly, the CVI integrates participatory consultation and expert judgment to establish weighting schemes, ensuring that local knowledge informs vulnerability assessments [79]. This approach enhances the relevance and applicability of the index, particularly in urban areas facing climate-related risks [28].

The EPI, on the other hand, employs a combination of data-driven approaches and expert evaluations to assess environmental performance at a global scale. This index serves as a benchmark for countries, facilitating cross-national comparisons and guiding policy decisions aimed at improving environmental outcomes [80].

While these indices provide valuable insights into vulnerability and environmental performance, it is crucial to acknowledge their limitations, such as potential biases in data selection and the inherent complexity of vulnerability as a multifactorial concept [41]. Furthermore, many vulnerability assessments rely on outdated data, limiting their applicability for real-time decision-making in risk management.

To ensure robustness in social vulnerability assessments, it is essential to conduct sensitivity analyses of aggregation methods. Studies have demonstrated that different weighting and aggregation techniques can lead to variations in results, which has implications for policymaking and risk management strategies [81,82]. Sensitivity analyses play a crucial role in identifying how variations in input factors, such as aggregation scales and weighting schemes, influence vulnerability index outcomes. This process enhances the reliability of assessments, ensuring they accurately reflect social vulnerabilities.

The importance of sensitivity analyses is highlighted in various studies. For instance, research on the Social Vulnerability Index in Sweden (SVIS) has shown that changes in scale and factor retention significantly altered the results of vulnerability assessments, demonstrating the need for methodological precision [41]. Similarly, a study on the Social Vulnerability Index (SoVI) found that weighting systems and indicator transformations were the primary sources of uncertainty, underscoring the necessity of carefully selecting aggregation methods to improve the accuracy of social vulnerability evaluations [25].

Given these methodological challenges, this study seeks to address gaps in the existing literature by evaluating the sensitivity of the SoVI in Ecuador using different weighting and aggregation strategies. This will provide a more robust assessment of vulnerability, allowing policymakers to better identify at-risk populations and allocate resources more effectively.

3. Data and Methodology

3.1. Case Study: Ecuador

Ecuador has been selected as the case study due to its exposure to multiple natural hazards and the diverse socioeconomic vulnerability contexts observed across its population of 17.64 million inhabitants, of which 64% reside in urban areas. These disparities contribute to significant differences in economic development levels, disaster risk perception, and coping capacities [83], ultimately influencing the country's overall vulnerability to disasters.

Despite being classified as a high human development country according to the Human Development Index (HDI), Ecuador still faces considerable socioeconomic challenges. One in four households lives below the poverty line, and the unemployment rate surged

to 35% due to the COVID-19 crisis [84]. Furthermore, climate shocks play a crucial role in exacerbating poverty and hindering development, highlighting the need for a deeper understanding of vulnerability patterns in the country. It is important to mention that the Ecuadorian territory is made up of diverse ethnic groups and wide social disparities, as it has one of the highest ethnic and cultural divisions in Latin America [85]. Specifically, 7 out of every 100 Ecuadorians self-identify as indigenous, representing the 14 indigenous nationalities in the country [86]. Additionally, Ecuador has a per capita income ratio of \$1.69 between urban and rural households, reflecting economic inequalities, particularly between the wealthiest urban population and the most vulnerable rural, indigenous, and low-income groups [85,87].

As already mentioned, the spatial research unit is Ecuador, located on the equator in South America, with a total area of 256,370 km² and an estimated population of 17,572,121 inhabitants for 2021. Ecuador is administratively divided into three levels: 24 provinces, 221 cantons, and 1024 parishes. This study focuses on 23 provinces and the five main cities, which are located within the cantonal division. The Galápagos Islands are excluded due to the low representativeness of statistical information. Figure 1 shows the geographical location of Ecuador, as well as the provinces in each of its four regions: the Insular (Galápagos), Coastal, Andean (Sierra), and Amazonian (Oriente) regions.

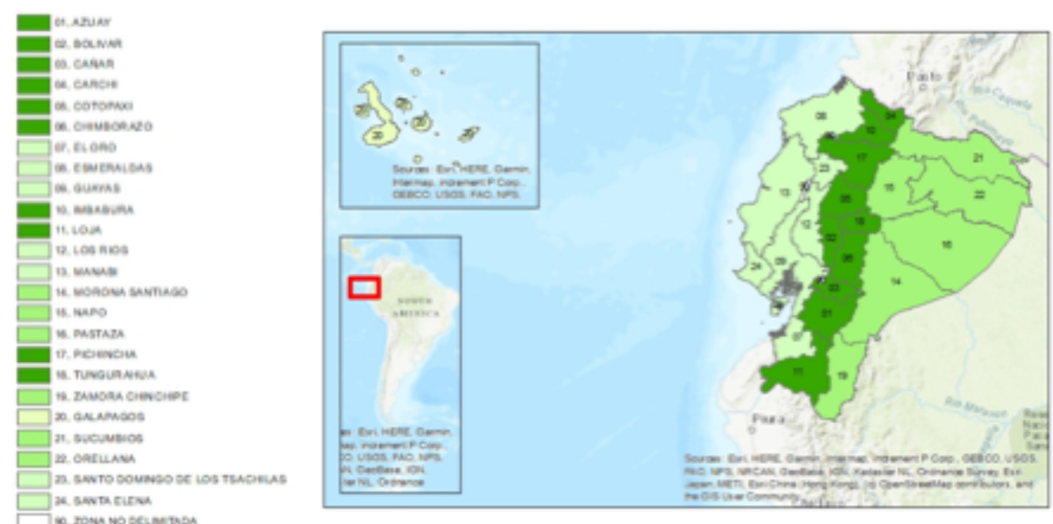


Figure 1. Geographical location of the study area Ecuador.

3.2. Data and Variables

The data used in this research were obtained from the National Institute of Statistics and Census (INEC) through the National Survey of Employment, Unemployment and Underemployment (ENEMDU) for 2016, which provides microdata from 30,338 households across 24 provinces and the five main cities: Ambato, Cuenca, Guayaquil, Machala, and Quito.

This source was selected because it is the only dataset that offers detailed information at the disaggregated territorial level, whereas the most recent Population and Housing Census was conducted in 2010. Although more recent ENEMDU surveys (e.g., 2020–2023) are available, they provide data only at national, urban, and rural levels and are restricted to education and labor market dimensions. Consequently, they exclude several critical aspects of social vulnerability, such as housing conditions, access to services, health, and environmental quality, that are essential for a multidimensional analysis.

Nonetheless, the use of 2016 data introduce a potential temporal limitation, as socio-economic and infrastructural conditions may have evolved since then. For example, INEC's 2022 statistics indicate that the national poverty rate declined from 22.9% in 2016 to 21.7%

in 2022, while access to basic sanitation improved by approximately 3 percentage points. Although these changes suggest gradual progress, the structural spatial disparities across provinces have remained largely persistent, which supports the relevance of the 2016 data for assessing relative patterns of vulnerability across territories.

Some studies have analysed vulnerability in Ecuador. Bucherie et al. [48] study vulnerability at the national level, considering the susceptibility perceived by households regarding floods. Ledesma and Cobos [88] conduct an analysis of seismic and volcanic vulnerability, where the objective is to identify vulnerable areas in Quito; while Arias-Muñoz et al. [52] and Alexandrino et al. [89] investigate the vulnerability of households to climate change in Cotacachi and Quito, respectively.

Based on these reference studies, a social vulnerability index was constructed using a set of multidimensional indicators, many of which had been previously implemented in similar research. These indicators include economic dependency, measured as the percentage of households with dependents under 14 or over 65 years old; educational attainment, referring to the percentage of the population without formal education; and material deprivation, which encompasses households lacking access to public drinking water, a sewage system, electricity, or garbage collection services. Additionally, housing conditions were considered, including housing deficits and overcrowding, alongside access to services, such as the distance to the nearest health facility and inadequate basic services. Finally, social factors were incorporated, including low trust in judicial institutions and insecurity in public spaces.

Taking these reference points into account, an index of social vulnerability has been constructed for our empirical analysis by using a list of indicators linked to the dimensions described. Subsequently, the index is calculated as a weighted average of the vulnerability characteristics:

$$SV = \sum_{k=1}^K w_k X_k \quad (1)$$

where SV is the deprivation index, X_k is the set of K variables that make up the index, and w_k is the weight assigned to each variable. Before applying the equation described above, all variables were standardized to ensure comparability across different units of measurement. Each indicator was expressed as a normalized proportion ranging from 0 to 1, representing the relative deprivation of each province in the corresponding dimension. Subsequently, for the aggregation procedure, these standardized values were converted into z-scores to eliminate scale effects and allow for the computation of weighted averages.

Table 1 presents the descriptive statistics of the 15 indicators encompassing five major dimensions of vulnerability: demographic composition, economic conditions, educational attainment, housing and infrastructure, and environmental and institutional security. The indicators are expressed as normalized proportions (values between 0 and 1) and were later transformed into z-scores for index construction. The table differentiates between urban, rural, and national levels, showing that all indicators were standardized to achieve a common measurement scale.

The family structure dimension incorporates the proportion of ethnic minorities, individuals over 65 years of age, and children under 14 years, representing population groups with differentiated levels of exposure and dependency. Rural areas exhibit higher vulnerability in this dimension, particularly in the proportion of ethnic minorities (0.318) and children (0.331), ethnic reflects structural inequalities and demographic pressures that may hinder community resilience.

The employment dimension, measured through the unemployment rate and economic dependence, reveals contrasting patterns between territories. Urban areas show higher unem-

ployment rate (0.061), while rural zones record greater economic dependence (0.037), indicating different forms of economic fragility that affect adaptive capacity and recovery potential.

Table 1. Standardized indicators of social vulnerability at the provincial level (normalized proportions and z-scores).

Dimension	Indicator	Urban Zone	Rural Zone	National
Family Structure	Ethnic group	0.098	0.318	0.187
	People older than 65 years	0.081	0.085	0.083
	People under 14 years of age	0.269	0.331	0.295
Employment	Unemployment rate	0.061	0.021	0.044
	Economic dependence	0.012	0.037	0.022
Education	Absence of basic education and high school	0.032	0.039	0.035
	Incomplete educational attainment	0.341	0.598	0.434
Housing	Overcrowding	0.744	0.784	0.760
	Housing deficit	0.387	0.652	0.488
	No excreta sanitation	0.170	0.271	0.209
	Inadequate basic services	0.742	0.857	0.789
	No garbage collection	0.033	0.377	0.164
Healthy Habit and Environment	Environmental pollution	0.012	0.004	0.009
	Insecurity in public spaces	0.074	0.044	0.062
	Low trust in public judicial institutions	0.029	0.017	0.024

The education dimension includes absence of basic or secondary education and incomplete educational attainment, both of them capture disparities in human capital and access to opportunities. Incomplete education is notably higher in rural areas (0.598) than un urban ones (0.341), evidencing persistent territorial gaps that weaken social adaptation mechanisms and access to information during crises.

The housing dimension encompasses indicators related to physical living conditions and infrastructure. Rural areas present significantly higher vulnerability in this domain, particularly for housing deficit (0.652) and inadequate basic services (0.857). Nonetheless, urban areas are not exempt from risk, showing substantial overcrowding (0.744) and deficiencies in service quality (0.742), which underscores that vulnerability in Ecuador extends beyond rural deprivation to include urban infrastructural stress and inequality.

Finally, the healthy habit and environment dimension integrates indicators associated with environmental quality and social stability. Rural territories show markedly higher values in lack of garbage collection (0.377), whereas urban areas report greater perceptions of insecurity (0.074). Although, the coexistence of institutional distrust (0.024) reveals forms of latent vulnerability linked to governance, cohesion and perceived safety. This findings demonstrate that social vulnerability in Ecuador is multidimensional and spatially heterogeneous, shaped by overlapping social, economic, and institutional inequalities that manifest differently across urban and rural contexts.

3.3. Aggregation Methods

One of the main objectives of this study is to analyze the sensitivity of the Social Vulnerability Index (SVI) and examine the normative implications of different aggregation methods. Specifically, this study explores the degree of substitution or complementarity between the dimensions of vulnerability. To achieve this, the study follows the methodological approaches proposed by Decancq et al. [90], Pinar [91], Bowen et al. [92], and Garrido & Gallo [93].

This study proposes four aggregation methods to assess social vulnerability (arithmetic mean, geometric mean, harmonic mean, and an endogenous weighting approach). The goal is to calibrate the index under different assumptions about the relationships between dimensions and ensure robustness in the findings.

Decancq et al. [90] highlight that the choice of weighting methods is crucial in defining trade-offs between dimensions in multidimensional indices. However, they also emphasize that no single method is inherently superior, as each approach—whether data-driven, normative, or hybrid—serves a different analytical purpose. Therefore, researchers must carefully select the most appropriate aggregation method based on the study's objectives and apply robustness and sensitivity analyses to account for variations in aggregation schemes.

In this sense, the arithmetic mean (equal weighting approach) assigns equal weights to all dimensions—family structure, employment, education, housing, healthy habitat, and environment—assuming perfect substitutability between them. In this framework, lower achievement in one dimension can be offset by higher achievement in another, meaning that provinces and cities may display similar overall vulnerability levels despite differing performances across dimensions. The geometric mean (balanced progress approach), on the other hand, penalizes regions with imbalanced achievements, requiring simultaneous progress in all dimensions to reflect overall improvement. Unlike the arithmetic mean, this method ensures that no single dimension disproportionately influences the aggregate index.

Meanwhile, the harmonic mean (Rawlsian approach-worst-case scenario) follows a normative perspective in which vulnerability remains high unless improvements occur in the most deprived dimensions. Here, the overall level of vulnerability is determined by the worst-performing dimension, favoring a strategy that prioritizes lifting the lowest-performing indicators rather than averaging across all dimensions. Lastly, the endogenous weighting approach (optimized trade-offs) applies variable weights to dimensions based on optimization criteria, allowing each province and city to have a customized weighting scheme. This method enhances analytical flexibility by maximizing or minimizing the impact of certain dimensions to highlight the most critical sources of vulnerability.

To ensure the validity and robustness of the Social Vulnerability Index (SoVI), several sensitivity analyses were conducted. First, different aggregation methods were compared to assess the impact of alternative weighting schemes on the final index values. Following Decancq et al. [90], these comparisons help determine whether different methodologies yield consistent vulnerability rankings.

Secondly, the robustness of the index was assessed through resampling and cross-validation techniques. Specifically, a non-parametric bootstrap procedure was applied to evaluate the stability of the weights and the variance of the index values under random perturbations of the original sample, generating 1000 random replications with replacement of the provincial observations. In addition, a k-fold cross-validation approach ($k = 5$) was implemented, dividing the sample into equivalent subsets to verify the consistency of the vulnerability ranking across training and testing sets.

The robustness of the results was evaluated using several statistical criteria, including the standard deviation of mean index values, the root mean squared error (RMSE), and the Spearman rank correlation coefficient between the rankings obtained in each iteration. Furthermore, an external validation was conducted by comparing the results with independent socioeconomic indicators, such as poverty rates and access to basic services reported by INEC, the World Bank, and UNDP, to examine the empirical coherence of the index. This procedure confirmed that the internal structure of the index and the spatial patterns of vulnerability remained stable across variations in aggregation methods, assigned weights, and data sources.

The results indicate that while the ranking of provinces remains relatively stable across different aggregation methods, variations in specific index values highlight the importance of carefully selecting the weighting approach. These findings underscore the need for cautious interpretation when using composite indices for policymaking, as different aggregation techniques can emphasize distinct aspects of vulnerability.

Mathematical Formulation

Given (n) provinces/cities and (J) dimensions, the maximization problem for province/city (i) can be expressed as follows:

$$SoVIC_i = \max_{w_{ij}} \sum_{j=1}^J w_{ij} D_{ij} \quad (2)$$

These equations are subject to the following constraints:

$$\sum_{j=1}^J w_{ij} = 1; \forall i = 1, \dots, n \quad (3)$$

Considering the weighting system for provinces and cities, the values of w_{ij} are constrained as follows:

$$\frac{1}{8} \leq w_{ij} \leq \frac{3}{8}; \forall i = 1, \dots, n \forall j = 1, \dots, J \quad (4)$$

Equations (1) and (2) define:

- $SoVIP_i$ and $SoVIC_i$ represent the vulnerability scores for province i and city i , respectively.
- w_{ij} is the weight assigned to dimension j in province/city i .
- D_{ij} is the deprivation value of dimension j in province/city i .

Equation (3) ensures that the sum of the assigned weights for each dimension equals 1, while Equation (4) restricts the value of each weight to a specific interval. In this case, the dimension with the highest vulnerability receives the highest weight ($3/8$), followed by the second most vulnerable dimension ($2/8$), while all other dimensions are assigned a baseline weight of $1/8$.

The choice of aggregation method significantly impacts the final ranking of provinces and cities based on their social vulnerability levels. The arithmetic mean produces a more balanced distribution, while the geometric mean penalizes territories with high variability across dimensions. The harmonic mean highlights worst-case scenarios, prioritizing improvements in the most vulnerable dimensions. Finally, the endogenous weighting approach provides a flexible and adaptive method that accounts for local variations.

Due to the way the synthetic indices are constructed and the type of indicators included, higher index values correspond to greater degrees of vulnerability. Therefore, sensitivity analyses are essential to ensure that the aggregation methodology does not introduce bias and that policy recommendations based on the index remain robust under different weighting schemes.

4. Results

4.1. Sensitive of the Measurement of the Social Vulnerability Index

The purpose of obtaining a single measure that approximates the degree of social vulnerability for each province and city is fulfilled. Figure 2 shows the results of the social vulnerability index after applying the five aggregation methods.

An interesting finding in the territorial units analysed in Figure 2 is the province of Santa Elena, which is located within the average values of the social vulnerability index; however, these values fluctuate above the mean according to the harmonic and geometric mean aggregation method. However, when analysing the dimensions of the province through the Rawlsian criterion, it is assumed that the level of vulnerability is determined through all the dimensions considered, which favours the promotion of perfectly balanced achievements between the dimensions of vulnerability. In this way, the dimensions with

the worst achievements in reducing vulnerability are compensated by the low levels of vulnerability that occur in the dimensions of education and housing conditions/services.

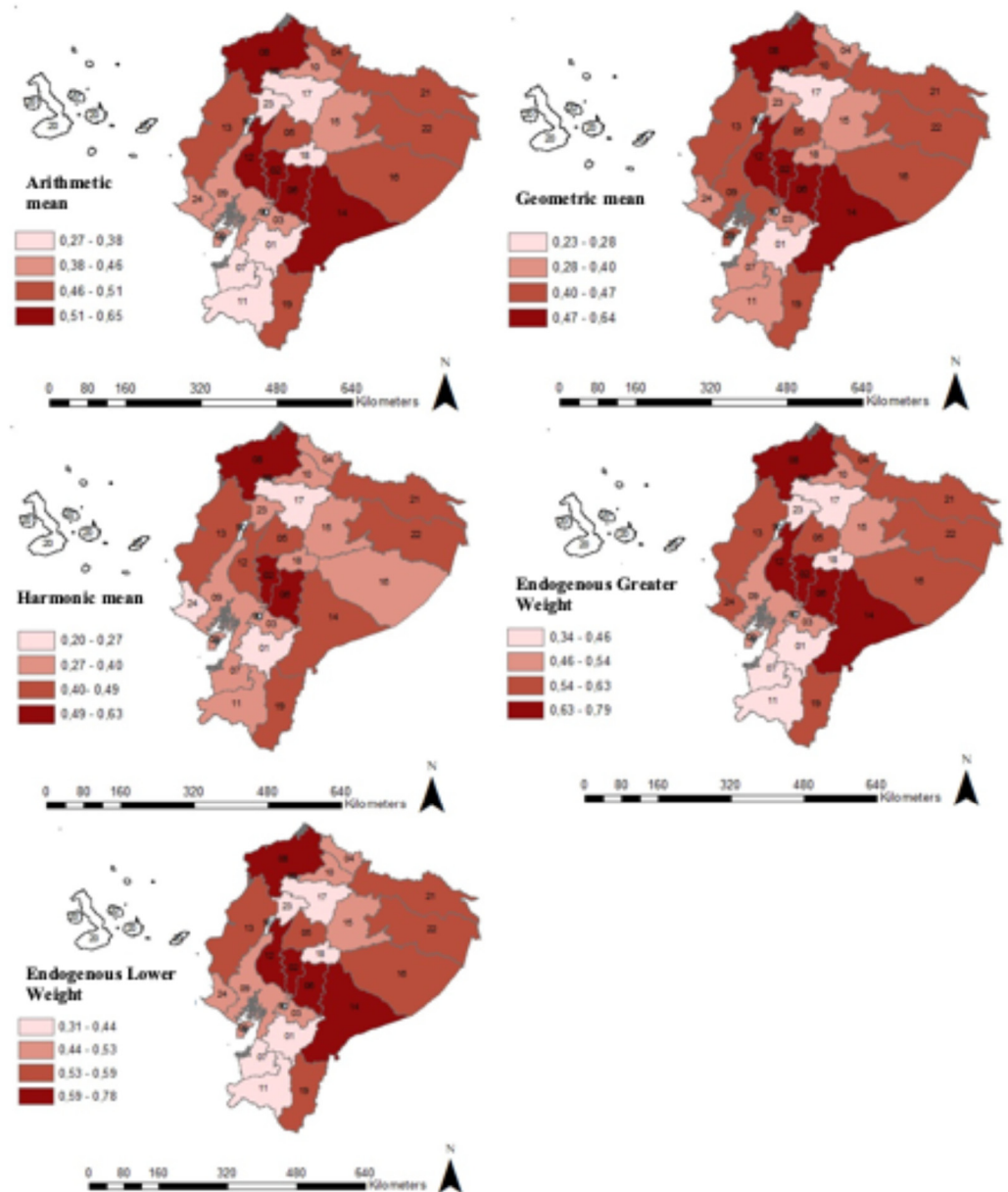


Figure 2. Social Vulnerability Index (SVI) in the provinces of Ecuador (2016) calculated using five aggregation methods: arithmetic mean, geometric mean, harmonic mean, and endogenous weighting approaches. Source: Own elaboration based on INEC [86].

The territories show great heterogeneity, which is why working with provinces as spatial units can hide the existence of territorial disparities between dimensions or smaller territorial units. Thus, the research also includes the five main cities that according to INEC projection, concentrate approximately 7 of the 17 million inhabitants in Ecuador as spatial analysis units.

This research also analyses the territorial disparities between the provinces and their respective capital, in order to determine whether the urban territorial units show greater vulnerability in the dimensions than their provinces. Figure 3 illustrates the comparative results of vulnerability for each dimension considered in the construction of SoVI, at both the provincial and city levels. The data reveal that, in general, urban territories tend to mirror the vulnerability patterns of their corresponding provinces; however, quantitative

comparisons show that certain cities exhibit markedly higher vulnerability in specific dimensions, particularly Housing and Education.

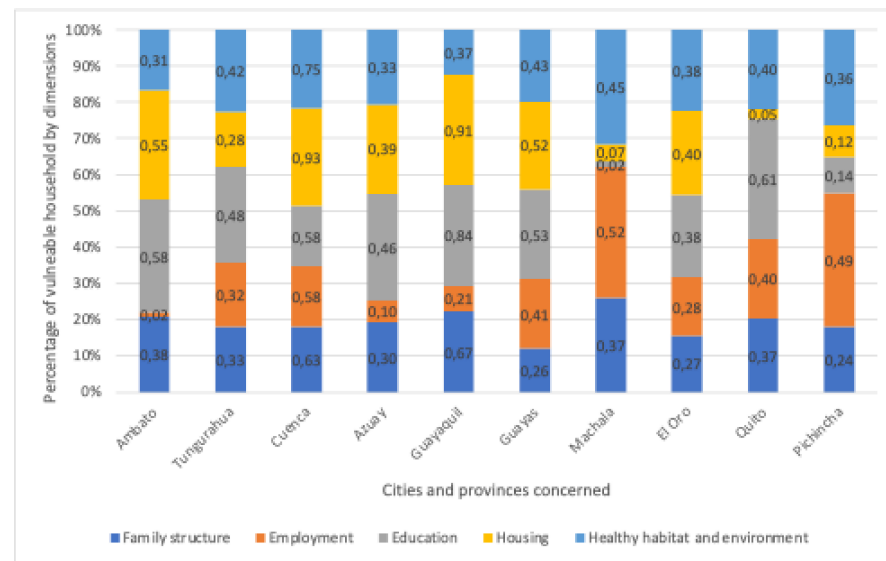


Figure 3. Dimensions of the social vulnerability index of the provinces and their respective capitals. Source: Own elaboration based on INEC [86].

For instance, in Guayas province, the capital Guayaquil records a Housing vulnerability of 0.91 and Education vulnerability of 0.84, considerably higher than the provincial averages of 0.52 and 0.53, respectively. Similarly, in Azuay, Cuenca shows higher values in both Housing (0.93) and Education (0.58) compared to the province (0.39 and 0.46, respectively). Ambato, in Tungurahua province, also presents higher vulnerability in Housing (0.55 vs. 0.28) and Education (0.58 vs. 0.48).

The graphs indicate that the urban territories maintain the same behaviour in terms of vulnerability as the corresponding provinces; however, some dimensions such as Housing and Education Conditions/Services show the existence of greater deficiencies in cities than in their corresponding provinces, since these territories have greater agglomerations of people or households that do not necessarily have access to optimal living conditions, one of the factors being internal migration, which according to Alvarado, Correa & Tituaña [94], is one of the main reasons for the accelerated process of urbanization in the country.

4.2. Conglomerates of Vulnerability in the Dimensions Considered

Scatter plots and the Moran index were employed to analyze spatial interactions [95] and assess heterogeneity (systematic differences) and spatial dependence among the dimensions included in the Social Vulnerability Index (SVI) across Ecuadorian provinces [96,97]. To compute the Moran index, a first-order spatial weights matrix was applied, allowing for the identification of relationships between neighboring territorial units.

The scatter plots for the family structure and employment dimensions reveal that most provinces are concentrated in quadrants III and IV (Low-Low and High-Low, respectively). In contrast, for the education, housing, and healthy habitat/environment dimensions, most provinces fall within quadrants II and IV (Low-High and High-Low, respectively). These patterns indicate a significant spatial autocorrelation between socioeconomic conditions and vulnerability levels in Ecuador (Figure 4).

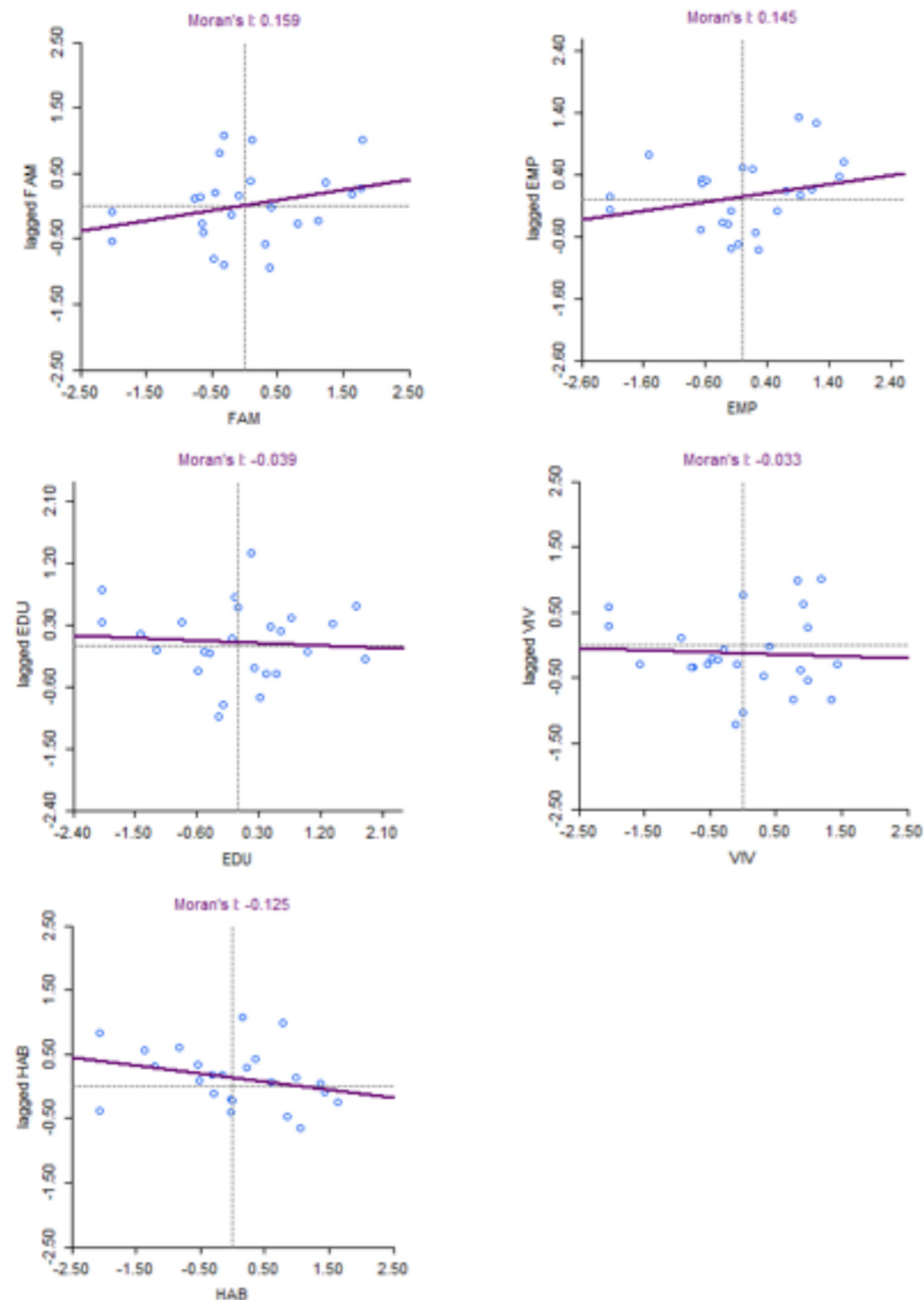


Figure 4. Dispersion graph of the Moran index for the SVI dimensions in the provinces, 2016. Source: Own elaboration based on ENEMDU [86].

It is a fact that Moran's I is significant (with a pseudo probability of less than 1% that spatial distribution is a random phenomenon). This leads to the clustering of neighbouring provinces with a high social vulnerability index, as well as the presence of contiguous provinces in which the dimensions considered are better satisfied.

These results can be contrasted in Figure 5, which shows the spatial correlation between the provinces of Ecuador with respect to the dimensions considered for the social vulnerability index. Within the family structure dimension, it can be observed that 5 provinces are in a situation of vulnerability, where the provinces of the Amazon (Napo and Orellana) have high vulnerability values and are surrounded by provinces with high values; this spatial pattern is also repeated in the Housing Conditions/Services dimension. Meanwhile, the province of Tungurahua has low vulnerability values, but the surrounding provinces

have high values. On the other hand, the province of Cotopaxi has high vulnerability values and is surrounded by provinces with low values.

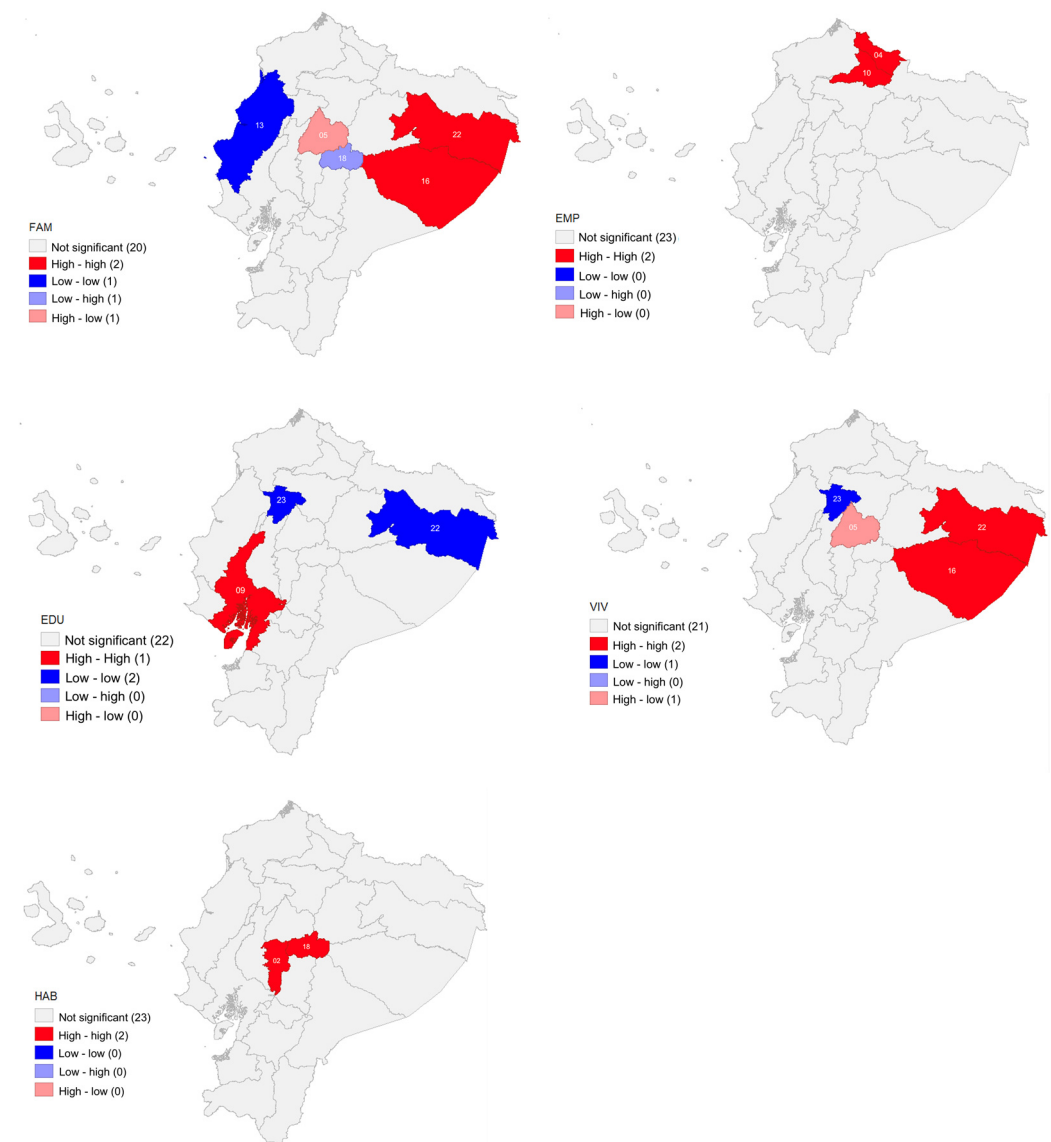


Figure 5. Cluster map of the Social Vulnerability Index (SVI) dimensions in the provinces of Ecuador, based on local Moran's I statistic and SVI values derived from four aggregation methods: arithmetic mean, geometric mean, harmonic mean, and endogenous weighting. Source: Own elaboration based on ENEMDU [86].

5. Conclusions

This study represents the first comprehensive analysis of the dimensions and spatial distribution of social vulnerability in the provinces and cities of Ecuador. By applying five different aggregation methods, arithmetic, geometric, harmonic, and endogenous means of greater and lesser weight, this research not only evaluates the spatial distribution of vulnerability but also assesses the robustness of different weighting techniques, addressing a key methodological gap in vulnerability assessments. The findings provide a multidimensional perspective on vulnerability, allowing for the identification of territories where multiple socioeconomic, environmental, and infrastructural risks overlap. A major contribution of this study is demonstrating that vulnerability extends beyond income deprivation, emphasizing the role of multidimensional deprivation factors that affect resilience and adaptive capacity.

The results reveal a heterogeneous and regionally clustered spatial distribution of vulnerability across Ecuadorian provinces, with notable disparities in the five key dimensions: family structure, employment, education, housing, and healthy habitat/environment. Border provinces exhibit higher levels of vulnerability, while provinces with higher per capita income display lower vulnerability levels. However, a critical finding is that urban centers within these provinces often experience heightened disparities across dimensions, particularly in housing and access to basic services. This is largely attributed to internal migration and rapid urbanization [94], which create new vulnerabilities not captured by traditional poverty indicators. These findings highlight the importance of localized policy interventions that differentiate between urban and rural vulnerabilities.

The application of spatial analysis techniques, such as the Moran Index and cluster analysis, confirms the existence of significant spatial dependence, meaning that provinces with high vulnerability levels tend to be surrounded by similarly vulnerable regions. This clustering effect suggests that vulnerability is shaped by broader regional dynamics, including governance structures, economic integration, and infrastructural disparities. These spatial patterns highlight the importance of designing targeted regional policies and interventions that consider not only individual provinces but also their surrounding areas to more effectively reduce social vulnerability.

From a policy perspective, the findings suggest that strengthening territorial governance and incorporating vulnerability assessments into regional development agendas could improve disaster risk reduction strategies. In particular, social vulnerability mapping should be used to guide investment in housing, education, and employment generation programs in high-risk territories. Integrating these findings into local risk management plans can improve resource allocation and promote resilience development among the most at-risk populations.

Policy Implications and Recommendations

Based on these findings, this study offers several recommendations for policymakers aiming to design effective social protection and risk reduction strategies.

First, localized policy approaches should be implemented to address the specific territorial contexts of urban and rural vulnerabilities. The results indicate that urban areas require targeted interventions in housing improvements and access to basic services, particularly in fast-growing cities where informal settlements are expanding. Meanwhile, in rural areas, reducing economic dependency and expanding educational access should be prioritized, as these factors were found to significantly influence vulnerability levels.

Second, integrating social vulnerability into risk management is essential. Given the strong spatial dependence observed in vulnerability clusters, disaster response agencies should incorporate social vulnerability maps into their decision-making processes. This approach would enable authorities to allocate resources more effectively to at-risk populations and enhance disaster preparedness and mitigation strategies, ensuring that interventions are tailored to the needs of each region.

Third, strengthening data collection at local levels is crucial for evidence-based policymaking. The study highlights a major limitation in the availability of updated and disaggregated socioeconomic data. National statistical agencies should enhance data collection and analysis at sub-provincial and municipal levels, allowing for more targeted interventions and improved monitoring of policy impacts over time.

Finally, urban planning and migration management should be integrated into social vulnerability reduction strategies. The study demonstrates that urban areas, despite higher per capita income, often exhibit severe deficiencies in housing and service provision. Local governments must implement sustainable urban planning policies that account for population growth and migration trends to ensure equitable service distribution and

adequate infrastructure development. Without such measures, vulnerability in fast-growing cities will likely intensify.

Future Research Directions and Methodological Improvements

To build on these findings, future research should explore additional dimensions of vulnerability, such as access to healthcare, environmental hazards, and climate change impacts, which were not fully captured in this study. Integrating geospatial risk assessment tools and combining the Social Vulnerability Index with hazard exposure maps (e.g., earthquakes, landslides, floods) and climate exposure indicators from sources such as the IPCC could provide a more comprehensive picture of high-risk areas, enhancing disaster preparedness strategies.

From a methodological perspective, future studies should test alternative aggregation methods, including machine learning-based weighting schemes, to assess the most reliable approaches for measuring vulnerability. Additionally, conducting longitudinal studies would allow researchers to evaluate how vulnerability evolves over time in response to policy interventions, economic shifts, and climate events.

Limitations and Potential Biases

Despite its contributions, this study has several limitations that must be acknowledged.

First, the availability of socioeconomic data at the provincial level imposes constraints on the granularity of the analysis. While this study provides valuable insights into regional disparities, future research should incorporate more localized data sources, such as municipal or parish-level surveys, to capture intra-provincial variations in vulnerability.

Second, although the selection of aggregation methods was methodologically rigorous, it introduces certain normative assumptions regarding the trade-offs among vulnerability dimensions. While sensitivity and robustness analyses were conducted, the inherent subjectivity in weighting choices remains a challenge, as different aggregation schemes may yield slightly different vulnerability rankings.

Third, the reliance on cross-sectional data from the 2016 ENEMDU survey limits the ability to observe temporal dynamics in vulnerability. Socioeconomic and environmental conditions have likely evolved since that year, particularly following recent national development policies and external shocks such as the COVID-19 pandemic. For instance, INEC data indicate that the national poverty rate decreased slightly from 22.9% in 2016 to 21.7% in 2022, while access to basic sanitation services improved by about 3 percentage points. Although these variations suggest gradual improvement, the persistence of structural spatial inequalities supports the continued relevance of the 2016 data for understanding relative vulnerability patterns. Future studies should therefore employ longitudinal or panel datasets to trace how vulnerability trajectories evolve in response to socioeconomic and policy changes.

Because this study relies on cross-sectional data, it does not capture the historical evolution of vulnerability across Ecuadorian provinces. However, understanding the temporal progression of risk and exposure is crucial for contextualizing current vulnerability patterns. Future research should therefore focus on constructing longitudinal vulnerability indicators to track changes over time and assess the long-term impacts of public policies and environmental events.

Overall, this study contributes to the growing literature on social vulnerability by offering a systematic, spatially explicit, and multidimensional assessment of deprivation in Ecuador. By highlighting territorial disparities and the impact of different aggregation methods, this research provides policymakers with actionable insights for designing targeted social protection and disaster risk reduction strategies.

Moving forward, enhancing data collection efforts and integrating vulnerability assessments into urban and regional planning will be crucial to reducing structural inequalities and strengthening resilience across Ecuadorian provinces and cities.

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