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ORIGINAL PAPER

Assessment of social vulnerability in terms of natural hazards in Türkiye based on entropy method

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Abstract

This study aims to assess social vulnerability (SV) to disasters at the provincial level in Türkiye. Although there are few studies on the assessment of vulnerability to disasters in Türkiye, there is no recent study on SV assessment using an objective method at provincial level. In line with the aim of the study, SV indicators, sub-indicators and their variables were determined using a deductive approach, considering the relevant literature review and Türkiye's socio-economic structure. Provinces in Türkiye were evaluated from a multidimensional perspective consisting of 9 sub-indicators and 34 variables representing under the indicators of demographic attributes, economic status, and adaptive capacity. Variables were weighted using the entropy method, and the results were evaluated at the provincial, geographical region, and national levels. According to entropy results, the top 5 variables with the highest weights are "Number of Syrians", "Population Density", "Single-Person Household", "Extended Family Household", and "Number of Women". The findings show that SV index values of the provinces are between 0,093 and 0,853, most vulnerable province Istanbul is significantly different from the other provinces, while the least vulnerable province is Tunceli. Moreover, regionally, the Southeast Anatolia, Marmara and Mediterranean regions have the highest SV, respectively, while the Black Sea region has the least vulnerability. The study results will provide a reference for decision makers and practitioners for disaster risk reduction.

Keywords Natural hazards · Disasters · Social vulnerability · Entropy method · Vulnerability assessment · Türkiye

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1 Introduction

The number and severity of disasters are increasing globally. According to the report published by the United Nations Office for Disaster Risk Reduction (UNDRR) in 2020 (CRED and UNDRR 2020), disasters and their consequences that occurred globally in the last 20 years of the twentieth century and the first 20 years of the twenty-first century are given as follows; Between 2000 and 2019, 7348 disasters occurred, killing 1.23 million people, affecting 4.2 billion people and causing a global economic loss of US$ 2.97 trillion. Between 1980 and 1999, 4212 disasters occurred, killing 1.19 million people, affecting 3.25 billion people and causing a global economic loss of US$ 1.63 trillion. Many factors such as climate change, rapid population growth, technological advances, consumer society, and the search for raw materials to meet the demands of mass production also contribute to these increases in the negative impacts of disasters on a global scale. In this current world order, which Ulrich Beck calls the risk society (Beck 1992), when disasters occur, consequences that are difficult to predict arise and the management of disasters become more complicated. Indeed, Pescaroli and Alexander (2015), provide many examples of cascading disasters that reflect this situation. With growing concern about the global impact of loss of life and property due to disasters, disaster risk reduction efforts have been emphasized since 1990 under the leadership of the United Nations (UN) (UNDRR 2007, 2009a, 2015). In addition to these direct initiatives of the UN, it is seen that disaster risk reduction is among the targets set to achieve the goals within the scope of the "2030 Agenda for Sustainable Development", considering that disasters are one of the important obstacles to sustainable development (UN 2015).

UNDRR defines risk as "The combination of the probability of an event and its negative consequences", while disaster risk is defined as "The potential disaster losses, in lives, health status, livelihoods, assets and services, which could occur to a particular community or a society over some specified future time a period" (UNDRR 2009b). In this context, disaster risk is regarded as a function of hazard and vulnerability; therefore, effective disaster risk reduction requires a comprehensive understanding of both the hazards that pose threats and the vulnerabilities of the potentially affected society, economy, built environment, and natural environment (Birkmann 2013a). From the perspective of natural hazards, if the occurrence of natural hazards such as earthquake, flood, storm and tornados cannot be prevented, the focus is on reducing vulnerability to reduce the risk of natural hazards. Indeed, assessing and determining vulnerability has an important place in terms of guiding decision makers for natural hazard risk reduction and adaptation (Fuchs et al. 2012; Birkmann 2013b; Fekete 2019; Guo and Kapucu 2020).

The literature shows that vulnerability is assessed using different methods (Nasiri et al. 2016). A literature review of these approaches is presented in Sect. 1.1. In short, among vulnerability assessment approaches in terms of disasters, the indicator-based or index-based assessment approach is recommended by many authors due to its ease of use and flexible structure, as well as its ability to enable a comprehensive analysis of vulnerability (Ciurean et al. 2013; Moreira et al. 2021a; Ajtai et al. 2023). In the index-based vulnerability assessment approach, the index development process typically consists of a series of sequential steps, such as indicator selection, normalization of data related to these indicators on a common scale, weight assignment, and aggregation of final values (Müller et al. 2011; Tate 2013). Despite the advantages of the approach outlined above, the human judgement

involved in each step of index creation, along with the differences in the selected methods, can significantly impact the resulting output (Papathoma-Köhle et al. 2019; Moreira et al. 2021b).

This study aims to assess the social dimension of vulnerability to disasters using an index-based approach. Therefore, the study generally includes information within the social vulnerability (SV) boundaries and does not include variables related to the biophysical dimension of vulnerability. Türkiye was selected as the study area, and the line with the purpose of the study, indicators and variables were determined using a deductive approach, considering Türkiye's socio-economic structure and theoretical findings and information in the literature. In this a hierarchical structure consisting of sub-indicators under the indicators of "demographic attributes (DA)", "economic status (ES)" and "adaptive capacity (AC)" and 34 variables representing them was created to assess SV. In the study, which assessed SV in terms of disasters at the provincial, geographical region, and national scale in Türkiye, most of data related to the variables were obtained from web portals published by various institutions in the country as open access. The obtained data normalized using the min–max scaling transformation method. The entropy method was used for variable weighting, which is the next stage in index creation. In this context, while a wide variety of approaches to variable weighting are used in the literature, the entropy method was used because it is an objective method based on the information provided by the original data, without data loss and not limited to expert opinion (Zhao et al. 2018). As a result of analyzing hierarchically constructed indicator sets, maps have been prepared for the spatial distribution of sub-indices, main indices and overall SV indices values obtained at the provincial level. Türkiye is a country where various types of hazards frequently occur and often turn into disasters. In this context, when the studies conducted on vulnerability assessments in the context of disasters in Türkiye are examined, it is seen that the number of studies on the subject is limited; in particular, the social dimension of vulnerability has not been sufficiently addressed in the existing studies. Therefore, this study, conducted at the provincial level, aims to fill an important research gap in the literature by revealing the current level of SV in Türkiye in terms of disasters and, in this respect, is pioneering. Based on the findings obtained within the scope of the study, the key factors that increase socio-economic vulnerability have been identified, and policy recommendations have been developed for these factors. In conclusion, the research findings provide policymakers and practitioners with an important framework for conducting assessments at different spatial scales and identifying priority intervention areas to reduce vulnerability to disasters.

Within the scope of this study, it is necessary to provide a brief explanation of the term "scale," which is frequently used. Indeed, the concept of scale can be used in different contexts across different disciplines. In short, Gibson et al. (2000) defines scale as spatial, temporal, quantitative, or analytical dimensions used to measure and examine any phenomenon. In this study, scale is used in a geographical context (geographical scale). Geographical scale refers to the spatial scope of a phenomenon or study (Marston 2000). In other words, scale is used to represent areas defined by administrative boundaries (provinces, regions, and national) in a spatial context.

The subsequent sections of the study are organized as follows: The next section provides a brief literature review of studies conducted on vulnerability and mentions studies conducted in Türkiye, the area of study, in terms of disasters. Section 2 presents the study area and its history of disasters, and the methodology of the study. In Sect. 3, statistical results of

the analyses and maps showing the spatial distribution of the results are presented. Section 4 of the study includes discussions and conclusions.

1.1 Literature review: SV assessment

In the literature on disasters, the concept of vulnerability first addressed in the study of O'Keefe et al. (1976) and frequency of use of the concepts of "vulnerable" and "vulnerability" gradually increased in the 1980s (Wisner and Luce 1993). There are different definitions of the concept in literature. This is because disaster studies are a multidisciplinary field of study (Ciurean et al. 2013). In this context, while the technical sciences perspective focuses mainly on physical vulnerability (Office of the United Nations Disaster Relief Co-ordinator (UNDRO) 1979), in the perspective of social sciences, attention is drawn on vulnerability parameters in physical, economic, social, environmental and institutional aspects (UN/ISDR 2004). The most known definition of vulnerability is as follows (UNDRR 2009b); "The conditions determined by physical, social, economic and environmental factors or process, which increase the susceptibility of community to the impact of hazards". On the other hand, SV, which is the focus of this study, refers to pre-existing conditions and natural circumstances that affect the preparedness, response, and recovery capacities of populations, organizations, and communities in the face of external stressors (Roncancio and Nardocci 2016; Ge et al. 2019). In this context, the concept of SV is a multidimensional process that emerges from social, economic, political, and institutional circumstances and interacts at scales ranging from local to international (Ge et al. 2021). Previous studies on SV have shown that SV is linked to the social characteristics of a society, such as socio-economic status, gender, race and ethnic origin, disability, population distribution, social inequality, beliefs and traditional values (Wisner et al. 2004; Cutter and Emrich 2006; Borden et al. 2007; Cutter and Finch 2008). While there is consensus in the literature on the main factors affecting SV, such as demographic characteristics, economic status, and social and spatial inequality (Guo and Kapucu 2020; Ge et al. 2021), there is no consensus on variables defined under these factors (Cutter et al. 2003). This situation stems from the temporal and spatial variability of SV.

Different methods are used to assess vulnerability, which has a multidimensional structure (physical, social, economic, environmental, etc.) (Carreño et al. 2007; Barbat et al. 2010; de Brito et al. 2018). These methods are summarized in general terms by Nasiri et al. (2016) as follows: "vulnerability curves", "disaster loss data", "computer modelling", and "index-based". Among these methods, it is possible to state that index-based assessment is frequently preferred because it reflects the multidimensional structure of vulnerability well. Indeed, this approach is understood by decision-makers and is easy to use, being clear and flexible (Ciurean et al. 2013); its ability to integrate different dimensions of vulnerability compared to other methods (Fuchs et al. 2011; Birkmann 2013b), and its potential to be preferred in policy contexts due to the ability to define, rank, or distinguish analysis units to achieve risk reduction goals (Eakin and Bojórquez-Tapia 2008). Despite the advantages of the index-based assessment method, the existence of a range of potential methodological options at each stage of index creation requires researchers to make choices. In this context, the use of different methods in the index creation phase has a significant impact on the final index results. In this context, the difficulties encountered in developing indices for vulnerability assessment are mentioned in different studies (Tate 2012; de Brito et al. 2018;

Moreira et al. 2021b), Müller et al. (2011) summarizes them as follows: (i) indicator selection, (ii) variable weighting, and (iii) data availability and validation results. Since this study assesses index-based SV, the reasons for choosing the methods used in this study are briefly explained below, with a brief review of different approaches to the challenges mentioned.

In vulnerability assessments, there are three main approaches to indicator selection: inductive, deductive, and hierarchical (Hinkel 2011; Tate 2012). The inductive approach is based on both indicator variables and data related to observed damage data. In (Burton et al. 2018) study, this approach is evaluated as follows: It starts with a large dataset consisting of 20 or more indicators, which are reduced to a smaller set of latent factors using Principal Component Analysis (PCA), and these factors are then aggregated to form the index. While this approach is considered useful in terms of reducing a region's SV to factors that potentially explain it, it is criticized for relying on subjective decision-making at critical stages and for causing uncertainty in model outputs (Tate 2012). The hierarchical model, on the other hand, is a model divided into groups sharing the same basic vulnerability dimension (Tate 2012). While requiring more theoretical organization than the deductive model, this model can rely on participant or expert knowledge for both variable selection and weighting (Burton et al. 2018). In this context, it requires more time and resources compared to other models (Tate 2012). The deductive model, in short, is an approach based on existing theoretical knowledge (Hinkel 2011). In other words, the deductive approach determines a limited number of variables through deduction to create an SV index, based on a priori theory and information obtained from existing literature (information available in the form of frameworks and models) (Hinkel 2011; Burton et al. 2018). The framework mentioned here refers to a set of concepts, a series of relationship between these concepts and the theory, and a more specific set of a relationship with the model (Ostrom 2005). Hinkel (2011) illustrates this as follows: According to the capability theory (Sen 1981) based on the approach that the ability to participate in political activities is important for reducing poverty, it can be concluded that variables measuring non-participation in politics will indicate vulnerability to poverty. Various vulnerability frameworks have been developed in the literature, including "The Double Structure of Vulnerability (Bohle 2001)", "The UN/ISDR Framework for Disaster Risk Reduction (UN/ISDR 2004)", "Vulnerability Framework (Turner et al. 2003)", "The Pressure and Release Model (PAR) (Blaikie et al. 1994)", "A Holistic Approach to Risk and Vulnerability Assessment (Cardona and Barbat 2000)", "BBC Framework (Birkmann 2013b)", "The MOVE Framework(Birkmann et al. 2013)", "Framework of a Second-Generation Vulnerability Assessment (Füssel and Klein 2006)", "IPCC SREX Framework (IPCC 2012)", and "The Hazards of Place Model (Cutter 1996)" are among the most frequently encountered frameworks. Although there is no consensus in the literature regarding these approaches to indicator selection, there are studies that compare these methods (Tate 2012; Yoon 2012; Pacheco-Romero et al. 2021). For example, Yoon (2012) compared inductive and deductive methods, highlighting the strengths and weaknesses of both methods, and concluded that there was no significant difference between the SV index values obtained using these methods. In summary, the inductive method allows understanding the dimensions underlying a broad set of variables and provides an advantage in establishing mathematical relationships between variables (Wood et al. 2010), but its complexity and the fact that it follows a statistical procedure that is not easily transferable make it difficult for decision-makers to use (Dunning and Durden 2011; Yoon 2012). On the other hand, the deductive method offers a simple and direct approach because it focuses on a smaller set of

SV variables (Yoon et al. 2017) and interpreting the results in the SV evaluation process is relatively easier (Dunning and Durden 2011). In this context, the variables used in the study were determined using a deductive approach, considering existing theoretical knowledge and Türkiye's socio-economic structure.

Another difference and challenge in SV assessment is the weighting of the variables used. Weighting is not only an important step in index creation but also has a significant impact on results (Papathoma-Köhle et al. 2019). There are different approaches to variable weighting in the literature (OECD 2008; Zhao et al. 2018). These approaches can generally be grouped into two main categories: equal weighting and weighting assignment (Serkendiz et al. 2023). Equal weighting of indicators is preferred when the relative relationship between indicators cannot be determined, rather than assuming that all indicators are of equal importance (Cutter et al. 2003; Burton et al. 2018). In other words, it is an option used under assumption that the relative importance of indicators cannot be determined. Indeed, in the Social Vulnerability Index (SoVI) approach developed by Cutter et al. (2003), which is the most cited in the literature on SV studies, all variables are given equal weight, assuming that it is not possible to assign values between variables. The fundamental criticism of the equal weighting approach is that it cannot fully reflect reality because not all variables and indicators are equally important (Frigerio et al. 2016; Nguyen et al. 2017). In contrast, various expert-based and statistical methods are used to weight indicators (OECD 2008). These methods are generally classified into two groups: subjective and objective. The subjective approach (or expert opinion/knowledge-based approach) relies on the assessments of experts in the relevant field or on information on which experts have reached a consensus (Gerçek and Güven 2023). Examples of weights methods used in the literature based on subjective approach include the Analytic Hierarchy Process (AHP) (Fatemi et al. 2017; de Brito et al. 2018; Zhao et al. 2018), the Delphi method, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). However, since these methods are limited to expert opinions or knowledge, they lead to uncertainty in the resulting indices (Shao et al. 2014; Zhang et al. 2017; Ge et al. 2021). Objective weighting approaches are data-driven and determine the importance of variables based directly on the information contained in the data set (Frigerio et al. 2016). In this context, PCA, Entropy method, Data Envelopment Analysis, and Catastrophe Progress methods are examples of methods used for objective weighting. In these methods based on existing data, data quality is a key determinant (Tapsell et al. 2010; Yoon 2012; Guan et al. 2024). Studies using objective approaches (Shao et al. 2014; Frigerio et al. 2016; Zhao et al. 2018) argue that subjective approaches based on expert opinion and being limited to expert opinion will cause differences in the results, and it is stated that it increases the reliability of the results because it is an approach based on information provided by the original data, without data loss and not limited to expert opinion. In this context, variable weighting was performed using an objective approach in our study. Although there are numerous objective quantitative evaluation methods in addition to the examples given above, these methods also have various limitations. For example, when using the PCA method, some information is removed, which affects the evaluation results (Shao et al. 2015). Furthermore, the meaning of the principal component is ambiguous and has been criticized for not being as clear as the original variables (Zhao et al. 2018). In this context, the importance weights of the variables were determined using the Entropy method within the scope of the study. The Entropy method is the most widely used objective method for determining the weights of criteria/structures (Teixeira et al. 2021; He et

al. 2021; Gong et al. 2022; Chen et al. 2023), and its most important advantage is that it does not involve subjective judgment in determining weights, as it is based on calculations using current value information of the variable (Luo et al. 2016; Bai and Liu 2023; Liu et al. 2024). In addition to the differences in the methods used in the steps mentioned above, different methods are also used in other index creation steps, such as data normalization and aggregation. These differences have a significant impact on the index results (de Brito and Evers 2016; Guan et al. 2024).

Most vulnerability studies related to disaster in Türkiye focus on physical vulnerability, qualitative assessments, or specific hazard types and limited geographic areas. For example, Kapucu (2012) and Kalaycıoğlu et al. (2023) examine existing policies and practices; Ansal et al. (2009), Gülkan et al. (1992), and Korkmaz (2009) examine physical vulnerability to earthquakes; Serkendiz and Tatli (2023), Serkendiz et al. (2023), and Sönmez et al. (2005) examine vulnerability to drought; Cankaya et al. (2016) and Tufekci et al. (2018) examine vulnerability to tsunamis; Ekmekcioğlu et al. (2021) and Taş et al. (2013) assess vulnerability to flood; Duzgun et al. (2011), Gerçek and Güven (2023), Kepekci and Ozcep (2011), Shafapourtehrany et al. (2022) and Yildiz and Karaman (2013) examined earthquake vulnerability at the level of a specific province or provinces. On the other hand, studies that assess SV to disasters based on indicators across Türkiye (at the provincial level) are limited (Ozceylan and Coskun 2012; Yaprak et al. 2022; Yükseler and Tenikler 2025). Considering the methodologies and data periods of existing studies, it is debatable to what extent they reflect current SV. For example, although the study by Ozceylan and Coskun (2012) is one of the first examples of an indicator-based SV assessment at the provincial level in Türkiye, it does not fully reflect the current socio-economic structure due to its reliance on a limited number of variables and expert opinions, as well as its use of data from before 2011. Türkiye's rapid population growth in subsequent years, the Syrian migration after 2010, and economic fluctuations have further highlighted these limitations. Yaprak et al. (2022) conducted a semi-quantitative analysis using 24 variables. However, applying the method without adapting it to Türkiye's socio-economic context, using outdated indicators such as "number of televisions per 1000 people," and excluding the variable related to Syrian migrants limited the validity of the results.

2 Materials and methods

2.1 Study area and historical disasters

Türkiye was selected as the study area. Türkiye is a country located between Europe and Asia, surrounded by seas on three sides: the Black Sea to the north, the Mediterranean Sea to the south and the Aegean Sea to the west (Fig. 1). Türkiye, which has hosted different cultures in history and has a strategically important position, covers a wide geography. Some biophysical and socio-economic characteristics of the country are shown in Table 1. The urban population in Türkiye has been higher than the rural population since 1985 and most of the country's population lives in urban areas (Kepekci and Ozcep 2011). In addition to population growth, the country has been experiencing major modernization in recent years, but despite these developments, it still experiences socio-economic challenges such as income inequality and regional inequality (Serkendiz et al. 2023). Moreover, the country

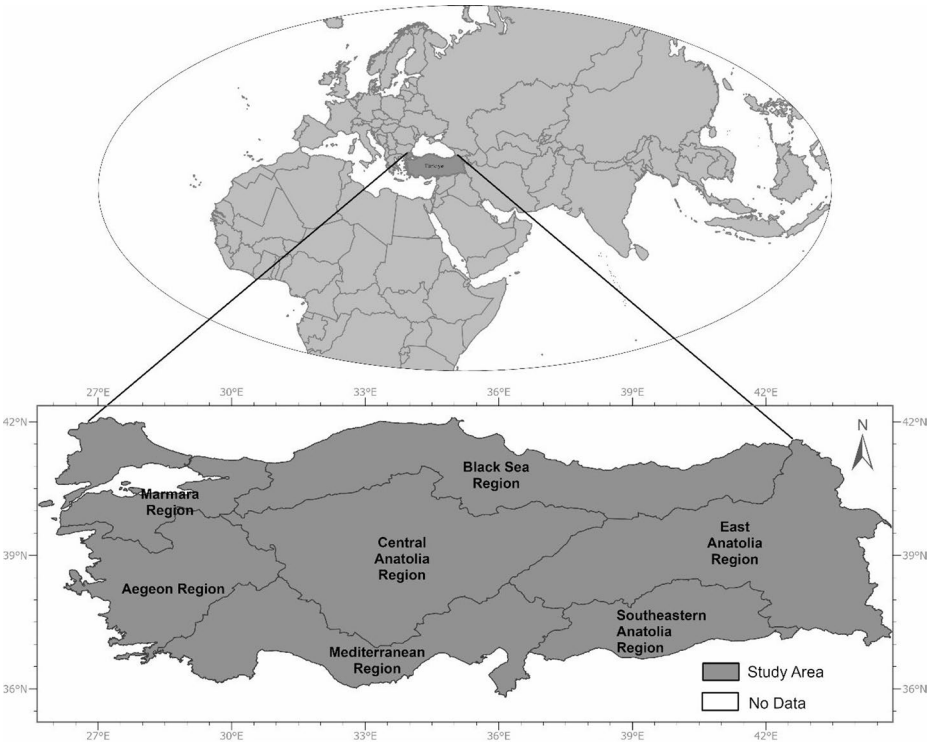


Fig. 1 The map of study area and geographical regions of Türkiye

Table 1 Some biophysical and socio-economic characteristics of Türkiye

Parameter	Description	Sources	Year
Geographical area (km^2)	786,560		
Number of provinces	81		
Number of Geographical Regions	7		
Population	85,372,377	TURKSTAT (2023 data)	2023
Syrian population	3,214,780	Presidency of Migration Management	2023
Median age	34	TURKSTAT	2023
Urban–rural population distribution	82,7% Urban Population	TURKSTAT	2022
GDP per capita	10,659 US$	TURKSTAT	2022

The abbreviation is flows: TURKSTAT is Turkish Statistical Institute

is a destination for migrants, especially for transit to Europe, and faces various economic and security challenges, such as hosting Syrians in the aftermath of the 2011 Syrian crisis.

In addition to being in a seismically active region, Türkiye is a country where disasters are experienced due to its topography and different climates. In seismic terms, Türkiye is in the Alpine-Himalaya geodynamic system, which is defined as one of the world's continen-

tal regions with a long earthquake history and ongoing earthquake activity (Duzgun et al. 2011). In terms of physical geography, especially in the Anatolia Peninsula, various climate types are observed due to physiographic features that vary over short distances (Serkendiz et al. 2023). Therefore, different types of meteorological hazards are observed in different geographical regions of the country. In addition, the Mediterranean basin, in which the country is located, is in a high-risk position in terms of hazards such as drought, climate change-induced food security, climate migration, according to future climate projections of IPCC (IPCC 2023).

In Table 2 presents the disasters that have occurred in Türkiye. According to this, earthquakes account for a significant majority of disasters occurring in the country and are also responsible for the largest share of deaths, injuries, exposure, and economic losses resulting from disasters. In this context, the effects of some earthquakes, which have caused losses with different negative aspects in the history of the country, have a determining effect on earthquake-related data. Table 3 shows the earthquakes that had the greatest impact in terms of losses caused by these earthquakes. Among these earthquakes, especially the 2023 earthquakes have left significant marks in historical collective memory. After these earthquakes, the loss of life due to earthquakes in Türkiye increased by 53%, while total of 7.7 million people was affected by previous earthquakes, causing this number to increase by 220% to approximately 17 million (Aktaş et al. 2024). Among the data given in Table 2 and Table 3, the adjusted total damage data from the earthquakes that occurred in 2023 has not been updated as the recovery works in the affected area are still on going. After these works, it can be stated that the economic loss due to the 2023 earthquakes will be greater.

2.2 SV indicators and proxy variables

The conceptual framework used in the study is shown in Fig. 2. This study aims to assess SV to disasters by obtaining an index from a set of indicators. For this purpose, Türkiye's

Table 2 Disasters and their consequences in Türkiye between 1990 and 2024

Disaster type	Number of disaster	Number of death	Number of injured	Total affected	Total damage, adjusted ('000 US$)
Earthquake	114	144,805	209,0507	16,971,842	79,235,335**
Flood	54	1504	605	1,811,323	43,384,543
Mass movement (wet and dry)	15	765	444	14,740	49,933
Storm	14	123	189	14,763	737,114
Epidemic	7	609	*	204,847	*
Extreme temperature	7	100	450	8,450	1,700
Wildfire	6	24	122	562,238	250,566

The table was prepared by using the data obtained from the Emergency Events Database (EM-DAT) website on April 19, 2024. *No data available. ** Current economic loss data related to the 2023 earthquakes has been included, and this value will change in the future as post-earthquake recovery efforts continue

Table 3 Some earthquakes with major impact in Türkiye

Earthquake year	Magnitude	Number of death	Number of injuries	Number of affected	Total damage ('000 US$)	Total damage, adjusted ('000 US$)
1939 Erzincan Earthquake	7.8	32,962	*	585,000	55,600	419,101
1999 Marmara Earthquakes (Izmit and Duzce)	Izmit Earthquake Mw: 7.6, Duzce Earthquake Mw: 7.2	17,972	48,901	880,000	1,583,901	21,000,000
2011 Van Earthquake	7.1	604	4152	32,938	1,500,000	1,951,560
2023 Earthquakes	7.8	50,783	107,204	9,207,204	34,000,000	**

The table was prepared using data obtained from EM-DAT website on April 19, 2024. *No data available. **No data available as recovery works are going

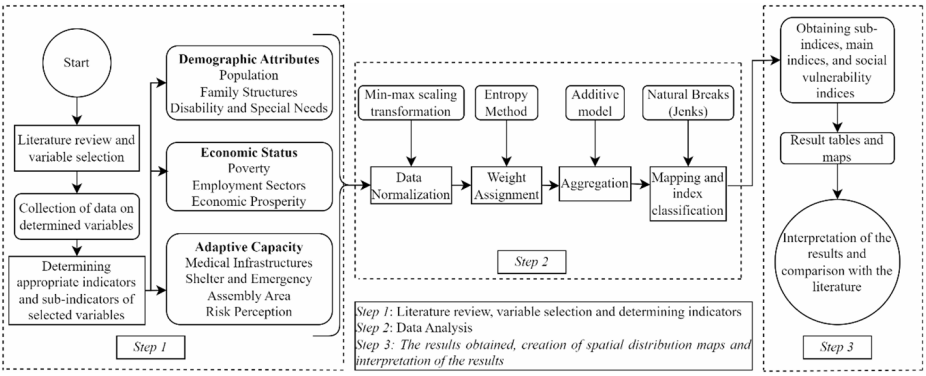


Fig. 2 Flow chart followed in the study to obtain SV index

social structure and access to data are considered, and the relevant literature is reviewed to select appropriate SV indicators and proxy variables. There are many factors that affect SV (Frigerio et al. 2016). In addition, due to the differences in the social structures of societies and the temporal variability of these structures, it can be said that there are no agreed-upon clear indicators for SV in literature. Moreover, different methods are applied to assess SV. In this context, in addition to some universal variables that have an impact on SV, variables specific to Türkiye's social structure were also selected. The indicators determined within the scope of the study, proxy variables under these indicators, the effects of these variables on SV, data sources and data years are shown in Table 4.

2.2.1 Data sources

The data used in this study were obtained from seven different sources (Table 4). Most of these data (19 datasets) were obtained from TURKSTAT, which shares institutional data in Türkiye. The data obtained from TURKSTAT are open access and free of charge and were obtained from the institution's online data portal (https://www.tuik.gov.tr/). Similarly, the

Table 4 Indicators and proxy variables used to assess SV

Major indicators	Sub-indicators	Proxy variables *(Impact of SV)*	Data year	Data source
DA	Population	Population density (People per km^2) *(+)*	2022	TURKSTAT
		Annual population Growth (‰) *(+)*	2022	TURKSTAT
		Number of Syrians *(+)*	2022	PMM
		Number of women *(+)*	2022	TURKSTAT
		Median age *(+)*	2022	TURKSTAT
	Family structure	Crude birth rate (‰) *(+)*	2022	TURKSTAT
		Extended family household *(+)*	2022	TURKSTAT
		Single-person household *(+)*	2022	TURKSTAT
		Average household size *(+)*	2022	TURKSTAT
	Disability and special needs	Number of people below 15 years *(+)*	2022	TURKSTAT
		Number of people over 64 Years *(+)*	2022	TURKSTAT
		Percentage of people with disabilities *(+)*	2011	MFSS
ES	Poverty	Gini index *(+)*	2022	TURKSTAT
		Poverty rate (%) *(+)*	2022	TURKSTAT
		Unemployment rate (%) *(+)*	2022	TURKSTAT
	Employment sectors	Agricultural sector employment (%) *(+)*	2022	TURKSTAT
		Industrial sector employment (%) *(+)*	2022	TURKSTAT
		Service sector employment (%) *(+)*	2022	TURKSTAT
	Economic prosperity	GDP(US$) *(−)*	2022	TURKSTAT
		Number of vehicles *(−)*	2022	TURKSTAT
		Number of banks *(−)*	2022	BRSA
AC	Medical infrastructures	Number of hospital *(−)*	2021	MH
		Number of hospital Beds *(−)*	2021	MH
		Number of family practice *(−)*	2021	MH
		Number of doctors *(−)*	2021	MH
		Number of emergency Medical Stations*(−)*	2021	MH
		Number of Ambulances *(−)*	2021	MH
	Shelter and assembly area	Shelter areas (m^2) *(−)*	2022	AFAD
		Shelter facilities person capacity *(−)*	2022	AFAD
		Emergency assembly area (km^2) *(−)*	2022	AFAD
	Risk perception	Natural disaster insured rate (%) *(−)*	2022	TCIP
		Number of college or faculty graduates *(−)*	2022	TURKSTAT
		Number of basic AFAD volunteers *(−)*	2022	AFAD
		Number of support AFAD volunteers *(−)*	2022	AFAD

The abbreviations used in the table is as follows: AFAD is the Disaster and Emergency Management Presidency; MH is the Ministry of Health; TCIP is the Turkish Catastrophe Insurance Pool; BRSA is the Banking Regulation and Supervision Agency; PMM is the Presidency of Migration Management; MFSS is the Ministry of Family and Social Services

data on health services used in the study were taken from the "Health Statistics Yearbook 2021" document (https://sbsgm.saglik.gov.tr/TR-93567/health-statistics-yearbook.html), which was shared by MH as open access. Data on refugees (Syrian population) were taken from data published as open access on the website of the official migration management agency (PMM) in Türkiye (https://www.goc.gov.tr/istatistikler). Furthermore, data on the number of banks and disaster insurance were obtained from data published as open access on the official websites of the BRSA (https://www.bddk.org.tr/BultenFinTurk) and TCIP

institutions (https://dask.gov.tr/tr/istatistikler), respectively. The data used in the study were obtained from seven data sources, and the data obtained from AFAD, one of these sources, are not published as open access. In this context, data were requested from the AFAD source through official correspondence, and the relevant data sets were included in the study.

This study focuses on 2021–2022 for the assessment of SV at the provincial level. In this context, the datasets consist mainly of data from 2021 and 2022. However, for one dataset (data on people with disabilities), data for 2021 or 2022 is not available. Data on people with disabilities in Türkiye is published by the MFSS with open access and free of charge. However, the most recent data on people with disabilities published by the institution at the provincial level is from 2011. In this context, the ratio of the number of people with disabilities published in 2011 to the total population data for 2011 was used to include the ratio of people with disabilities at the provincial level in the study. The aim in converting the data into a ratio of the provincial population was to represent estimates that were as close as possible to other datasets.

2.2.2 Causal and functional relationship between variables used in research and SV

This section addresses the causal and functional relationships between the identified variables and SV. In this context, it briefly discusses why the variables used under the three main indicators specified in Table 4 are used and the direction of their functional relationship (increasing or decreasing vulnerability) with the SV index based on this causality. In summary, this section attempts to answer questions such as: What kind of causal relationship exists between the population density variable and SV? Does SV increase or decrease based on this causal relationship?

Population density. In the PAR model, rapid urbanization, presented as one of the dynamic pressures, directs the root causes of vulnerability toward unsafe conditions due to the increase in population density (Wisner et al. 2004). Increasing population density increases the number of people exposed to disasters and the demand for public resources (Cutter et al. 2003; Armaş and Gavriş 2013; Duan et al. 2022) and exacerbates economic and human losses by complicating evacuation and emergency management (Holand et al. 2011). *Annual population growth.* It is one of the key determinants of SV. Rapid population growth increases pressure on housing, infrastructure, health, and education services, creating capacity shortages and spatial inequalities (Anderson 1995; Clarke and Munasinghe 1995). This situation increases vulnerability to disasters, particularly in areas of unplanned urbanization and high migration, by spreading settlements into hazardous areas (Cutter et al. 2003). *Number of Syrian.* Minorities, migrants, and groups temporary protection status are more vulnerable to disasters due to marginalization stemming from lack of access to resources, cultural differences and racial inequality (Cutter et al. 2003; Wachtendorf et al. 2013). In Türkiye, the sudden population increase by forced migration increases SV due to pressure on infrastructure and services and integration difficulties (Ceritoglu et al. 2017; Serkendiz and Tatli 2023). This situation deepens vulnerability for both refugees and the local population (Morrow 1999). Considering Türkiye's demographic structure, the Syrian refugee variable has been identified. Consequently, there is a positive (increased SV) relationship between the number of Syrian refugees and SV. *Number of women.* Gender-based inequalities, social roles, and limited access to resources are important determinants of SV (Fordham et al. 2013). Women are more vulnerable to the effects of disaster than men due

to their caregiving responsibilities, low economic status, and limited autonomy (Morrow 1999; Cutter et al. 2003). This situation leads to pre-disaster disadvantages continuing into post-disaster recovery process (Ikeda 1995; Wisner et al. 2004). *Median age.* The increase of median age indicates that the aging trend of the population reveals that older individuals are at greater risk in terms of health and wellbeing in the face of disasters (Ngo 2001). This variable is widely used to assess the impact of age structure on SV (Cutter et al. 2003; Holand and Lujala 2013; Chen et al. 2013), and it is accepted that SV increases as the median age rises. *Crude birth rate.* It is an indicator of population growth (Zarghami and Dumrak 2021), and rapid population growth puts pressure on public resources, increasing SV (Cutter et al. 2003; De Oliveira Mendes 2009). In Türkiye, particularly in the eastern and southeastern regions, high birth rates make this variable an important parameter in terms of SV. *Extended Family Household.* Although extended families can provide certain advantages in terms of social solidarity after disasters (Wachtendorf et al. 2013), they are more vulnerable to disasters due to the burden of care and limited economic resources (Cutter et al. 2003). In addition, large households living in low-income or high-risk areas tend to move to hazardous areas to make a living and face additional difficulties in post-disaster recovery (Gaillard et al. 2007). *Single person household.* The increase in single-person households raises vulnerability to disasters due to social isolation, limited economic resources, and low resilience (Benassi et al. 2024). Wachtendorf et al. (2013) note that limitations in insurance, evacuation, and response decisions increase disaster exposure, regardless of household size. Furthermore, Chen et al. (2013) found that the one-child policy and urbanization process in China, which led to smaller families, increased SV, particularly among older individuals, by increasing the empty nest phenomenon. *Average Household Size.* Household size is an important factor affecting SV as one of the fundamental elements of family structure (Chen et al. 2013; Cutter et al. 2003). Large households are disadvantaged in the post-disaster recovery process due to high living costs and limited resources (Wachtendorf et al. 2013). Therefore, it is accepted that an increase in household size raises SV (Cutter et al. 2003). *Number of people below 15 years.* They are one of the most vulnerable population groups in disasters. This population group is known to experience long-term physical and psychological effects (Abramson and Garfield 2006; Hewitt 2007). Furthermore, due to their dependence on others and the deterioration of living conditions after disasters, they may be more susceptible to SV, and the psychosocial effects of disasters slow down recovery process (Norris et al. 2002). *Number of people over 64 years.* Older individuals are more affected by disasters due to low income, limited mobility, chronic illness, and insufficient preparedness prior to disasters (Holand et al. 2011; Thomas et al. 2013a; Lee 2014). Therefore, as the proportion of the elderly population increases, SV in terms of post-disaster injuries, deaths, and recovery time also increases (Cutter and Finch 2008). *People with disabilities.* They are a group with special needs who are highly likely to require financial support, transportation, medical care, or assistance with daily living after a disaster (Flanagan et al. 2011). Past disasters have shown that these people face a higher risk of injury, death, and displacement compared to the general population (Smith and Petley 2009). Post-disaster deterioration in living conditions further limits the independent living capacity of people with disabilities, increasing both individual vulnerability and disaster response costs (Lee 2014).

Poverty rate. Poor people are defined as those with income levels below the consumption standards of society (Sen 1981) and constitute one of the fundamental elements of SV due to their limited access to resources (Adger and Kelly 1999). From a disaster risk reduction

perspective, poverty alleviation is directly related to disaster preparedness and development processes (Wisner et al. 2004). Therefore, poverty limits coping capacity of individuals through marginalization and lack of resources, reducing their resilience to the effects of disasters (Adger and Kelly 1999). *Unemployment rate.* Numerous studies in the literature show that high unemployment rates parallel high SV (Adger 1999; De Oliveira Mendes 2009; Burton 2010). Unemployed individuals are not only deprived of the resources to prepare for disasters, but they also become more vulnerable to the risk of being unable to cover post-disaster income and health expenses. Therefore, as unemployment rates increase, the social impacts of disasters and the level of instability also increase (Chen et al. 2013). *Gini index.* The Gini coefficient is an indicator that measures inequality in income and wealth distribution and is calculated using the Lorenz curve. Increasing income inequality can increase SV by preventing the fair distribution of resources and limiting access opportunities during times of crisis (Adger and Kelly 1999). Indeed, Yohe and Tol (2002) found a positive relationship between income inequality and vulnerability. In summary, the Gini coefficient has been considered an indicator that increases SV. *Agricultural sector employment.* The agricultural sector is one of the sectors most vulnerable to hydrometeorological hazards (Serkendiz and Tatli 2023). Although natural hazards affect all sectors, direct economic losses are most evident in agriculture; for example, disaster-related losses in the US rose from $4.5 billion in the 1970s to $20 billion in the 1990s (Mileti 1999). Similarly, the earthquakes of February 6, 2023, caused serious economic and employment losses in the agricultural sector in Türkiye (Demirdag and Nirwansyah 2024). Therefore, it is accepted that as employment in the agricultural sector increases, social vulnerability also rises. *Industrial sector employment.* The industrial sector is one of the employment areas that can be highly vulnerable to disasters. Past disasters have been decisive in direct and indirect economic losses due to the role of industrial systems in the local economy (Khazai et al. 2013). Effects such as production interruptions, job losses, and infrastructure damage (Jiang et al. 2005; Hackman 2008) make the sector vulnerable; therefore, industrial employment is considered a variable that increases SV. *Service sector employment.* The service sector employment rate has been considered as a variable that increases SV in the study, as it is one of the job sectors that can be most affected at the sectoral level in disasters. Job losses arising after a disaster slow down the recovery process (Cutter et al. 2003). The service sector, which has become dominant in the economy since the second half of the twentieth century (Özsağır and Akın 2012), is vulnerable to serious losses during/after disasters, and its negative effects on GDP and employment are highlighted in the literature (O'Brien et al. 2006; Holand et al. 2011). *GDP.* GDP is recognized as one of the fundamental indicators of economic wealth and prosperity and is widely used in vulnerability analyses (Lung et al. 2013; Lixin et al. 2014; Serkendiz and Tatli 2023). According to the literature, as GDP increases, the capacity of coping and adaptation of individuals and societies strengthens, thereby reducing vulnerability to disasters (De Stefano et al. 2015). Therefore, the GDP per capita variable was used as the primary indicator of economic wealth in the study. *Number of vehicles.* Vehicle ownership was used in this study as an indicator of economic well-being and because it provides a significant advantage in post-disaster evacuations. Access to exit routes, road quality, and vehicle use are decisive factors in preventing injuries and deaths during evacuations (Fatemi et al. 2017). Indeed, Tapsell et al. (2010) note that evacuation plans for New Orleans were prepared on the assumption that the public had access to vehicles, whereas only 1 in 5 people had this opportunity. Furthermore, 55% of those who did not evacuate after Hurricane

Katrina stated that they did not have a vehicle or other transportation options. Therefore, since the lack of access to personal vehicles hinders access to safe areas (Eisenman et al. 2007; Karaye et al. 2019), the number of vehicles was considered a variable that reduces vulnerability in this study. *Numbers of banks.* The destruction of produce capital stock has negative effects on economic performance (Rose et al. 1997; Khazai et al. 2013; Sseruyange and Klomp 2021). Access to financial instruments such as insurance, credit, and fiscal incentives increases resilience in mitigating these effects (Eakin and Lemos 2006). Therefore, an increase in the number of bank branches strengthens economic resilience (Burton 2015; Scherzer et al. 2019), reducing vulnerability to social damage after disasters.

Health quality of life is a fundamental indicator of safety and well-being throughout the disaster management cycle. Health is related to demographic characteristics and is also a critical infrastructure and vulnerability indicator (Thomas et al. 2013b). Access to health services after a disaster is decisive in the relief and recovery process (Cutter et al. 2003; Chen et al. 2013). In this context, six variables have been defined under the medical infrastructures sub-indicator. The causal and functional relationship between variables and SV can be summarized as follows. *Number of hospitals*. Insufficient resources such as medical personnel, facilities, and medicines significantly affect living conditions before and after disasters (Scandlyn et al. 2013). International disaster risk reduction conferences also emphasize the strengthening of facilities such as hospitals and schools (UNDRR 2007, 2015). Therefore, the number of hospitals has been considered an indicator of institutional capacity in coping with disasters, and it has been accepted that as this number increases, SV decreases. Furthermore, as mentioned above, not only health facilities but also medical personnel, the quality of health facilities, and the availability of necessary equipment and supplies are important parameters for coping capacity. In this context, in addition to the number of hospitals, the variables *number of hospital beds* (Lee 2014); *number of doctors* (Thomas et al. 2013b; Villagrán de León 2013); *number of family practice*; and *number of 112 stations and ambulances* (Cimellaro et al. 2013) are also defined within the scope of the study, and it is accepted that SV decreases as this capacity increases.

Post-disaster shelter areas are critical elements that not only protect individuals from hazardous areas but also support the process of coping with stress and adapting (Cruz et al. 2017; Zhao et al. 2017). Therefore, post-disaster evacuation and shelter planning are of great importance in terms of strengthening social resilience and reducing vulnerability. In the context of Türkiye, the sub-indicator of shelter and emergency assembly areas was defined within the scope of this study; considering data availability, the variables *shelter areas, Shelter Facilities Person Capacity,* and emergency assembly area size were used. Emergency assembly areas serve as safe gathering and information centers during disasters (Çınar et al. 2018; Gerdan and Şen 2019). Furthermore, increasing the size of shelter areas and the capacity of facilities facilitates meeting temporary shelter needs after a disaster, thereby reducing SV.

A comprehensive assessment of SV should include not only factors that increase exposure and susceptibility, but also the strengths and resources of communities (Thomas et al. 2013a). In this regard, social awareness is important, as well as institutional capacities under coping capacity. Within the scope of this study, the risk perception sub-indicator was defined to represent this relationship, and the variables of education level, disaster insurance status, and volunteering were examined in this regard. *Number of college or faculty graduates* is a fundamental indicator representing disaster and emergency awareness. The

literature indicates a strong relationship between education level and vulnerability; it is emphasized that as education level increases, risk perception and coping capacity also increase (Cutter et al. 2003; Brooks et al. 2005; De Stefano et al. 2015). For example, Cutter et al. (2003) states that low educational attainment limits the capacity to understand disaster warnings, while Chen et al. (2013) states that high educational attainment increases the capacity to respond to disasters. Therefore, it is accepted that as the number of higher education graduates increases, SV decreases. The rate of disaster insurance coverage is an important coping mechanism that reduces the economic impacts of disasters through risk transfer (Serkendiz et al. 2023). Insurance coverage increases recovery capacity at both the individual and societal levels (Cutter et al. 2010) and facilitates the compensation of losses. For example, Cutter et al. (2010) linked Florida's high disaster resilience to previous disaster experiences and insurance prevalence. In this context, it is accepted that as the disaster insurance rate increases *(Natural Disaster Insured Rate data was used within the scope of the study)*, SV decreases. Disaster risk management includes not only physical measures but also institutional capacity and community participation (Yükseler et al. 2024). International initiatives emphasize that strengthening local volunteer activities can lead to less damage in disaster response and recovery processes (UNDRR 2015). Therefore, volunteer activities play an important role in risk reduction (Cutter et al. 2010). Within the scope of the study, the *number of basic and support AFAD volunteers* was used to represent volunteering at the provincial level. *A basic AFAD volunteer* refers to individuals who have basic knowledge about disasters and have completed awareness training. Within the scope of the study, an increase in the number of basic AFAD volunteers was considered a factor that reduces SV. *Support AFAD volunteers* include individuals who have completed basic training and received practical training in areas such as search and rescue, social assistance, firefighting, and first aid. Therefore, an increase in the number of support AFAD volunteers was considered a factor that reduces SV.

2.3 Calculation of SV

2.3.1 Data normalization

Because data related to the variables used in the study express different meanings and unit differences (such as percentage, per thousand, number of people per km^2), the data must be normalized for data analysis. In the literature, z-score and min–max scaling transformation methods can be used to ensure that data with different units are between 0 and 1 (Moreira et al. 2021a). In this context, by using the min–max scaling method in the study, the variables that cause SV to increase or have a positive effect are normalized with Eq. (1), while variables that cause SV to decrease or have a negative effect are normalized with Eq. (2).

$$X'_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{1}$$

$$X'_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{2}$$

where X'_{ij} is the normalized value of the *i*th evaluating variable on *j*th indicator, x_{ij} is original value of a variable, x_{min} is the minimum value of a variable, x_{max} is the maximum value of a variable.

2.3.2 Entropy method for weight assignment

In index-based vulnerability assessment, assigning weights for each variable after normalizing the data is one of the important steps for index creation. In this study, the objective approach entropy method was used for weight assignment. This is because subjective approaches, which are frequently used in literature, are based on expert opinion and are limited to expert knowledge, which may affect the results. In this context, objective weighting methods are preferred in literature, and among these approaches, the entropy method is the most frequently preferred weighting method in vulnerability assessments (Xia et al. 2021; Chen et al. 2023, 2024). The entropy method, which is one of the objective method approaches among the weight assignment methods, has a significant advantage because it can make a calculation based on the existing variable value information and does not include subjective expert opinion in weight determination. Entropy is a measure of the degree of disorder in a system (Liu et al. 2024). The basic idea of entropy weight assignment theory is to determine the value differences between variables evaluated on the same indicator (Zhang 2009; Liu et al. 2016). The variable with the highest value among the determined values is the most important variable in that indicator (Zhao et al. 2018). In this way, while the weight assignment becomes more scientific and appropriate by considering the uncertainty of each indicator data, the problem of limiting the weights to expert knowledge or assigning excessive weights to certain indicators is eliminated (Yoon et al. 2017; Bai and Liu 2023). The steps followed for the entropy weight assignment of each variable used in the study are shown in Eqs. 3–6 (Zhao et al. 2018).

(1) The proportion of the *i*th evaluating variable on the on *j*th indicator is calculated, as shown in Eq. (3):

$$Y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{3}$$

(2) The entropy of each evaluating variable can be defined as shown in Eq. (4):

$$e_j = -k \sum_{i=1}^{m} Y_{ij} . \ln(Y_{ij}) \tag{4}$$

where, e_j entropy value of *i*th, $k > 0$, ln is the natural logarithm, $k = 1/\ln m$, and m is the number of evaluating object.

(3) In the next step, the difference coefficient/degree of differentiation (d_j) is calculated, as shown in Eq. (5):

$$d_j = 1 - e_j \tag{5}$$

(4) The weight of entropy of each evaluating variable is calculated, as shown in Eq. (6):

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} (0 < w_j < 1, \sum_{j=1}^{n} w_j = 1) \tag{6}$$

where w_j is the each of variable weight, n is the number of variables. Weight for all indicators and sub-indicators is shown in Fig. 3.

2.3.3 Calculation of SV index

To create a comprehensive SV index, the data of the 34 variables used in the study were first normalized, and then the weight values were obtained by using the entropy method to assign weights to each variable. To calculate the total values of the obtained values, the value of

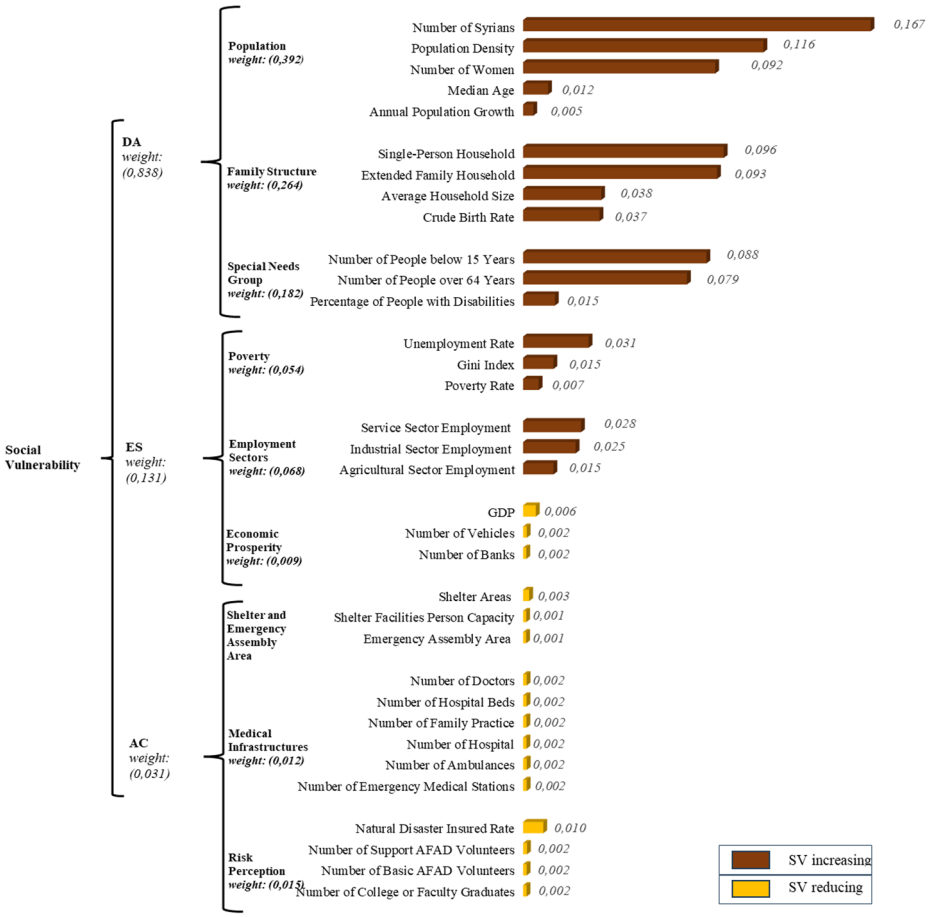


Fig. 3 Schematic depiction of the weight values of indicator and proxy variables calculated via the entropy method

the substance/variable evaluated in many studies is calculated with the following Eq. (7) (Lianxiao2019; Liu et al. 2024):

$$V_i = \sum_{j=1}^{n} X_{ij}\prime * w_j \tag{7}$$

where V_i is value of SV index, $X_{ij}\prime$ is normalized value of each variable and w_j is weight of each variable.

There are different approaches in the literature to calculating the SV index. Due to these differences in approach, SV scores also differ. To calculate drought vulnerability, Serkendiz et al. (2023) used the IPCC's vulnerability equation, added exposure and sensitivity values, subtracted them from adaptive capacity values and obtained a vulnerability score. Zhao et al. (2018) obtained a vulnerability index by averaging values. Cutter et al. (2003) choosing an additive model to produce the SoVI score in the USA, stated that each factor they determined had an equal contribution to the overall vulnerability. In this study, SV scores were obtained by summing the values (additive model) of 3 determined indicators (demographic attributes, economic status and adaptive capacity). In addition, since the effect (positive or negative) of the selected variables on vulnerability is calculated in the normalization step of the data within the scope of the study, there is no need to remove variables with a negative effect in obtaining the SV score after this step.

In this study, the results were mapped using ArcGIS Pro to obtain the spatial distribution of the obtained results. In literature, different methods are used for data classification, such as the standard deviation method and the quantile method, when preparing maps to assess vulnerability. According to the study by Moreira et al. (2021a), which compares these different classification methods using the same data set, the natural breaks points (jenks) method was found to deliver the best performance. In this context, we used the natural breaks method for index classification in the study. The method chosen to obtain the study results objectively (Zhao et al. 2018) minimizes the diversity within the class and maximizes the diversity between classes without the influence of artificial factors (Liu et al. 2017). In this classification process, SV degrees were reclassified into 5 different degrees: "very low", "low", moderate", "high" and "very high".

3 Results and discussion

3.1 Weighting results of indicators, sub-indicators and variables

There is no standard approach in the literature regarding the level at which weighting should be performed (indicator, sub-indicator, or variable. For example, Serkendiz and Tatlı (2023), sensitivity and adaptive capacity indicators were given equal importance, and weights were assigned at the sub-indicator and variable levels. Lianxiao (2019) and Zhao et al. (2018) assigned weights using the entropy method, and the sum of the weight values is equal to 1. A similar approach was applied in this study. The weight assignment findings are presented in Fig. 3. According to these findings, DA is the most important indicator in terms of SV (total weight: 0.838). This is followed by ES (0.131) and AC (0.031). It was determined

that that variables under DA have the highest impact, while the AC indicator has the lowest impact. These results are consistent with similar studies in the literature (Uddin et al. 2019; Kirby et al. 2019; Ajtai et al. 2023). Although the areas and methods examined in the studies differ, the DA indicator has generally been identified as the most effective component. In contrast, AC was found to have the lowest importance weight in this study. This finding differs from the study conducted by de Brito et al. (2017) on flood vulnerability in Brazil. In that study, AC was determined to be the indicator with the highest importance using the Delphi method based on expert opinions. The difference is thought to stem from the method and set of variables used.

At the sub-indicator level, population (0.392), family structure (0.264), and disabilities and special needs (0.182) are the most dominant sub-indicators in terms of SV. In contrast, shelter and emergency assembly areas (0.005), economic prosperity (0.009), and medical infrastructures (0.011) have the lowest weight values. Based on variables, the five variables that most affect SV to disasters among 34 variables are, in order, the Syrian population (0.167), population density (0.116), single-person households (0.096), extended family households (0.093), and female population (0.092). Based on the approach that different ethnic groups have higher vulnerability to disasters (De Loyola Hummell et al. 2016; Uddin et al. 2019), the Syrian population variable, which is an important demographic component in Türkiye, was used and determined to be the factor with the highest impact. This finding is consistent with the study by Serkendiz and Tatli (2023), which determined variable weights using the AHP method and similarly identified the Syrian population as the most influential factor. Furthermore, population density and female population variables are also among the variables with high impact. This is explained by the fact that evacuation and rescue activities become more difficult as population density increases (Cutter et al. 2003) and women are disproportionately affected by disasters due to their limited economic resources (Wood et al. 2010). Extended and single-person households, which are included in the family structure sub-indicator, are also variables that increase SV. Extended families become more vulnerable due to limited financial resources (Cutter et al. 2003; Siagian et al. 2014). Contrary to the traditional family structure, the number of single-person households is increasing due to factors such as divorce, education, and job opportunities (Fatemi et al. 2017); this situation makes single-person households more vulnerable to disasters. On the other hand, variables under AC (particularly the capacity of shelter facilities and emergency assembly areas) have the lowest weights. Overall, the components of this indicator are the variables with the most limited impact on SV compared to other indicators.

3.2 Main indicator indices

3.2.1 DA index

Three sub-indicators are recognized under the DA main indicator, represented by 12 variables. As a result of the index calculation, the spatial distribution map of the sub-indices and the DA index is presented in Fig. 4. According to the spatial distribution of 5-variable population sub-index scores (Fig. 4a), at the provincial level, Istanbul has very high scores, while Gaziantep, Sanlıurfa, Mersin, Adana, Hatay, Izmir and Bursa have high SV scores. At this point, especially based on these provinces, it is observed that vulnerability of the provinces where Syrians have been resettled is high and among these provinces, Istanbul stands out

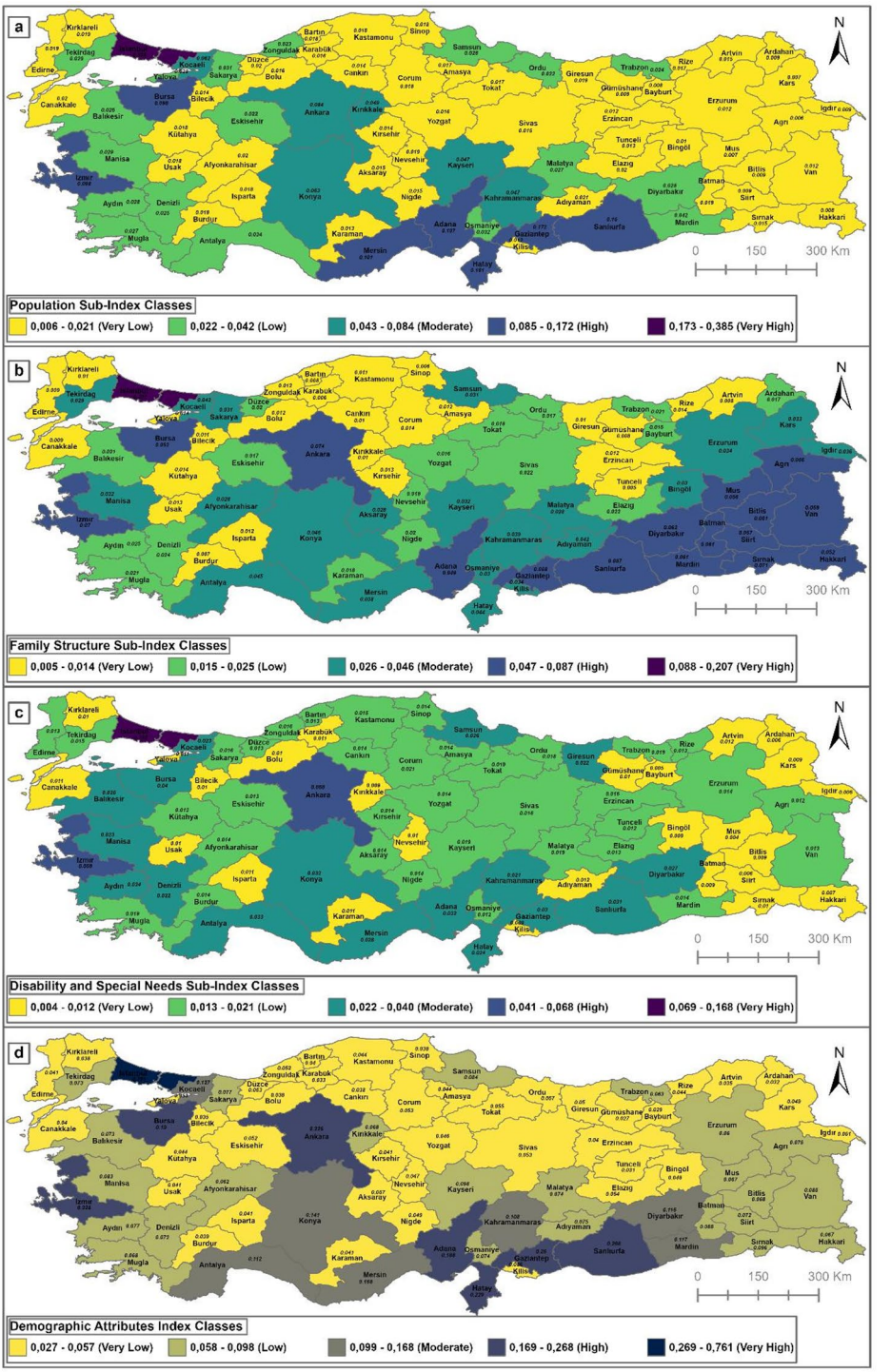


Fig. 4 Spatial distribution of DA Index and Sub-Indices: **a** population sub-index, **b** family structure sub-index, **c** disability and special needs sub-index, and **d** DA Index

from other provinces. Moreover, the population sub-index score of Istanbul (0.385) is more than twice the score of Gaziantep (0.172) the closest province. It can be suggested that this is because Istanbul constitutes approximately 19% of the country's population. Additionally, another reason for the high index values of the provinces of Bursa and Izmir, located in the west of the country along with Istanbul, can be attributed to the high employment opportunities in these regions, which attract Syrian citizens to live there. Indeed, Serkendiz et al. (2023) assess this situation as follows: the pattern of high and very high population sub-index values in coastal regions outside the country's Northwest and Black Sea regions reflects the country's industrial centers, tourism sector, and regions with better living conditions. On the other hand, it is observed that most of the provinces with high index values are in the southeastern part of the country. This situation reflects the population density in the region, as well as the proximity of these provinces to the Syrian border and the fact that approximately half of the Syrian population in the country lives in this region. Indeed, following the earthquakes that hit Türkiye on February 6, 2023, it was observed that Syrian individuals were one of the sub-population groups most vulnerable to high levels of damage. In this context, studies conducted after the earthquakes (Sevinin et al. 2023; Soqia et al. 2024) concluded that the disaster response phase, including search and rescue and access to aid, was not carried out equally for Syrians, and that this increased their vulnerability after the disaster. A study examining the effects of earthquakes on Syrian refugees indicated that traumas like those experienced during the war were repeated and characterized by social, economic, and psychological difficulties (Nasır et al. 2025). Furthermore, while language barriers (e.g., Syrians not speaking Turkish) increase the vulnerability of migrants, the difficulties experienced by the local population in resource sharing and intervention processes make it critical to revise Türkiye's disaster management system to take ethnic diversity into account to reduce the vulnerability of both groups (Yükseler and Tenikler 2025). In terms of other provinces, Ankara, Konya, Kocaeli, Kayseri, Kırıkkale and Kahramanmaras have moderate scores, while the rest of the provinces in the country have low scores with low scores with very low weighting. Regionally, all provinces in the Eastern Anatolia region except Malatya have very low population sub index scores, while the Black Sea region, Aegean region, Marmara region and Central Anatolia region have very low and low scores, respectively, except for some provinces with very high and high scores.

According to the results of the family structure sub-index consisting of 4 variables (Fig. 4b), it is seen that the vulnerability of the west, central Anatolia and north of the country is less than other regions, except for some large cities (Istanbul, Ankara, Izmir, and Bursa). At this point, the family structure scores of the Eastern and Southeastern regions are regionally high. It can be said that this situation is due to the high birth rate in the region compared to other provinces and the traditionally dominant extended family structure. As a matter of that, it is seen that the average number of households is high in the Southeastern and Eastern Anatolia regions, where the crude birth rate is highest. On the other hand, the reason why the vulnerability of the provinces of Istanbul, Ankara, Izmir, and Bursa, located in the west of country, is very high and high is that these provinces have many job opportunities, a high number of universities and are the regions where trade is most intense. For these reasons, it can be said that the high number of single-person households, as well as the extended family structure in these regions, has an impact on family sub-index scores. The findings of this study are consistent with the SV assessment conducted at the provincial level by Yükseler and Teniker (2025). In that study, comparisons were made using different

objective methods to assign weights to variables, and the results obtained are consistent with the findings of the family structure sub-index. Both studies observed similar spatial distributions at the regional level, but differences emerged in the SV rankings of the provinces.

The spatial distribution map of the disability and special needs sub-indicator analysis, which combines the variables of the population under 15 years of age, the population over 65 years of age, and the disabled population, is presented in Fig. 4c. The groups defined in this sub-indicator may require external support compared to other individuals under normal circumstances, and this situation may increase further following disasters and emergencies (Morrow 1999; Fatemi et al. 2017). Indeed, previous studies show that breastfeeding or pregnant women and minorities, as well as other vulnerable groups, face a higher risk of illness, injury, mental health problems, and especially premature death during and after disasters or emergencies (Nick et al. 2009; Balikuddembe 2022). According to disability and special needs index distributions (Fig. 4.), at the provincial level, Istanbul has very high, Izmir and Ankara have high index values, while most of the remaining provinces have low and very low scores. In general terms, it is seen that the score of Istanbul is quite high due to its very high population density, while the score of Ankara, one of the provinces closest to this province's score, is approximately 2.5 times higher. Although the vulnerability of the South and East of the country is high in terms of population and family structure indices, it is seen that this reason for this is the high birth rates in these parts of the country and relatively low number of elderly and disabled populations.

The results of the DA indicators show that Istanbul, which has the highest vulnerability score in all sub-indices, is the most demographically vulnerable province to disasters in Türkiye (Fig. 4d). It is seen that the demographic vulnerability of Istanbul is approximately 2.5 times higher than the province of Sanliurfa, which has the closest score. According to these results, Istanbul's population density (one-fifth of the country's population), its hosting of people from different ethnic groups, and its status as a place with a high concentration of other vulnerable groups make this situation expected. In this context, it is of great importance that disaster risk reduction and response plans, especially in Istanbul, are organized to cover all dimensions of vulnerability. Indeed, in the event of a major disaster, meeting individuals' needs and effectively carrying out evacuation and shelter processes must be planned with the existing demographic structure in mind (Yükseler and Tenikler 2025). From a regional perspective, the demographic vulnerability of the Black Sea region appears to be largely very low. The Eastern Anatolia region appears to have predominantly low and very low demographic vulnerability. On the other hand, it seems that vulnerability is mostly low in the Aegean region, except for Izmir province. Provinces with high demographic vulnerability have high and very high population density compared to other provinces due to factors such as the number of Syrians, crude birth rate and average household size. At this point, it can be said that the high demographic vulnerability of the country's capital Ankara and the western provinces of Istanbul, Izmir and Bursa may be due to reasons such as high job opportunities and development, as well as the factors in question.

3.2.2 ES index

The ES has a direct impact on the vulnerability of individuals and communities before, during, and after a disaster (Yükseler and Tenikler 2025). Disaster preparedness and risk reduction initiatives are often difficult goals to achieve for poor segments of the popula-

tion (Burton 2010). In contrast, higher income levels can reduce vulnerability to disasters (Siagian et al. 2014; Fatemi et al. 2017). In this context, in line with studies in the literature, unemployment, income inequality, poverty, and employment in sectors directly affected by disasters are considered variables that increase SV, while regional economic mobility indicators such as high GDP, vehicle ownership for post-disaster evacuation, and number of banks are used in the study as factors that reduce SV. The ES index consists of 3 sub-indicators (poverty, employment sectors and economic prosperity) and 9 variables representing these sub-indicators. As a result of the index calculation, the spatial distribution maps of the ES index and sub-indices are presented in Fig. 5. According to the spatial distribution of poverty sub-index values (Fig. 5a), it is seen that provinces in the Southeastern and Eastern regions have very high scores, while the provinces in the eastern Mediterranean region and in the Northeastern Anatolia region have high poverty scores. Additionally, it is seen that poverty sub-index scores are low in the Aegean and Marmara regions, except for Istanbul and Izmir provinces. It is seen that the provinces in Central Anatolia have moderate level scores, except for the high score of Ankara. When evaluated in terms of provinces, the provinces where vulnerability is very high (Van, Hakkari, Sırnak, Siirt, Batman, Mardin, Bitlis, Mus) are the provinces with the highest unemployment rate, which is of the greatest importance in the calculation of this indicator. The reason for this is that these provinces are underdeveloped in industry, agriculture and service sectors compared to other provinces due to their geographical conditions (such as rugged terrain, high altitude, cold weather days), poverty and income inequality are high. In addition, the provinces of Bingöl, Elazıg, Malatya and Tunceli in the Eastern Anatolia Region, Kastamonu and Sinop in the Central Black Sea Region and Cankırı in the Central Anatolia Region are in the opposite direction to the regional vulnerability due to low Gini index, poverty rate and unemployment rate in these provinces. It can say that the reason for this is low population density of Tunceli, Bingöl, Kastamonu, Sinop and Cankırı, and the presence of different jobs in Elazıg and Malatya provinces. The high vulnerability of Adana, Mersin, Kahramanmaras, Osmaniye and Hatay provinces located in the south of the country is due to the high poverty rate and income inequality in the region. In addition, the dense population of the region is an important factor in the high rates. Finally, it seems that the vulnerability of the provinces in the west, except for the major cities such as Istanbul, Izmir, and the capital Ankara, is low. It can be said that poverty scores are low in these provinces due to the presence of lands suitable for agricultural activities as well as industrial and tourist areas. In addition, although Istanbul, Ankara, and Izmir have many job opportunities, they are provinces with high unemployment rates due to population density and income inequality. The findings of this study are as expected when considering regional economic development in Türkiye. Indeed, these findings are consistent with the results of previous studies (Ozceylan and Coskun 2012; Serkendiz and Tatli 2023; Yükseler and Tenikler 2025). In summary, the results of this study indicate the need for more investment in these sub-regions. This would reduce the unemployment rate, poverty rate, and income inequality, thereby reducing the SV of these sub-regions.

The employment sectors sub-index consists of a combination of 3 variables. These variables have an increasing impact on vulnerability, as they are sectors of employment that may stop or be interrupted when disaster occurs. Indeed, previous studies have shown that employment sectors are directly or indirectly affected by disasters (Schmidtlein et al. 2008; Villagrán de León 2013). Cutter et al. (2003) specifically states that certain sectors are more

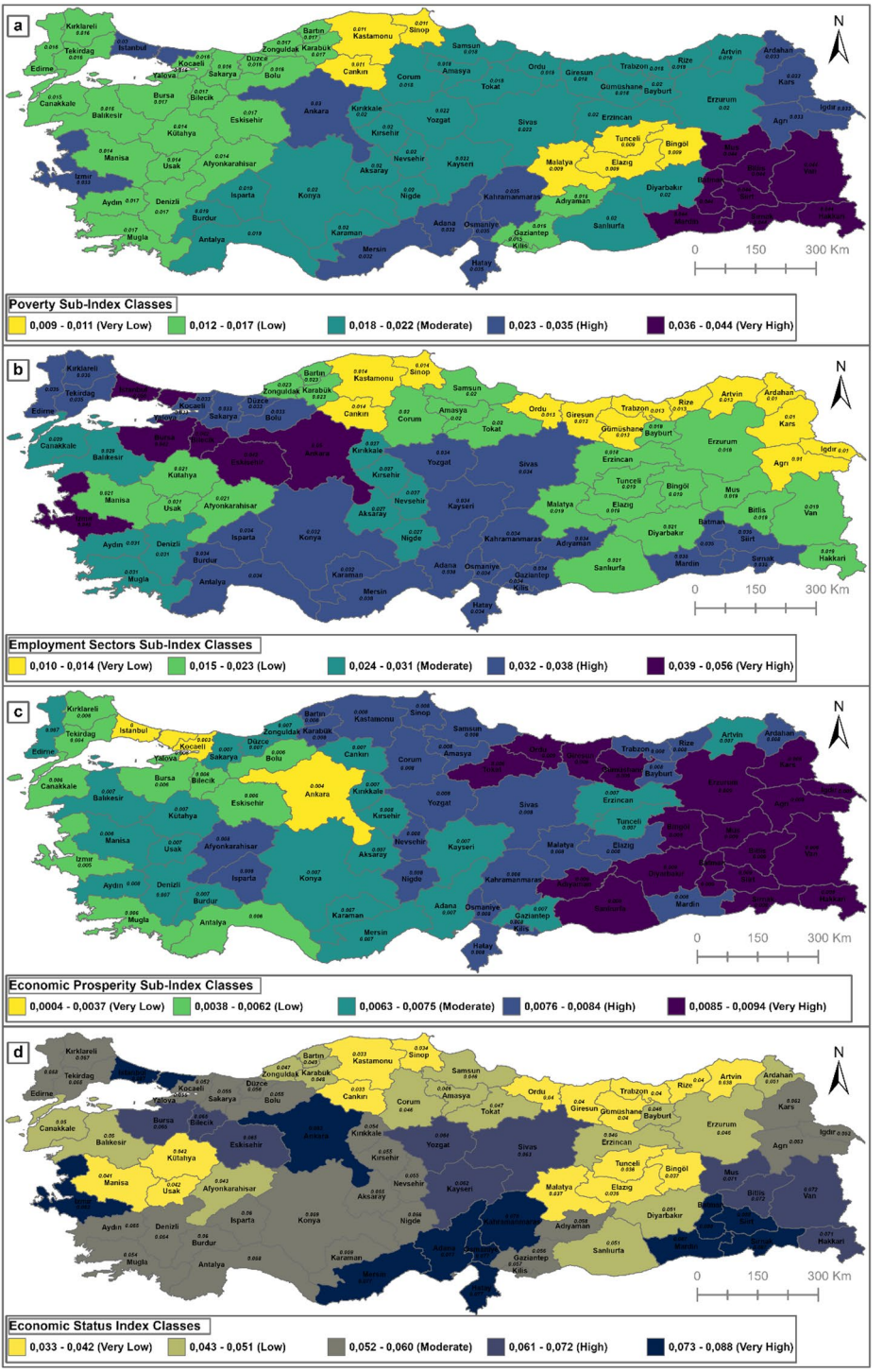


Fig. 5 Spatial distribution of ES Index and Sub-Indices: **a** poverty sub-index, **b** employment sectors sub-index, **c** economic prosperity sub-index, and **d** ES Index

likely affected by disasters, illustrating this situation as follows: while the fishing industry may experience loss of equipment and infrastructure as a result of disasters, making it impossible to sustain livelihoods, workers in the agriculture and service sectors may face production interruptions, reduced income, and the risk of unemployment. The spatial distribution in Fig. 5b shows that the vulnerability of the northwest region, where the industrial and service sectors are concentrated, has very high and high scores. The provinces in this region, in addition to being the region where the country's industrial sectors are centered, have land suitable for agricultural activities, which increases the employment rate of these sectors. The region consists of provinces where industrialization and service are intense (Istanbul, Bursa, Ankara, Eskisehir, Tekirdag, Kocaeli, Sakarya), as these provinces are cities with strong logistics and transportation infrastructures as well as provinces with suitable lands for agriculture sectors (Edirne, Kırklareli, Bilecik, Düzce, Bolu) is formed. On the other hand, according to the findings of the provinces affected by the earthquakes of February 6, 2023, the employment sector index values are seen to be at a high level. According to the findings of the study by Demirdag and Nirwansyah (2024), it was concluded that the affected provinces experienced sectoral losses of 16% in the industrial sector, 15% in the service sector, and 12% in the agricultural sector after the earthquakes, compared to the previous year. These losses were calculated based on directly obtained data and do not include the long-term and indirect effects of the earthquake. In this context, according to the findings of the study, it can be said that in the event of a large-scale disaster, especially in provinces with higher index values than these provinces, sector-based economic losses would be higher.

According to the results of the economic prosperity sub index, which is a combination of GDP, number of banks, number of vehicles variables (Fig. 5c), it is seen that the vulnerability of the Eastern, Southeastern and Central Black Sea region is very high and high levels. The spatial distribution pattern of these sub-index values is consistent with the findings of the study by Yükseler and Teniker (2025). It can be said that this situation is due to reasons such as income distribution inequality, job opportunities and differences in geographical conditions between the east and west of the country. On the other hand, Istanbul, Ankara and Kocaeli are the provinces with lowest economic prosperity vulnerability, as these provinces are the centers of activity of different sectors. In other words, the underlying reason for the very low and low index values prevailing in the western provinces of the country, in contrast to the very high vulnerability of the provinces in the eastern and southeastern regions, is the presence of stronger industrial and economic structures in this part of the country. Therefore, the findings of the study's economic prosperity sub-index present a spatially consistent model when the country's economic structure is considered. Additionally, the provinces affected by the February 6, 2023, earthquakes generally have medium, high, and very high economic prosperity values. Demirdag and Nirwansyah (2024) noted that these provinces' contribution to GDP decreased by 14.2%, while Şenol Balaban et al. (2025) stated that the economic cost of the earthquakes to the country was approximately 9% of GDP. These findings show that similar disasters can cause greater losses in economically strong provinces.

The spatial distribution of ES index, which is the combination of all these sub-indicators, is presented in Fig. 5d. ES index values are highest (very high level) in the southeast provinces of Batman, Siirt, Sırnak and Mardin provinces. In addition to Istanbul, Ankara and Izmir, Adana, Mersin, Osmaniye, Hatay and Kahramanmaras are also among the provinces with very high levels. This is due to factors such as income inequality in these provinces,

high poverty rates, and high employment rates in sectors may be damaged in the aftermath of disasters. On the other hand, the Black Sea region of the country has very low and low vulnerability in general. The findings indicate that the provinces affected by the February 6, 2023, earthquakes are among those that could suffer the highest economic damage. As mentioned above, these earthquakes have led to economic decline both at the provincial level and nationally. It is predicted that the reconstruction of cities with the economic and social ties necessary for the country's future development will take many years (Şenol Balaban et al. 2025). This situation shows that similar losses are inevitable in major disasters that may occur in other provinces with high economic vulnerability. A potential disaster in Istanbul, due to the city's cultural, social, economic, and geopolitical importance, would have long-term effects on the country's economy. Indeed, numerous studies indicate that a destructive earthquake is expected in the near term, particularly in the Marmara region where Istanbul is located (Şenol Balaban et al. 2025). In this context, it is necessary to strengthen the economic structure against disasters, especially in Istanbul and other provinces that could suffer high economic damage, to revise development plans to take disaster risks into account, and to develop economic risk transfer mechanisms. In conclusion, the earthquakes of February 6, 2023, serve as an important warning for the country, and it is vital to take strategic steps to reduce economic vulnerability.

3.2.3 AC index

Based on the approach Cardona et al. (2012) that vulnerability assessment should not only focus on the negative aspects of vulnerability, in addition to DA and ES, which are important in SV assessment, AC indicator was also identified in the determination of indicators and variables. In this context, within the scope of the study, medical infrastructures, shelter and emergency assembly area and risk perception sub-indicators were determined to represent the AC main indicator and they had a reducing or negative effect on SV. AC index consists of the combination of these sub-indices and 13 variables defined under them. The spatial distribution of the AC index and sub-indices is presented in Fig. 6.

Medical infrastructures are one of the important drivers of SV, as community access to healthcare resources has a direct impact on reducing risks before disaster, as well as reducing the impact of potential losses after a disaster (Morrow 1999). At this point, having weak medical infrastructures is associated with socio-economic status in the literature (De Oliveira Mendes 2009). For this reason, it can be said that different elements such as the correct use of public resources, high public awareness, and high level of economic development are interrelated and have a direct impact on disaster risk reduction efforts. The medical infrastructure sub-indicator consists of 6 medical service variables. According to the distribution map by provinces (Fig. 6a), the vulnerability score of Istanbul, the most populous and developed city of the country, is very low, while the vulnerability score of Izmir and Ankara is also low. This is because these provinces are developed compared to other provinces and that they are the provinces with the highest population density to provide health services. In addition, the fact that these provinces are developed, and health investments are made in these provinces shows that the health infrastructure of neighboring provinces is relatively more vulnerable. In other words, significant differences exist between provinces in terms of medical infrastructure. Furthermore, spatial distributions show that provinces with very low and low levels of healthcare infrastructure are disproportionately located next to provinces

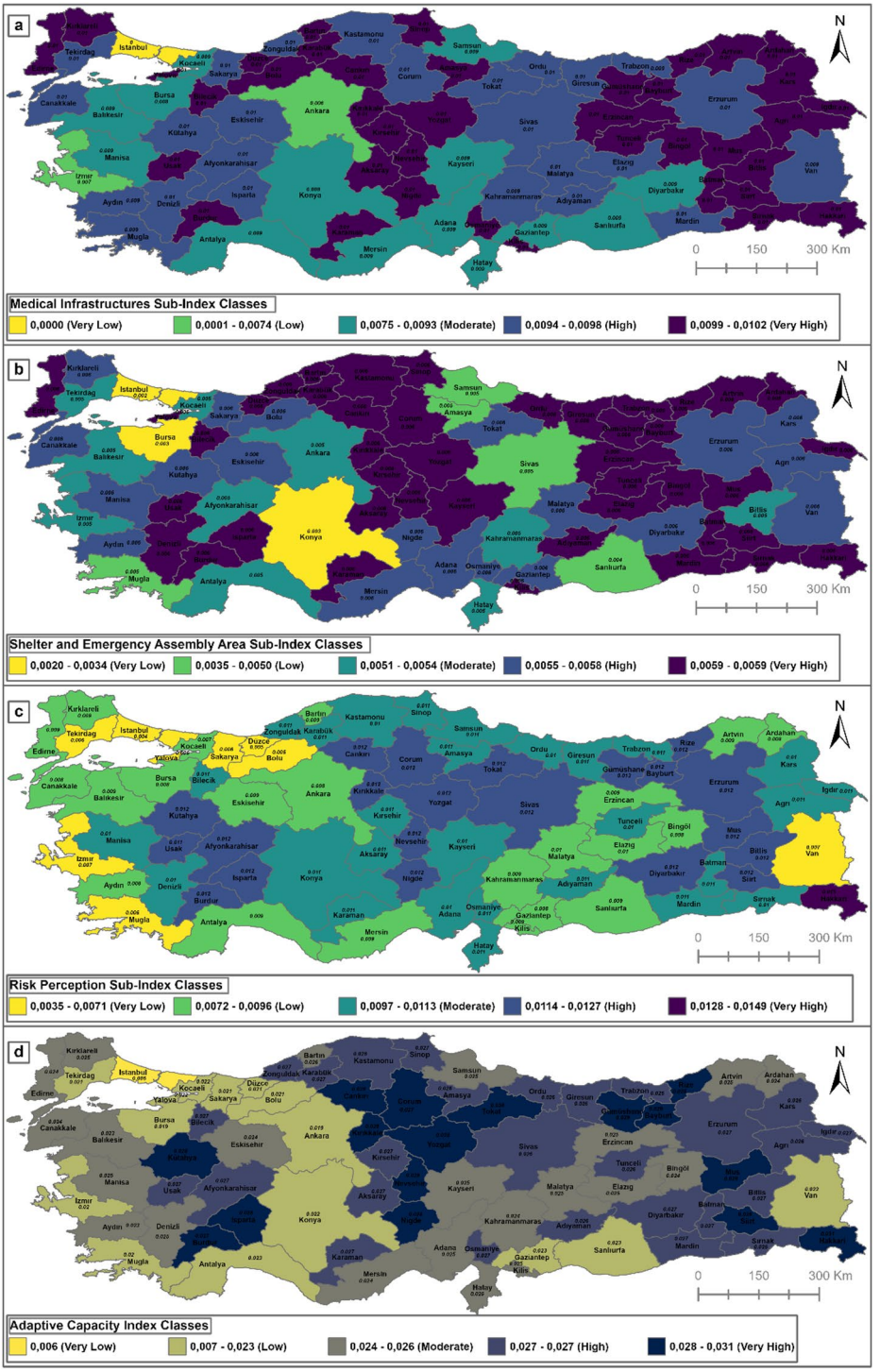


Fig. 6 Spatial distribution of AC Index and Sub-Indices: **a** medical infrastructures sub-index, **b** shelter and emergency assembly area sub-index, **c** risk perception sub-index, and **d** AC Index

with high and very high levels. In other words, it can be said that there is no spatial pattern between neighboring provinces. In this context, when evaluated regionally, it is seen that the provinces in the Marmara region, especially those surrounding Istanbul, which has a very low index value, have medium, high, and very high index values. For example, since Yalova is surrounded by the provinces of Bursa, Kocaeli and Istanbul and the population density is low, the vulnerability of the health infrastructure is very high. This situation is also valid for the provinces neighboring the capital Ankara and Konya in the Central Anatolia Region. On the other hand, the same situation is valid for Usak in Aegean Region, Burdur and Osmaniye in the Mediterranean Region, Kilis in the Southeastern Anatolia, and Amasya and Sinop in the Central Black Sea Region. In addition, it is seen that provinces in the Eastern and Southeastern Anatoli regions have very high and high scores. In these regions, the provinces of Erzurum, Van, Diyarbakır, Gaziantep and Sanlıurfa are more developed than the surrounding provinces and are the health services centers of the region. However, although these provinces have lower index scores compared to other surrounding provinces, vulnerability is at a high score in these provinces. In summary, this disproportionate distribution significantly increases the vulnerability of critical medical infrastructure following disasters and emergencies. Indeed, the provision of medical services is a costly process that requires qualified personnel and infrastructure even under normal conditions, and the likelihood of disruption to life-sustaining activities during disasters makes this situation even more critical (Yükseler and Tenikler 2025). In this context, it is necessary to anticipate potential clinical and public health issues, strengthen infrastructure, train human resources, and prioritize research and development (Bayram et al. 2023).

Shelter and emergency assembly area sub-index; it was calculated using the variables person capacity and emergency assembly area. According to the spatial distribution map of the sub-index (Fig. 6b), the vulnerability of the shelter and emergency assembly area of most of the country is very high, high, and moderate. Among these, the class with the very high number of provinces is quite high. On the other hand, it is seen that this capacity has very low index values in provinces such as Istanbul, Bursa, Konya, and is at a low score in Mugla, Samsun, Amasya, Sivas and Sanlıurfa provinces. In summary, the distributions of these sub-index values indicate that they could be very high and high level vulnerable in terms of shelter and emergency assembly areas. However, in addition to the data we used for this sub-index, data on the infrastructure of shelter areas could not be obtained, and even if shelter areas are identified, the adequacy of their infrastructure is of critical importance for these areas. Indeed, past disaster experiences show that infrastructure deficiencies significantly affect the post-disaster recovery process. For example, according to the results of studies conducted after the 2023 earthquakes, 2.2 million people left the region in the first week after the earthquakes (Sağıroğlu et al. 2023); Sevinin et al. (2023) stated that this number reached 3.3 million as of March 1, 2023, and that this included Syrian refugees, who made up approximately 12% of the region's population. Şenol Balaban et al. (2025) emphasized that the lack of shelter was one of the most urgent problems in the first two weeks after the earthquake and that the existing areas were inadequate in terms of infrastructure, transportation, and security. Furthermore, it was noted that some shelter areas were exposed to secondary disaster risks; for example, it was reported that areas designated after the tsunami in the Gulf of Iskenderun became unusable, and that fires broke out in Osmaniye and Hatay due to insufficient distance between tents. These findings reveal the need to reorganize the

location selection, infrastructure, and security standards of shelter areas in accordance with international norms.

Risk perception sub-index values are presented in Fig. 6c. Four variables are defined under this index: natural disaster insurance rate, number of basic AFAD volunteers, number of support AFAD volunteers, and number of college or faculty graduates. All variables under this sub-indicator are interrelated. In fact, education and awareness are interrelated elements. Highly educated individuals can obtain insurance before a disaster and participate in volunteer activities related to disasters, while after a disaster they can access resources more easily, have their losses covered by insurance companies, and help those affected. On the other hand, the literature on education and awareness argues that a decline in education and awareness will limit access to information and rescue assistance (Cutter et al. 2003; Komac et al. 2010; Fatemi et al. 2017). In terms of spatial distribution, Hakkari is at very high risk, while Istanbul, Tekirdağ, Düzce, Sakarya, Yalova, Bolu, Muğla, İzmir, and Van are the provinces with the lowest risk perception. In general, the western part of the country appears to be less vulnerable than the eastern part. It can be said that the high level of education in the western part of the country and the associated increase in insurance coverage contribute to this situation. However, natural disaster insurance is not mandatory for rural areas of the country. Therefore, due to the density of rural areas, there are provinces with high and very high vulnerability. Furthermore, in terms of volunteer rates, the high number of volunteers due to population density in the west has a mitigating effect on the vulnerability of these provinces. Overall, this sub-index distribution is as expected when considering the socio-economic structure of the provinces.

The spatial distribution map of the AC index obtained by calculating the three sub-indices is shown in Fig. 6d. In general, when provinces are compared along the east–west axis, it is observed that eastern provinces mostly have high and very high index values, while western provinces have very low or medium index values. At the provincial level, 14 provinces are in the very high index class, namely Hakkari, Gümüşhane, Bayburt, Muş, Kırıkkale, Çankırı, Isparta, Tokat, Rize, Yozgat, Siirt, Kütahya, Nevşehir, and Niğde. Additionally, 18 provinces are high, 31 are medium, 17 are low, and 1 is very low. Istanbul has a very low index value, followed by Ankara, Bursa, Izmir, Mugla, and Tekirdag. Western provinces are at a high level in terms of both institutional capacity and social awareness, meaning they have a low level of vulnerability. This distribution shows that neighboring provinces generally have similar or one level of difference in their vulnerability. In this context, according to Türkiye's current disaster response plan (AFAD 2022), neighboring provinces are designated as support provinces for affected provinces in the event of disasters and emergencies. However, the 2023 earthquakes showed that this approach was insufficient for effective and rapid response. Indeed, the affected provinces were defined as each other's support provinces according to the response plan, but the planned response could not be implemented because most provinces in the region were affected. Therefore, it is necessary to increase the capacity to cope with disasters and develop alternative capacities to the current management approach, especially in the Marmara region, which has the highest population density in the country and is of critical importance to the country's economy.

3.3 Overall SV of Türkiye

3.3.1 SV on a national scale

The SV index values obtained by calculating the main indicators (DA, ES, and AC) were evaluated at the national, regional, and provincial levels. The natural breaks method was used to classify the index values, which were divided into 5 classes (very low, low, moderate, high and very high). The distribution according to this classification at the national level is presented in Table 5. There is a large difference in the five-class distribution of SV. Spatially, very high SV corresponds to 1.2%, well below the other 4 classes. The area of high SV corresponds to approximately 9.9%, much higher than the area of very high SV. The proportion of moderate SV is approximately 18.5%, while the proportions of low SV and very low SV are approximately 44.4% and 25.9% respectively. The differences in area ratios according to SV classes differed within the number ratio of provinces. Firstly, low vulnerable provinces have the highest share compared to other classes with a share of about 42%. The very low vulnerability class with about 25.9% of the number ratio of provinces is the second highest in terms of area ratios. Secondly, provinces in the high and very high SV classes have lower area ratios and number of provinces compared to other classes. This may be because factors such as population density, number of Syrians, economic situation and income inequality are driving forces in these provinces compared to other classes.

In summary, based on the distribution of SV to disasters at the national level, 11% of provinces (15% in terms of area) are at high and very high level of vulnerability. Proportionally, although the percentage and spatial distribution of provinces with very low and low vulnerability levels is high, a large portion of the country's population lives in provinces with very high and high vulnerability levels. Indeed, according to the 2022 TURKSTAT population data used in the study, the country's population is approximately 85.3 million. In this context, the population of Istanbul, the only province at the very high level, is approximately 16 million, and the total population of the provinces at the high level (Şanlıurfa, Gaziantep, İzmir, Ankara, Adana, Bursa, Mersin, and Hatay) is approximately 24.7 million. As a result, 46% of the country's population is at a very high and high level of SV to disasters. Considering this situation, strategic steps must be taken, especially for provinces with very high and high vulnerability. In this context, the SV structure is presented hierarchically to determine the variable and indicator-based root causes of SV at the provincial level. This makes it easier to identify the factors that increase SV at the provincial level.

Table 5 SV classification

Index classes	Range	Average	Area ratio (%)	Number ratio of provinces (%)
Very low	0.093–0.120	0.108	19	25.9
Low	0.121–0.159	0.137	42	44.4
Moderate	0.160–0.230	0.193	24	18.5
High	0.231–0.342	0.313	14	9.9
Very high	0.343–0.853	0.853	1	1.2

3.3.2 SV on a regional scale

Regional-level distributions of SV are important for understanding the current regional capacity and vulnerability in the face of potential future disasters. In this context, as mentioned above, disaster response standards in Türkiye and the disaster response plan covering public institutions and organizations, the private sector, NGOs, and individuals have defined roles and responsibilities in the face of potential disasters (AFAD 2022). Response plans need to be improved, considering past experiences with disasters and the temporal and spatial changes in the socio-economic structure. In this context, the results obtained at the provincial level in this study, as well as the vulnerability distributions at the regional level, have the potential to guide the preparation of plans for disasters and emergencies.

To evaluate the regional differences in the study results, the analysis was conducted at the level of the 7 geographic regions in the country. This evaluation was performed by taking the regional average of the SV scores of the provinces within each region. The spatial distribution map at the regional level is presented on Fig. 7, and the region-based evaluation results are shown on Fig. 8. Accordingly, a comparison of the average scores of the provinces in the regions show that the region with the highest vulnerability is the Southeastern Anatolia Region. This region is followed by the Marmara Region and the Mediterranean Region, where there is not much difference on average. At this point, the driving score behind the Marmara Region, being the 2nd most vulnerable region is due to the province of Istanbul (0.853). Moreover, while there are 11 provinces in the region, 2 of these provinces (Istanbul and Bursa, 18% of the provinces in the region) have above-average social SV values. On the other hand, the Aegean and Central Anatolia regions are the 4th and 5th most vulnerable regions in terms of SV, respectively. At this point, there is only 1 province with an average above the Aegean average (Izmir, 13% of the region-province), which affects average. In the Central Anatolia region, where the vulnerability ranking is 5, the driving force is Ankara (0.328), Konya (0.222) and Kayseri (0.186), which are 3 provinces above the regional average (23% of the region-province). Regionally, the Black Sea Region has the lowest average SV, followed by Eastern Anatolia. The Black Sea region has the highest number of provinces among the regions and 44% of these provinces have SV score above

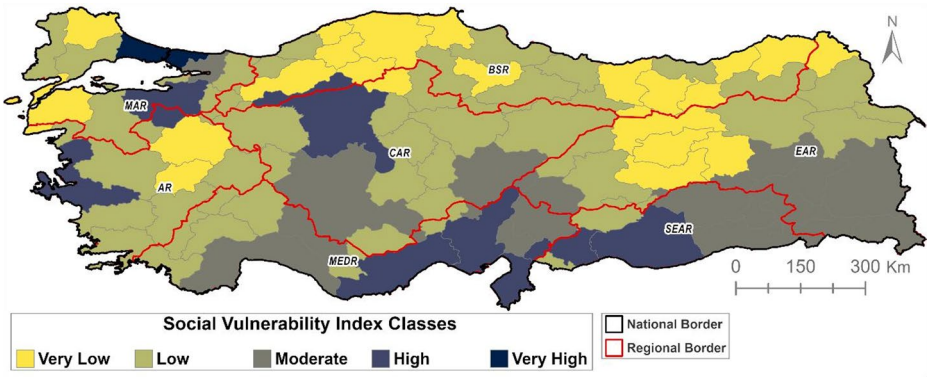


Fig. 7 Spatial distribution of SV by regions. The abbreviations EAR denotes the Eastern Anatolia Region, SEAR the South Anatolia Region, CAR the Central Anatolia Region, MEDR the Mediterranean Region, AR the Aegean Region, MAR the Marmara Region

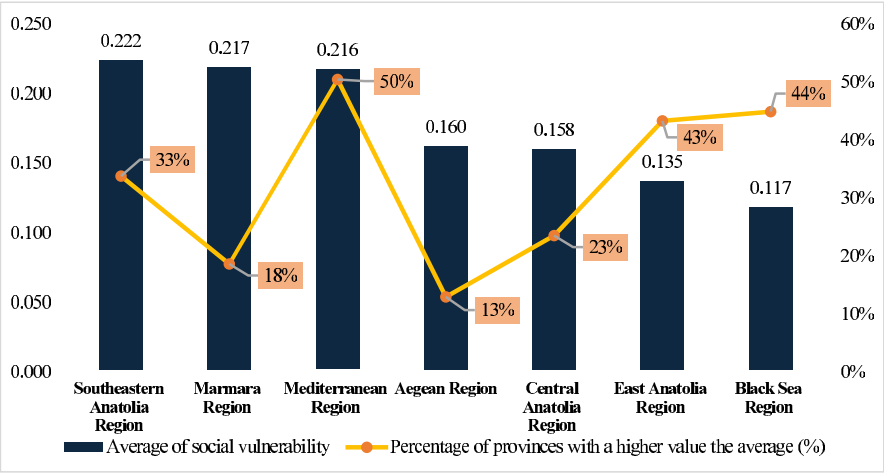


Fig. 8 Statistics of SV at geographical region scale

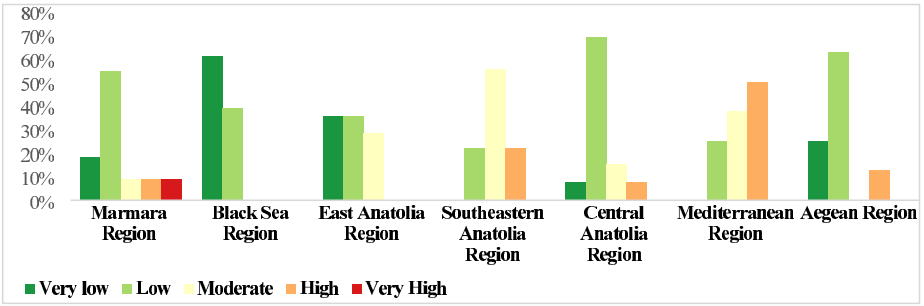


Fig. 9 Distribution of SV classes in different regions

the regional average. In Eastern Anatolia, the average SV is 0.135 and 43% of the provinces have a score above the regional average.

Figure 9 shows the percentage distribution of SV classes in different regions. Accordingly, the Black Sea region has the highest percentage of very low SV scores (61%), followed by Eastern Anatolia (36%), Aegean (25%), Marmara (18%), and there are no very low provinces in Southeastern Anatolia and Mediterranean regions. According to the low SV score, Central Anatolia (69%), Aegean (63%), Marmara (55%), Black Sea (39%), Eastern Anatolia (36%), Mediterranean (25%) and Southeastern Anatolia (22%) regions, respectively. The Southeastern Anatolia region has the highest proportion of moderate SV scores, while moderate SV scores account for 38% of the SV classes in Mediterranean, 29% in Eastern Anatolia and 15% in Central Anatolia and there are no provinces with moderate score in the Black Sea and Aegean regions. In the region distribution of high SV scores, the Mediterranean region has the highest value (50%), followed by Southeastern Anatolia (22%), Aegean (13%), Marmara (9%) and Central Anatolia (8%), while the Black Sea and Eastern Anatolia regions have no provinces with high scores. Finally, the Marmara region is

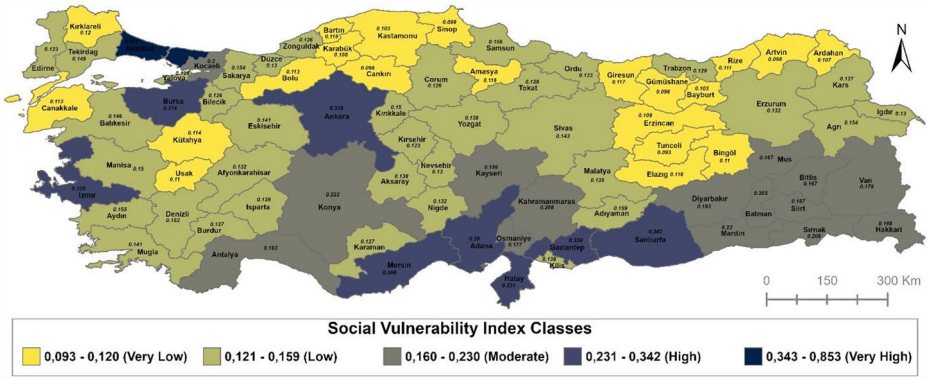


Fig. 10 Spatial distribution of the SV

the only region with a very high SV score, while the other regions do not have any provinces with very high class.

3.3.3 SV on a provincial scale

The index values and spatial distributions of SV classes at the provincial level are shown in Fig. 10. SV index values range from 0.093 to 0.853. In this context, SV increases as the index value increases. In general terms, 21 provinces show very low, 36 provinces low, 15 provinces moderate, 8 provinces high and 1 province very high levels of SV. The only city with a very high SV in terms of disasters is Istanbul. As a matter of fact, Istanbul's SV differs significantly from other provinces. When compared SV of Istanbul (0.853) with the closest score of Sanlıurfa (0.342), it has a value approximately 2.5 times higher. Indeed, considering factors such as Istanbul being home to approximately one-fifth of the country's population, having the highest concentration of Syrian refugees, and having a very high economic vulnerability, it is expected that its SV would stand out compared to other provinces. Highly vulnerable provinces (consisting of 10% of all provinces (Table 5)), are mainly concentrated in the eastern Mediterranean and Southeastern Anatolia regions, and these provinces include Sanlıurfa, Gaziantep (0.339), Hatay (0.331), Izmir (0.329) and Ankara (0.328) provinces have relatively similar score of vulnerability. While provinces with moderate vulnerability constitute 19% of the provinces, approximately %70 of the provinces have low and very low social vulnerability. The 5 very low vulnerable provinces (<0.100) are Tunceli (0.093), Gümüshane (0.096), Artvin (0.098), Cankırı (0.098) and Sinop (0.099), respectively.

As noted in the literature review section of the study, there are limited studies in Türkiye that have conducted SV assessments for disasters at the provincial level (Ozceylan and Coskun 2012; Yaprak et al. 2022; Yükseler and Tenikler 2025). In this context, the study findings differ from the results of previous studies. This situation can generally be attributed to the steps followed by the researcher(s) in the index creation stages, the data sets used, temporal differences, and the methods preferred for weight assignment. Indeed, objective methods (based on expert opinion) have been used for weight assignment in previous studies. In fact, numerous studies in the literature have tested the significant effects of different weighting methods on index results (Papathoma-Köhle et al. 2019; Moreira et al. 2021a). Furthermore, in indicator-based assessments of SV, the selection of appropriate variables,

both temporally and spatially, is of critical importance (Cutter et al. 2003; Yoon 2012; Lee 2014). Accordingly, the index values obtained are directly influenced by the selection of variables.

4 Conclusions

This study aims to evaluate SV multidimensionally in terms of disasters in Türkiye. An indicator-based approach has been adopted from quantitative evaluation approaches; indicators, sub-indicators, and proxy variables have been selected by considering the literature and Türkiye's socio-economic context. Accordingly, three sub-indicators were defined under the main indicators DA, ES, and AC, and a total of 34 variables were included. Variable weights were determined using the entropy method, and SV indices were calculated at the provincial level. The resulting index distributions and spatial patterns at the provincial, regional, and national levels serve as initial data and scientific guidance for policy design addressing the social dimension of disaster risks. In other words, the driving factors and spatial distributions of SV provide concrete clues to national/local decision-makers for risk reduction strategies. Based on the results of the study, policy recommendations for disaster risk reduction in Türkiye can be summarized as follows:

- *Inclusive disaster planning* Türkiye is a country where different ethnic and demographic groups live together. Therefore, provincial-level disaster response plans can be updated to cover not only citizens but also temporary and permanent migrants.
- *Urban population planning* Findings show that SV is high, especially in large cities such as Istanbul. Accordingly, there is a need to review population and settlement planning to reduce the risks associated with intensive urbanization.
- *Family-sensitive policy* Single-person households are a growing group due to factors such as increasing divorce rates, education, and labor mobility. Indeed, according to the study results, it is one of the variables with the highest weight. Social support systems can be developed to protect this group from loneliness and lack of support after a disaster.
- *Increasing economic resilience* Provinces with high poverty and unemployment rates may be more vulnerable to disasters. Increasing employment opportunities and supporting sectoral diversity in these provinces will accelerate post-disaster recovery. New employment opportunities can be developed by avoiding economies based on a single sector.
- *Balanced distribution of health infrastructure* According to the findings of the study, health services are concentrated in certain provinces in terms of human resources and infrastructure. Future investments should address regional imbalances and plan health infrastructure in a homogeneous manner.
- *Shelter and assembly areas* It is not enough to simply design temporary shelter and assembly areas after a disaster; these areas must be supported by infrastructure suitable for long-term use and prepared in accordance with international standards.
- *Social awareness and risk sharing* Individual awareness and risk perception regarding disasters are fundamental elements of coping capacity. In this context, awareness-raising efforts can increase awareness and, consequently, the number of volunteers, who

are an important human resource in disasters and emergencies, while also proportionally increasing insurance rates, which are a key driver of disaster risk transfer.

- *Data access and transparency* Data availability and quality are critical for reliably measuring SV. Sharing data produced by public institutions in a timely, accessible, and open data format will increase the reliability and effectiveness of disaster risk reduction efforts.

4.1 Limitations and future research recommendations

While the study provides important insights into SV, some aspects need to be critically examined to increase the robustness of the findings. The study focuses on quantitative variables based on the socio-economic dimension of vulnerability to disasters. This approach can simplify the complex nature of SV while providing a structured framework for assessing SV. This is an important challenge of the need for multidimensional approach to SV. Indeed, intangible elements such as political and cultural factors cannot be fully quantified. In this context, for more comprehensive SV assessments, combining existing quantitative indices with qualitative data and the perspective of society with a governance approach can provide a holistic assessment (Liu et al. 2024). Moreover, data availability and data quality have a significant impact on the selection of variables during SV assessment, especially in developing countries (Ge et al. 2021). Therefore, in the relevant literature, variables such as person capacity and equipment capacity of emergency and disaster response organizations under AC and data on economic status such as home ownership and tenant status could not be used due to lack of access to relevant data. Despite data collection attempts, there were data limitations. Furthermore, as noted in the data sources section of the study, the most recent data on people with disabilities used in the study is from 2011, which constitutes one of the significant limitations of the study in terms of data. In future studies, these situations can be mitigated by using more up-to-date data with high data quality. Therefore, although the study provides a multidimensional assessment of SV, not all aspects may still be fully covered.

In the literature, there are studies on vulnerability assessment that show how vulnerability changes temporally as well as spatially (Cutter and Finch 2008; Fekete 2019). However, there is a very limited number of studies on SV assessment in Türkiye, while temporal assessment has not been conducted. In Türkiye, where the socio-economic structure is changing rapidly due to different reasons as of the twenty-first century, further studies are needed to determine the vulnerability to disasters, their temporal changes, and to analyze with different approaches.

Our study is a pioneering attempt to comprehensively evaluate SV in disasters in Türkiye. The findings of the study not only provide valuable information for determining SV at the provincial level in Türkiye and taking strategic steps towards this but also create a remarkable theorical and practical framework for countries with similar socio-economic structures. For example, for Türkiye, according to the findings of this study, the fact that shelter and emergency assembly area have high and very high SV values in most provinces is an important guide for decision makers and practitioners to reduce vulnerability in this respect. However, as mentioned above, it is seen that different theoretical approaches and methods are applied in the literature to evaluate SV. Therefore, comparing different SV measurement methods provides emergency and disaster managers with meaningful and

practical guidance for emergency and disaster management and planning (Yoon 2012). In this way, important clues can be provided to decision makers and practitioners to reduce vulnerability.

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Data availability Data will made available on request.

Declaration

Competing interest The authors declare that they have no financial interests or personal relationships that could have influenced the reported study in this paper.

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