International Journal of Disaster Risk Reduction 143 (2026) 106306

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Census to sense: Decoding spatio-temporal dynamics of social vulnerability to disasters in Nepal

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ARTICLE INFO

Keywords:
Disaster risk
Climate risk assessment
Natural hazards
Multi-hazards
Disaster vulnerability
Resilience

ABSTRACT

Climate change and socio-economic transitions are intensifying disaster risks, calling for integrated, cross-disciplinary mitigation strategies. The complex dynamics of disaster vulnerability pose challenges for risk management, particularly in resource-constrained countries. Existing assessments often focus on composite vulnerability scores and obscure the multifaceted dynamics of vulnerability and its components, limiting their relevance for risk management. Addressing this gap, our study analyses spatio-temporal changes in social vulnerability and its components – sensitivity and adaptive capacity – across Nepal by applying Principal Component Analysis to municipal census data from 2011 to 2021. We (i) map vulnerability into five classes for both years, (ii) quantify decadal changes in social vulnerability and its components, and (iii) identify distinct social vulnerability transition pathways. National social vulnerability declined by 35% by 2021, as a 63% adaptive capacity gain outweighed a 28% rise in sensitivity, with spatially heterogeneous patterns. We reveal notable structural changes in dominant indicators: Sensitivity reflects persistent demographic pressures alongside growing influences of urbanization and population mobility. Adaptive capacity reflects stable contributions from critical services and asset ownership, augmented by improvements in housing quality and connectivity. Furthermore, by investigating the interaction between the shifts in sensitivity and adaptive capacity, we identify three social vulnerability transition pathways (escalating sensitivity, adaptive balance, and resilience transition) that yield actionable and spatially explicit insights for prioritising disaster risk reduction. Our refined component-focused approach offers nuanced insights beyond conventional social vulnerability assessments, is transferable to any country with census data, and is valuable in data-scarce settings.

1. Introduction

The recent surge in extreme climate events has become the new normal, representing a significant and continuing shift in global environmental conditions, which are challenging to foresee [1,2]. Earth's energy imbalance is accelerating beyond the projections of

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https://doi.org/10.1016/j.ijdrr.2026.106306
Received 4 March 2026; Received in revised form 5 July 2026; Accepted 8 July 2026
Available online 9 July 2026

the Intergovernmental Panel on Climate Change (IPCC), potentially resulting in escalating environmental impacts [2,3]. Additionally, society's exposure and the capacity to cope with climate hazards are evolving due to rapid urbanisation, demographic changes, and economic transformations [4,5]. Low- and middle-income nations are expected to experience more severe exposure and impacts, as escalating hazards intersect with constrained resources and insufficient adaptive capacity [6–8]. Thus, it is more crucial than ever to comprehensively assess disaster risks and their dynamics to understand future risks and build long-term resilience.

Disaster risk is defined as the probability of severe consequences arising from the dynamic interaction among hazard, exposure, and vulnerability [9,10].[1] Compared to other risk components (i.e., hazard and exposure), vulnerability is the most multifaceted construct influenced by socioeconomic, demographic, infrastructural, and physical factors [11]. IPCC defines vulnerability as "propensity to be adversely affected" [9], which is commonly conceptualised through two components: sensitivity to be harmed by hazardous processes, and lack of capacity to cope or adapt [9,12,13]. Sensitivity refers to the exposed system's internal characteristics that increase the potential harm and damage induced by hazards, whereas adaptive capacity reflects the exposed system's ability to adjust, cope, respond, and recover from the harmful impacts of hazards [14]. Previous studies largely assessed vulnerability through its environmental, social, and economic dimensions [15,16] where indicators of sensitivity and adaptive capacity are often combined despite the components' opposing influences on overall vulnerability. As a result, understanding the dynamic interactions between the components that contribute to or reduce vulnerability is limited.

Measuring vulnerability and its indicators presents challenges due to their complex construct and dynamic nature [17]. Moreover, the indicators related to the economy, such as poverty, present challenges due to the mixed use of subjective or objective indicators [18]. Despite such challenges, proxy indicators extracted from national census data, such as migration, age, gender, and access to different facilities, have enabled increasingly robust assessments of social vulnerability across various scales [19–23]. Census data are particularly valuable for social vulnerability assessment in data-scarce regions that are common, especially in low- and middle-income countries [24]. To integrate multi-dimensional vulnerability indicators, methods such as Factor Analysis, Principal Component Analysis (PCA), and Cluster Analysis are frequently employed to calculate the composite Social Vulnerability Index (SOVI) [15]. SOVI assessments vary in scale of analysis, indicator selection, methods for indicator reduction, normalisation, aggregation, and weighting of indicators, limiting the comparison across the studies [15,25,26]. While composite indices such as SOVI effectively aggregate multiple dimensions of vulnerability into one score, information on individual indicators might be lost due to the inherent dimensionality reduction and aggregation methods [17,27]. Nevertheless, SOVI serves as a powerful tool to assess the dynamics of social vulnerability within the context of disasters [26].

Social vulnerability is inherently dynamic, influenced by human mobility, demographic, and socio-economic changes [28,29]. Further, it can be altered by disasters that disrupt communities' ability to cope in the post-disaster phase [30]. Such socio-environmental changes call for spatio-temporal analysis of social vulnerability to comprehend historical trends and inform future predictions. However, only very few studies have explored spatio-temporal dynamics of social vulnerability, typically by analysing changes in SOVI and its explanatory factors over time [31–33]. While these aid our understanding of the absolute changes in social vulnerability, they fail to explore the spatio-temporal changes and interactions between the two vulnerability components.

We address these research gaps by developing an enhanced framework for assessing spatio-temporal transitions in social vulnerabilityand its underlying components within the disaster context. In this study, our emphasis is on social vulnerability to disasters (hereafter, social vulnerability), and the term social vulnerability is used consistently throughout the article. We apply the framework to Nepal, a data-scarce context and a country with high environmental risk that has been affected by numerous severe disasters in recent decades [34]. Thereby, we answer the following research questions:

1. How can we assess spatio-temporal dynamics of social vulnerability to disasters and its core components, i.e., sensitivity and adaptive capacity, in data-scarce areas?
2. What changes occurred between 2011 and 2021 in the structure and indicator contributions of social vulnerability, sensitivity, and adaptive capacity across Nepal?
3. How did shifts in sensitivity and adaptive capacity interact between 2011 and 2021, and what distinct social vulnerability transition pathways emerged from their interaction?

Previous social vulnerability assessments in Nepal span local to national scales using census-based, survey-based, and integrated risk assessment approaches [34–38]. Some studies operationalised risk components by integrating exposure, sensitivity, and adaptive capacity in basin-scale studies [38]. Census-based national-scale studies provide cross-sectional assessments while disregarding the temporal evolution of social vulnerability and its components [35,37]. Building on these previous studies, we advance social vulnerability assessment by incorporating updated administrative units and the most recent 2021 census data. This research transitions from static assessments of social vulnerability to a dynamic analysis over the past decade in Nepal. Moving beyond traditional SOVI comparisons across time periods, we adopt IPCC's vulnerability framework and disentangle social vulnerability transitions into shifts in sensitivity and adaptive capacity, providing a more nuanced understanding of the temporal interaction and co-evolution of these components. By analysing the directional changes in these components between 2011 and 2021, the study identifies distinct social vulnerability transition pathways. We demonstrate that relying solely on SOVI scores can be misleading, highlighting the need to understand changes in individual vulnerability components to develop effective risk-reduction strategies. Our enhanced social

[1] The IPCC's risk definition is illustrated in Figure 1.5 of Climate Change 2022: Impacts, Adaptation, and Vulnerability (see https://www.ipcc.ch/report/ar6/wg2/figures/chapter-1/figure-1-005a).

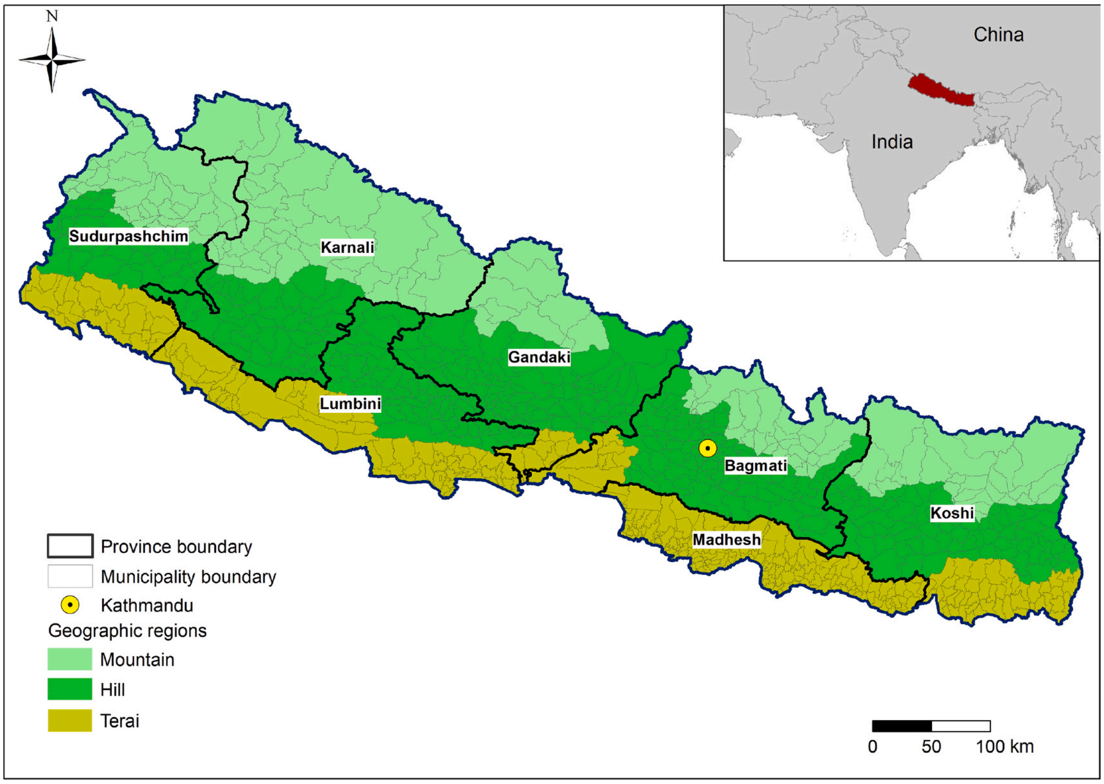

Fig. 1. Map of Nepal and its seven provinces, 753 municipalities, its capital city Kathmandu, and the three geographical regions of mountains, hills, and terai. Administrative boundaries courtesy of Hermes Engineering Solutions [39].

vulnerability assessment provides an evidence-based framework for targeting future interventions in any data-scarce settings, supporting local authorities, emergency managers, and policymakers in strategic planning and decision-making across various levels of interventions.

2. Study area

Nepal is a landlocked country between India and China. Following the federalisation in 2015, Nepal has been divided into seven provinces, 77 districts, and 753 local administrative bodies (which include six metropolitan cities, 11 sub-metropolitan cities, 276 municipalities, and 460 rural municipalities), replacing the previous system of nearly four thousand local units. Hereafter, the local administrative bodies are collectively termed municipalities. Geographically, Nepal is divided into mountain, hilly, and Terai districts (Fig. 1). Mountain districts lie in the northern part of Nepal, covered with snow, glaciers, rugged and rocky terrain, steep slopes, and active seismic plates, thereby prone to glacial lake outburst floods, avalanches, and landslides [40]. The middle region, the hills, exhibits the greatest percentage of the total area of Nepal. The major metropolitan cities, Kathmandu, Pokhara, and Lalitpur, are in the valleys of the hilly districts. The most common hazards in this region include landslides, floods, fire, and debris flows [41]. The Terai represents the lowlands sharing the boundary with India, being characterised by flat plains and alluvial deposits with fertile land where most of Nepal's agricultural goods are produced. It is thus exposed to seasonal floods, heat and cold waves, drought, and fire hazards [41].

Nepal is a country of rich geographical features; the country of 147,516 km^2 (Fig. 1) represents an extreme elevation range from 59 m above sea level at the south to 8849 m at Mount Everest (the world's highest peak), within a narrow band of 150 to 250 km from South to North. Features such as its diverse topography, young mountains and geology, active tectonic activity, steep slopes, significant climatic variations, and erratic monsoon rainfall patterns contribute to Nepal being a hotspot for multiple hazards [42]. During the

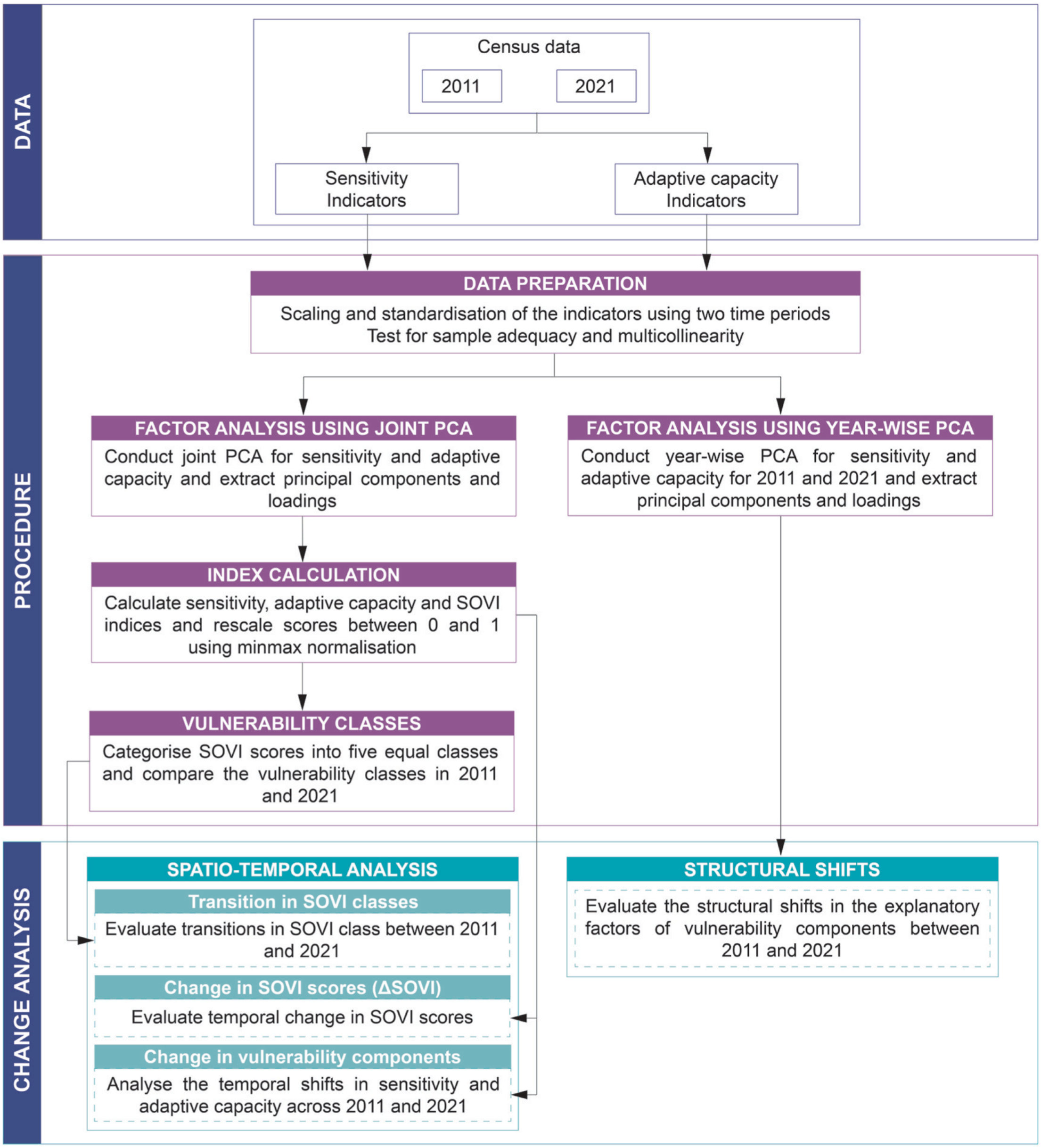

Fig. 2. Schematic diagram of methodology adopted in this study (SOVI = Social Vulnerability Index, PCA = Principal Component Analysis, ΔSOVI $=\text{SOVI}_{2021} - \text{SOVI}_{2011}$).

monsoon season (from June to September), floods affect nearly 50% of Nepal's districts. Historical floods, such as the Central Nepal flood 1993, the Koshi flood 2008, the Far-West flood 2008, the Seti Flood 2012, and the major flooding in 2017, have caused significant socio-economic impacts [43–46]. A record-breaking rainfall in late September 2024 resulted in flooding with over 200 casualties, infrastructure collapse, and direct impacts on more than 15,000 houses in and around the Kathmandu Valley [47]. Most notably in recent history, the 2015 mega earthquake with a moment magnitude of M7.8 claimed nearly 9000 lives and caused an estimated $10 billion in damage [48]. In 2017 and 2018 alone, Nepal experienced over 6000 hazardous events, primarily fires and landslides, resulting in 968 casualties and affecting nearly 27,000 families [42].

In addition to the frequency and magnitude of hazardous events, social vulnerability factors such as gender, age, socioeconomic status, and dependencies strongly modulate the resulting socio-economic impacts [49]. Particularly vulnerable groups, such as the elderly, children, and the disabled, require substantial resources for post-disaster response [19]. Minorities, such as Dalits, often face barriers in accessing financial resources after disasters [11]. As the majority of rural housing in Nepal consists of non-engineered and low-quality structures, these dwellings are generally less resilient than reinforced concrete or steel buildings and may offer limited time for evacuation during hazard events. Furthermore, access to potable water and sanitation mitigates risks of water-borne epidemics [50]. Centralized urban development prompts migration to urban centres or abroad for work, reducing manpower available for disaster response and recovery [35]. People in rural areas frequently depend on information received via text messages, radio, and television, while students use social media for critical hazard-related warnings [51,52]. This underscores the significance of internet access and mobile phone ownership in disseminating early warnings. Furthermore, the change in administrative structure due to federalisation has directly affected the resource distribution, infrastructure planning, and disaster risk management.

3. Methods

We refined the index-based social vulnerability assessment method to assess spatial and temporal changes in Nepal's social vulnerability to disasters and its components, i.e., sensitivity and adaptive capacity. Our methodological scheme consists of three main steps (Fig. 2). First, we identified suitable indicators for the two components of social vulnerability using census data from 2011 to 2021. Second, we calculated composite SOVI scores for 2011 and 2021. Finally, we explored temporal changes by assessing social vulnerability transitions over the decade as well as shifts in sensitivity and adaptive capacity.

3.1. Indicator selection and data sources

Selecting the indicators representing social vulnerability is a crucial yet complex process, and no universally accepted approach exists to date [25,53]. Both inductive and deductive approaches typically guide the choice of indicators for calculating social vulnerability indices [26,54]. These approaches vary across different stages of index construction, including indicator selection, normalisation methods, factor retention methods, weighting, and the aggregation process into a composite index [25,26,55]. Each method offers distinct advantages and disadvantages; however, indicator selection should, in any case, be tailored to reflect location-specific and contextual characteristics of social vulnerability [23,35].

Commonly used interdisciplinary indicators employed for social vulnerability analysis encompass socio-demographic, infrastructural, and economic variables, including age, gender, ethnicity, economic status, educational status, migration, housing quality, and access to critical infrastructures (health and schools), transportation, communication, water, and sanitation [11,12,35,36]. Starting from the broad range of related indicators available in the national census of Nepal [56], we critically reflected on their relevance and retained only those clearly pertinent to social vulnerability within the disaster context in Nepal (see Section 2 and Table 1, column "Rationale"). Among the published census rounds in Nepal, only the two most recent (2011 and 2021) contained sufficiently relevant and comparable indicators for our social vulnerability analysis, and this defined the temporal horizon for our analysis. It is good to note that following federalisation in 2015, the administrative structure of Nepal changed, but the census data for 2011 was retrospectively updated by the National Statistics Office [56] to reflect the new administrative units. To ensure cross-year consistency, we considered only officially published indicators available for both 2011 and 2021.

The indicators selection process resulted in a final set of 23 indicators capturing social vulnerability (Table 1). The 23 indicators comprehensively capture various characteristics of social vulnerability across socio-demographics, dependency groups, education and literacy, migration, access to water supply and sanitation, communication, critical facilities, and housing quality. Although somewhat skewed towards the socio-demographic characteristics due to the limited range of indicators in the census, the set of indicators still captures broader physical and infrastructural characteristics (e.g., housing quality and access to critical facilities) that influence various stages of the disaster risk management cycle. Among the selected indicators, some increase social vulnerability while others decrease it; this directional influence on social vulnerability is often termed cardinality. Higher sensitivity raises social vulnerability and thus has positive cardinality, while higher adaptive capacity lowers it and thus has negative cardinality [9]. Following this logic, we categorised the 23 indicators of social vulnerability into 9 sensitivity and 14 adaptive capacity indicators, aligning with the categories used in prior studies, such as Jaafari et al. [12] and Rani & Tiwari [57].

Table 1
Details of the 23 indicators selected for the study: nine sensitivity and 14 adaptive capacity indicators. All indicators are at the municipal level except those marked with an asterisk (*), which were available only at the district level and were used uniformly across all municipalities within each district. Reference studies for indicator selection are Aksha et al. [35], Bhochhibhoya & Maharjan [36], Cutter et al. [11], and Jaafari et al. [12].

Social vulnerability component	Theme	Indicator	Acronym	Rationale
Sensitivity	Demography	Proportion of the female population	FEMALE_%	Women are more vulnerable to disasters during response and recovery
		Household (HH) density	HH_DENSITY	Higher household density and size pose challenges during different phases of disasters, e.g., earthquake impacts might be intensified in areas with high HH density (i.e. a proxy of urban level)
		Average HH size	HH_SIZE	
	Dependent groups	Proportion of elderly people (>65 years)	AGE>65_%	Elderly people, children, and the disabled population have limited mobility, cannot take responsive actions, and thereby lack resilience
		Proportion of children (<5 years)	AGE<5_%	
		Proportion of the disabled population	DISABILITY_%	
	Literacy	Illiteracy, i.e., the proportion of the population that cannot read and write	ILLIT_%	People who cannot read and write have a limited ability to understand warning information and act accordingly
	Ethnicity	Proportion of the Dalit population	DALIT_%	People from the lower caste often have limited access to different services during disasters
	Migration	Proportion of the absent population	ABSENT_%	Migration decreases the availability of the population to respond to disasters
Adaptive capacity	Access to WASH	Proportion of households having access to drinking water at home	WATER_%	Access to basic Water Supply, Sanitation, and Hygiene (WASH) services increases resilience to cascading hazards
		Proportion of households having access to toilet facilities at home	TOILET_%	
	Housing quality	Proportion of households with a reinforced-concrete foundation	RCC_%	Reinforced concrete foundations and cement-bonded walls increase the structural resilience of buildings to natural hazards such as earthquakes, floods, and landslides
		Proportion of households with their wall having cement-bonded bricks/stone	HIGHWALL_%	
	Education	Proportion of the population completing school level (Grade 10)	SCHOOL_%	Individuals with higher education have an increased ability to read, understand, act, and respond according to the requirements before, during, and after disasters
		Proportion of the population having a college degree or higher degree	COLLEGE_%	
	Access to critical facilities	Population per public health station	HOSP_POP*	Owning vehicles and having access to critical facilities such as health care and schools improve the capacity to respond
		Population per school	SCHOOL_POP*	
		Proportion of households owning vehicles	TRANSPORT_%	
	Access to communication	Proportion of households owning both radio and TV	RADIO_%	Access to communication facilities increases access to critical warning information
		Proportion of households owning a smartphone	MOBILE_%	
		Proportion of households having access to the internet	INTERNET_%	
	Economic condition	Proportion of households owning a house	OWNH_%	House ownership can aid disaster recovery through governmental benefits, and access to electricity for lighting supports preparedness and evacuation during nighttime hazards
		Proportion of households having electricity for lighting	ELEC_%	

3.2. Calculation of Social Vulnerability Index (SOVI)

We calculated composite SOVI and its components through factor analysis using PCA, building on the methods used in previous studies:

- ***Data standardisation:*** Indicators were standardised to a zero mean and unit variance using a standard scaler approach [58] to remove the scale differences between the variables and cross-time period comparison.
- ***Pre-PCA evaluation***: The sample adequacy for PCA was assessed using the Kaiser-Meyer-Olkin (KMO) test, and the multi-collinearity between the variables was tested by analysing the Pearson correlation matrix and percentage of variance explained, as performed by Santos et al. [33]. The overall KMO for both years was larger than 0.5, and none of the indicators had correlations

larger than 0.8. Furthermore, the initial set of 23 indicators explained over 60% of the variance. Therefore, the full set of 23 indicators was used as the final set of indicators (Table 1).

- ***Factor analysis using PCA:*** PCA was conducted using Varimax rotation with Kaiser normalisation, and all the principal components with Eigenvalues larger than 1 were extracted.
- ***Influence of the principal components (Cardinality):*** Component loadings are often multiplied by −1 to correct for the influence of the indicators on overall vulnerability [11,59]. In contrast to the common practice of not decomposing social vulnerability into sensitivity and adaptive capacity, our study differentiates these components by assigning positive cardinality to sensitivity and negative cardinality to adaptive capacity, in alignment with the definitions provided by IPCC [9].
- ***Principal Component scores:*** Component scores were calculated by multiplying standardised indicators by respective component loadings. To address the influence of sensitivity and adaptive capacity on SOVI, the absolute values of component loadings were taken to compute component scores as suggested by UNDP [59].
- ***Index calculations:*** All component scores were given equal weightage and summed up to calculate respective indices (Equations (1a), (1b) and (2)) following the approach by Rani & Tiwari [57].

$$\text{Sensitivity Index} = \sum_{i=1}^{n} PCs_i \tag{1a}$$

$$\text{Adaptive Capacity Index} = \sum_{i=1}^{n} PCa_i \tag{1b}$$

$$\text{SOVI} = \text{Sensitivity Index} - \text{Adaptive Capacity Index} \tag{2}$$

where PC_s and PC_a represent the principal component scores for sensitivity and adaptive capacity, respectively.

3.2.1. Joint PCA and year-wise PCA

PCA was conducted following two approaches:

- **Joint PCA**, used for spatio-temporal analyses: First, a joint standardisation for each of the 23 indicators was performed on pooled data (i.e., all data from 2011 to 2021 are standardised together), followed by joint PCA for each of the two components of social vulnerability. The component loadings for sensitivity and adaptive capacity were the same for both years to support the temporal comparability of index scores across the census years and were therefore used as the base for all spatio-temporal analyses of social vulnerability (Section 4.2). It is hereafter termed "joint PCA".
- **Year-wise PCA**, used solely for identifying the dominant PCs in 2011 and 2021 separately: The second approach involved a joint indicator standardisation (same as joint PCA), followed by year-wise PCAs for each of the two components of social vulnerability.

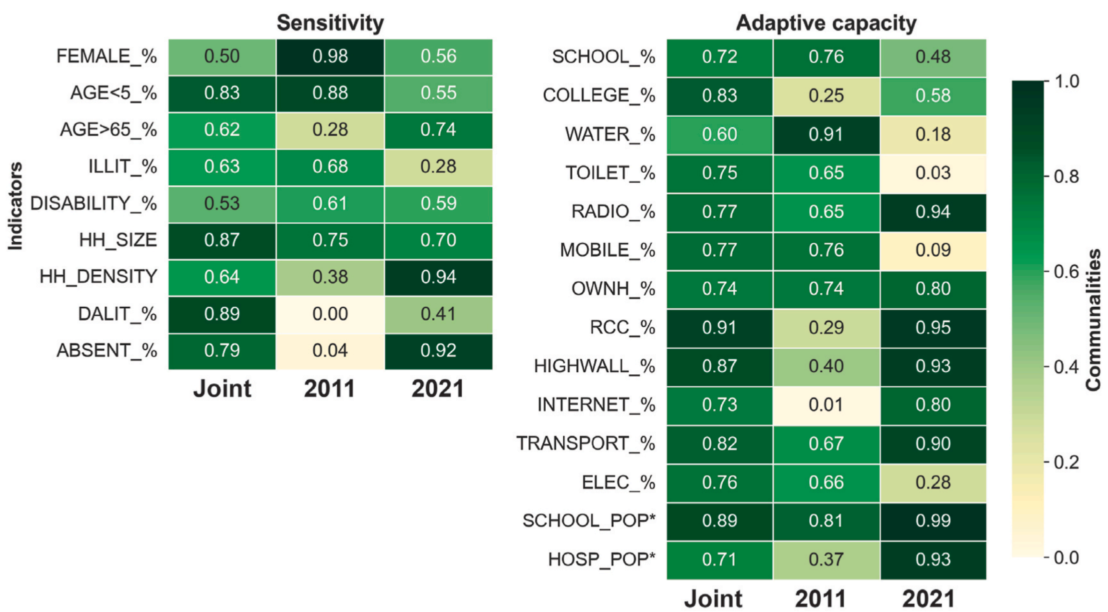

Fig. 3. Communalities for sensitivity and adaptive capacity indicators for the two PCA approaches conducted in the study: Joint PCA based on pooled data from both years, and year-wise PCAs for 2011 and 2021. The higher the communalities, the better the representation of indicators in the PCA.

This approach was used to analyse how the set of selected explanatory factors of sensitivity and adaptive capacity changed between 2011 and 2021. It allowed us to assess which explanatory factors were driving social vulnerability and its components in 2011 and which in 2021, and it is hereafter referred to as “year-wise PCA”.

For joint PCA, the social vulnerability and component indices resulting from Equations (1a), (1b) and (2) were each normalised using pooled indices from both years and rescaled to a 0-1 range using minmax normalisation [58] for 2011 and 2021. The normalised SOVI scores were subsequently classified into five equal-interval classes: Very High, High, Medium, Low, and Very Low.

3.3. *Spatio-temporal assessment of social vulnerability and its components*

The spatio-temporal changes in social vulnerability and its components were assessed using a joint PCA approach (for details, refer to Section 3.2). The SOVI classes for all municipalities (n = 753) were mapped to visualise the spatial distribution of social vulnerability for the years 2011 and 2021. These maps were utilised to identify patterns in the transitions of social vulnerability classes between the two reference years. Based on the municipal SOVI scores from Section 3.2, we analysed temporal change for each municipality as the difference in SOVI scores between 2021 and 2011, where positive values indicate worsening social vulnerability conditions, while negative values indicate improving conditions. To assess the national-scale social vulnerability across Nepal in 2011 and 2021, we aggregated municipal SOVI scores for each year into national SOVI values, using municipality-level population portions as weights. We then quantified SOVI change as the percentage difference relative to 2011 to track the shift in aggregated national SOVI from 2011 to 2021. Finally, we calculated and mapped the changes in sensitivity and adaptive capacity indices for each municipal unit and investigated their co-evolution to understand social vulnerability transitions over the decade.

4. Results

4.1. *Principal components and indicator communalities for joint and year-wise PCA*

The communalities derived from our two PCA approaches (Section 3.2) revealed the importance of age-related indicators to explain sensitivity (Fig. 3). While some indicators, such as household size (HH_SIZE), showed relatively high communalities in both years, several indicators (AGE>65_%, HH_DENSITY, DALIT_%, ABSENT_%) were weakly represented in 2011 but strongly represented in 2021. The increase in communalities suggested that these indicators became more strongly integrated with the underlying sensitivity structure over time. Overall, demographic, ethnicity, and migration-related characteristics demonstrated a strengthening internal coherence of sensitivity across the decade.

The results of the communalities for adaptive capacity across the two approaches provide complementary insights: the joint PCA demonstrated a stable overall structure, with communalities for all 14 indicators exceeding 0.6 (Fig. 3). Conversely, the year-wise PCA highlighted the temporal variations, with certain indicators (RADIO_%, TRANSPORT_%, and HOSP_POP*) increasing their contribution to adaptive capacity over the decade. OWNH_% and SCHOOL_POP* consistently showed high communalities in both years. However, some indicators, such as WATER_% and MOBILE_%, saw a decrease in their communalities from 2011 to 2021. These results indicate that while certain adaptive capacity indicators remained consistently important, others evolved, reflecting dynamic changes

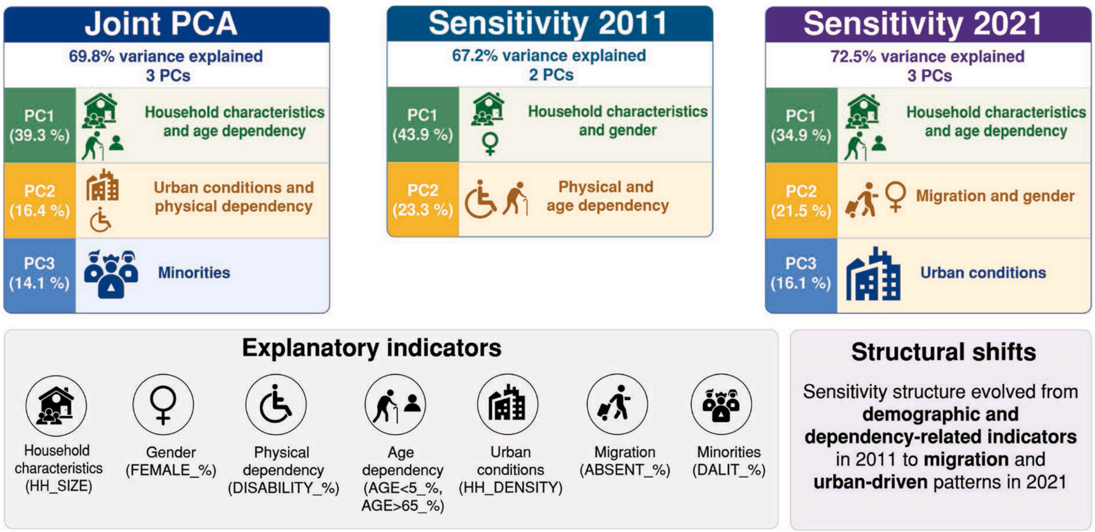

Fig. 4. Principal components (PCs), explanatory indicators, and structural shifts for sensitivity using the two Principal Component Analysis (PCA) approaches, i.e., joint and year-wise PCA. The explanatory indicators for each PC are the high-loading indicators, and their values are in the Supplementary Table S1 (A).

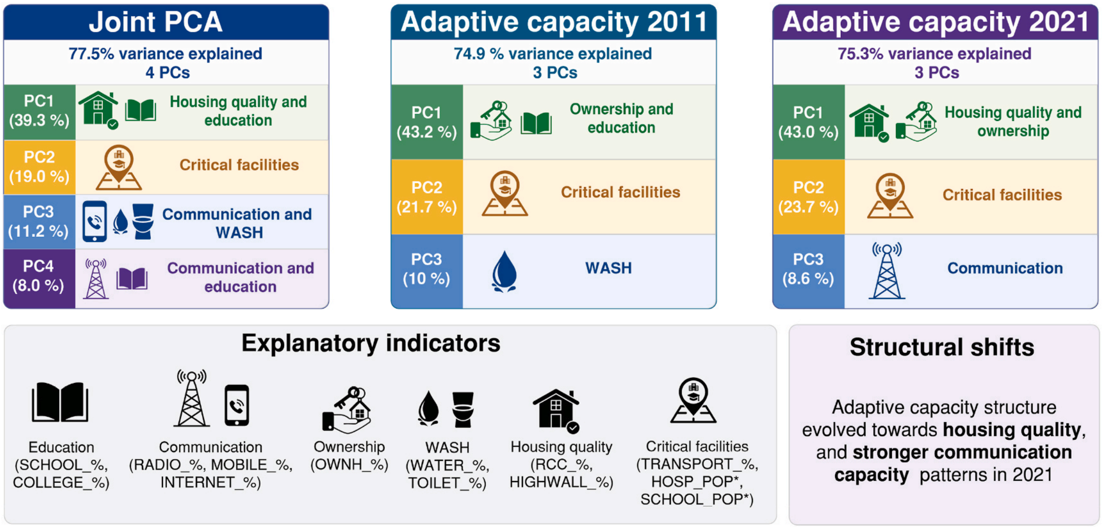

Fig. 5. Principal components (PCs), explanatory indicators, and structural shifts for adaptive capacity using two Principal Component Analysis (PCA) approaches, i.e., joint and year-wise PCA. The explanatory indicators for each PC are the high-loading indicators, and their values are in the Supplementary Table S1 (B).

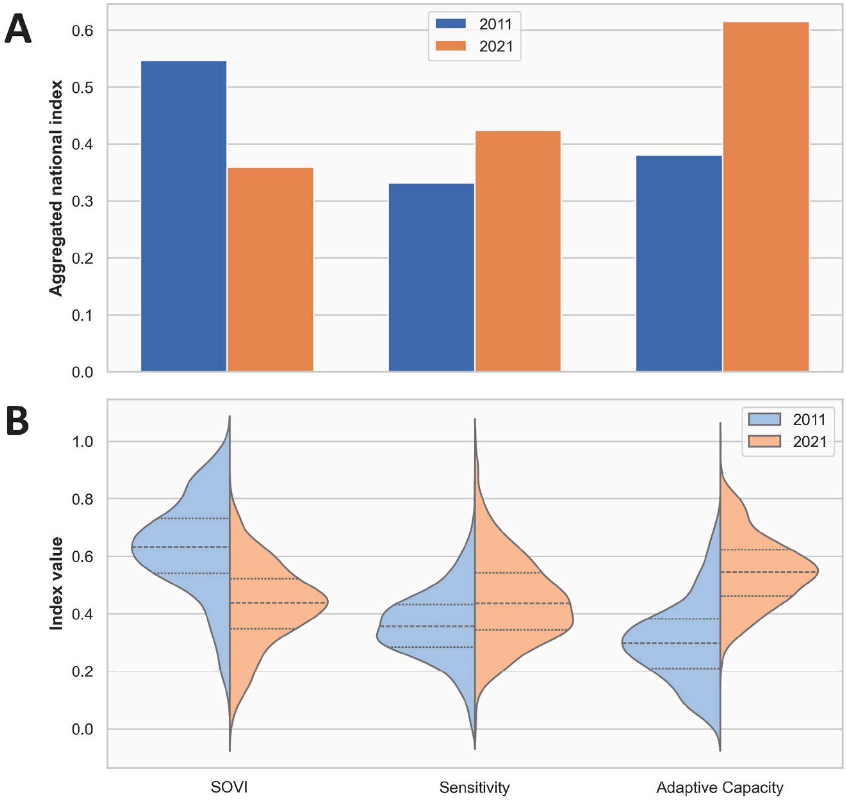

Fig. 6. A) Nationally aggregated indices, and B) Distribution of municipality-level values for sensitivity, adaptive capacity, and SOVI (Social Vulnerability Index) across the decade. Adaptive capacity has significantly improved, while sensitivity has moderately increased, resulting in an overall reduced SOVI. The dashed lines indicate the median and interquartile range.

in national resources and infrastructure.

The PCA captured sensitivity well, as the included principal components captured over 65% of the total variance of the data, with slight differences in component structures between the joint and year-wise PCA (Fig. 4). In the year-wise PCA, the variance explained by the principal components (PCs) increased from 67.2% (2011) to 72.5% (2021), demonstrating that these effectively capture substantial information from the indicators in both years. Further, the number of PCs exhibiting eigenvalues larger than one changed from two (2011) to three (2021). Household size was the primary driver associated with the first PC across both approaches. While minorities were one of the drivers in the joint PCA, it was not significant in the year-wise PCA. Migration and urban conditions emerged as new key drivers for sensitivity in the year-wise PCA for 2021. These findings highlight the multidimensional and evolving structure of sensitivity from demographic and dependency-related dimensions towards increasing migration and urban-driven patterns over the decade.

For adaptive capacity, the PCs explained an even higher proportion of variance (>70%; Fig. 5). The joint PCA approach identifies four PCs, whereas both years in the year-wise PCA represent adaptive capacity through three PCs. Critical facilities remained significant in both approaches. Housing ownership, housing quality, education, communication, and WASH were pivotal drivers, although their associated PCs and relative influence varied. Notably, communication and housing quality emerged as new drivers in 2021 in the year-wise PCA. Overall, the adaptive capacity structure became more streamlined in 2021, suggesting a more coherent

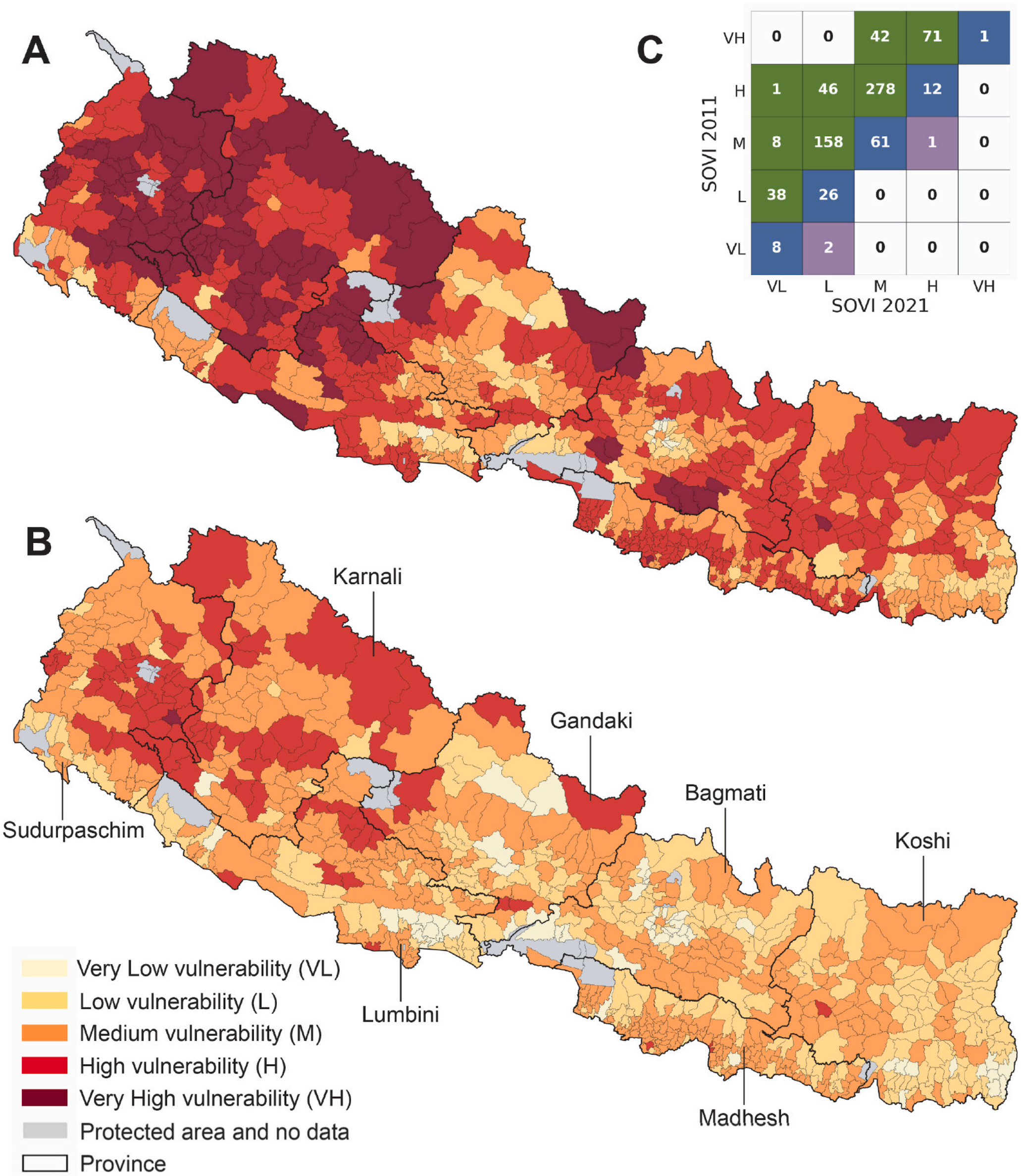

Fig. 7. Spatial distribution of Social Vulnerability Index (SOVI) for A) 2011 and B) 2021 for each municipality (N = 753). C) Count of municipalities for different SOVI class transitions between 2011 and 2021. Green indicates a transition to a lower SOVI class, blue indicates no change, and purple indicates a transition to a higher SOVI class. The seven provinces are indicated with their names in panel B. Source of administrative boundaries: Hermes Engineering Solution [39].

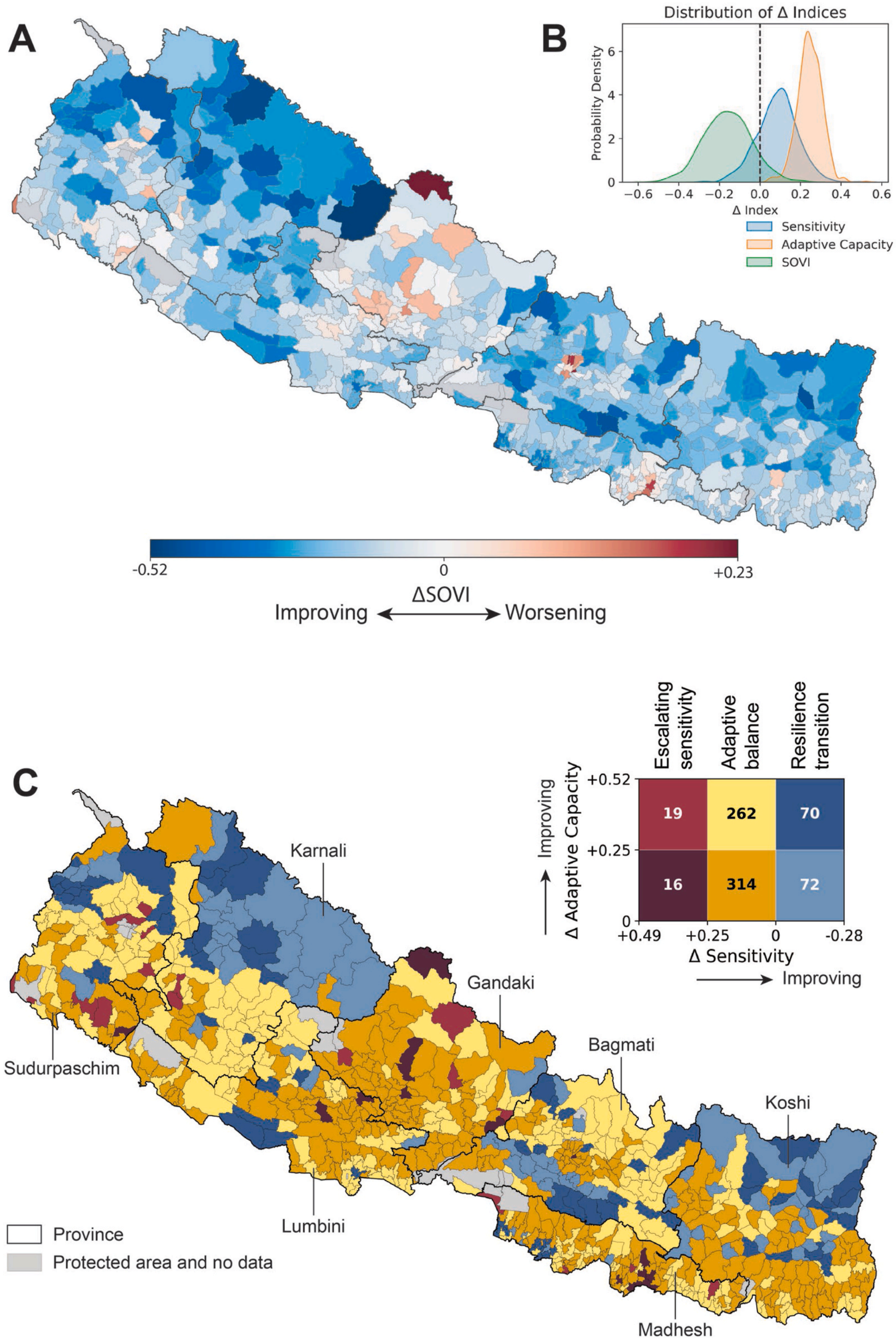

Fig. 8. (A) Temporal change (trend) in SOVI score between 2011 and 2021. (B) Distributions of the changes in the three indices, and (C) Changes in sensitivity and adaptive capacity. In C), the numbers in each cell of the matrix indicate the corresponding number of municipalities. The seven provinces are indicated with their names. The number of municipalities in each of the three social vulnerability transition categories is summarised by province in Supplement Table S4.

allocation of resources and capabilities across the municipalities.

4.2. Spatio-temporal assessment of social vulnerability and its components

4.2.1. Change in nationally aggregated indices

The aggregated national SOVI was high across Nepal in 2011 (Fig. 6A). Karnali, Sudur Paschim, and Madhesh provinces exhibited relatively higher scores among the seven provinces (Supplementary Table S2). Aggregated national sensitivity and adaptive capacity indices were both moderate (between 0.3 and 0.4), with national adaptive capacity slightly higher than sensitivity in 2011 (Fig. 6A and B). Provincially, sensitivity was highest in Sudurpaschim and lowest in Koshi, while adaptive capacity was lowest in Karnali and highest in Bagmati.

By 2021, the nationwide aggregated SOVI score (for details on the computation of scores, see Section 3.2) showed a noticeable decline of 35% ($SOVI_{2011} = 0.55$ to $SOVI_{2021} = 0.36$), indicating a lowered composite social vulnerability profile compared to 2011. At the provincial level, all seven provinces experienced a decrease in their aggregated SOVI scores (Supplementary Table S2), with the most significant decline in north-western Karnali province ($\Delta SOVI = -0.24$). Despite the significant improvement from 2011, Karnali, Sudurpaschim, and Madhesh provinces remained among the most vulnerable in 2021 (Supplementary Table S3). Furthermore, Koshi province's social vulnerability improved when compared with other provinces, while Bagmati province persistently demonstrated the lowest rank for social vulnerability among the seven provinces (Supplementary Table S3).

Nationally, the decline in social vulnerability was driven by a 63% increase in adaptive capacity, which outweighed a modest 28% rise in sensitivity (Fig. 6). By province, Gandaki showed the largest increase in aggregated sensitivity, while Karnali and Sudurpaschim experienced the greatest gains in aggregated adaptive capacity index (Supplementary Table S2).

4.2.2. Transitions in SOVI classes

The spatial distribution of the SOVI classes has changed, mostly shifting from a higher social vulnerability to a lower social vulnerability profile. In 2011, High and Very High SOVI were primarily concentrated in the Hills and Mountains districts of the Karnali and Sudurpaschim provinces, with scattered areas in Koshi and Madhesh provinces. Despite the nationwide improvements, social vulnerability was still predominantly high in Karnali and Sudurpaschim provinces, with a few scattered areas across other regions in 2021. In contrast, all other regions showed significant improvements over the decade.

Approximately 85% of municipalities transitioned towards lower SOVI classes between 2011 and 2021 (Fig. 7C). Only three out of 753 municipalities transitioned to a higher SOVI class, with one municipality shifting from Medium to High SOVI (Lomanthang rural municipality) and two from Very Low to Low SOVI (Madhyapur and Tokha municipalities).

4.2.3. Shifts in social vulnerability and its components

Over the decade, SOVI scores changed noticeably across municipalities, with a major decline (up to $\Delta SOVI = -0.52$) overshadowing minor increases (up to $\Delta SOVI = +0.23$) as compared to 2011, as shown in Fig. 8A. Approximately 9% of municipalities witnessed an increase in SOVI scores from 2011. These areas were predominantly located in the surroundings of the capital city, Kathmandu, the hills of Gandaki province, and the Madhesh Province. However, this increase was large enough to shift the SOVI class towards a higher social vulnerability profile in only three municipalities. On the other hand, the most significant improvements in social vulnerability were observed in Bagmati, Karnali, and Sudurpaschim provinces.

Despite these trends in SOVI scores, density plots still showed strong variations in the underlying components of social vulnerability (Fig. 8B). These disparities became even more evident when inspecting changes in the core components of social vulnerability, i.e., sensitivity and adaptive capacity, at the municipal level (Fig. 8C). Approximately 45% of municipalities exhibited a significant rise in adaptive capacity ($\Delta > 0.25$), with no observed decline in adaptive capacity. Meanwhile, around 80% of the municipalities experienced increased sensitivity, with the majority facing only a slight rise ($\Delta < 0.25$).

The sensitivity-adaptive capacity interaction matrix reveals distinct social vulnerability transition pathways based on directional changes between 2011 and 2021 (Fig. 8C). A simultaneous improvement in adaptive capacity and sensitivity representing a "resilience transition" was present in 142 out of the 753 municipalities (19%). These municipalities were predominantly located in the mountains of Koshi and Karnali provinces and the Hills in the Bagmati province, with some dispersion in other provinces (Fig. 8C and Supplementary Table S4). In contrast, improvements in adaptive capacity were partly offset by increased sensitivity in 81% of municipalities (categorised as "adaptive balance"). Thirty-five municipalities experienced a large increase in sensitivity, overshadowing adaptive capacity gains (extreme left column of the matrix in Fig. 8), clearly indicating worsening social vulnerability transitions, which we categorise as "escalating sensitivity". These municipalities were distributed largely across Madhesh, Sudurpaschim, and Gandaki provinces (Supplementary Table S4).

5. Discussion

With this study, we provide an enhanced methodological framework for assessing social vulnerability to disaster across time, and further, we advance the understanding of the spatio-temporal dynamics of social vulnerability between 2011 and 2021 in Nepal. In this section, we discuss the strengths and limitations of our approach and put our results for Nepal into context with the findings of previous studies.

5.1. Methodological contribution

Methodological choices can critically shape the dynamics of transitions in social vulnerability. While comparing SOVI using a joint PCA approach is a common practice to assess changes in social vulnerability [31,33], this approach typically answers two fundamental questions: where has SOVI increased or decreased, and by what magnitude. Following this approach, our results reveal transitions in SOVI classes across the decade, highlighting the necessity of a deeper investigation into their dominant drivers over time (Fig. 7). However, joint PCA limits the identification of structural changes in factors affecting components of social vulnerability [33]. To address these concerns, we conducted additional year-wise PCAs for each census round separately and compared the results with the joint PCA approach. We found that several indicators, such as migration and gender in sensitivity and housing ownership in adaptive capacity, had small importance in the principal components of joint PCA, but emerged as salient in year-wise PCA. This divergence shows that the underlying structure of principal components evolves over time, underscoring the need to align method choice – joint or year-wise PCA – with the study objective.

Interactions between the changes in sensitivity and adaptive capacity shape social vulnerability trajectories more than composite scores. By examining their co-evolution, we show that improvements in adaptive capacity were often insufficient to offset rising sensitivity in many Nepalese municipalities, and such observations enable the identification of spatially heterogeneous social vulnerability transition pathways. Locating areas experiencing resilience transitions, escalating sensitivity, or more balanced social vulnerability trajectories enhances the practical relevance of social vulnerability assessment for targeted interventions. Such interventions can be designed based on persistent and emerging drivers of principal components for sensitivity and adaptive capacity, as pinpointed by our method (Figs. 4 and 5).

5.2. Comparison to previous studies on social vulnerability in Nepal

Our findings showed improvements in social vulnerability across Nepal, though with high spatial heterogeneity. The national-level decline in social vulnerability, particularly due to gains in adaptive capacity, is consistent with changes in indices published by the European Commission Joint Research Centre (https://drmkc.jrc.ec.europa.eu/inform-index) and findings reported by Chapagain et al. [34]. We observed that mountain and hill districts in Karnali, Sudurpaschim, and Koshi Provinces, which showed high SOVI in 2011, demonstrated greater improvements than lowland areas in the Terai, indicating a partial convergence in resilience capacity across the country. Nevertheless, these regions, particularly Karnali and Sudurpaschim provinces, remained among the most vulnerable in the country in 2021. The observed reduction in social vulnerability was primarily driven by improvements in adaptive capacity; however, sensitivity also increased over the same period, partially offsetting overall gains and pointing to an adaptation paradox.

To unpack the social vulnerability transitions, we examined the drivers of sensitivity and their spatio-temporal variation across Nepal in the past decade. Sensitivity is mainly driven by household characteristics. Year-wise PCA highlights household size and density as the most influential indicators in both years (Fig. 4). These indicators also demonstrated high importance in previous social vulnerability assessments in Nepal [35,36]. The substantial growth in urban population and built-up areas (related to household characteristics) in the Terai region along the border with India has potentially contributed to increased sensitivity in these areas. The increased significance of age-related indicators in 2021, such as the share of the elderly population, accords with the rapid increase in the elderly population highlighted by Chalise [60]. Another emerging indicator is migration (Fig. 4), resonating with the increasing labour migration due to open borders and higher wages in other countries [61–63]. In addition, domestic migration from rural to semi-urban and urban areas has contributed to increased housing density in urban areas and can affect the availability of human resources for disaster response. Sensitivity is further exacerbated by the prevailing low educational levels in the Terai, as well as the Hills and Mountain regions of Karnali and Sudurpaschim [64,65]. A significant proportion of the population in these two regions also comprises Dalits and other marginalised communities [66], partly explaining the prevailing high social vulnerability levels in the Far-Western regions.

For adaptive capacity, the key drivers across time were household ownership and access to critical facilities such as schools, hospitals, and transportation (Fig. 5). The spatial patterns of adaptive capacity (Fig. 8C) indicate that metropolitan cities and their surroundings, as well as municipalities along the major transportation corridors and Terai regions in general, experienced lower increments in adaptive capacity, potentially influenced by existing barriers to housing ownership. A notable surge in land values, such as a 300% increase in Kathmandu Valley since 2003, has increased inequalities in housing acquisition for low-income groups [67,68]. Housing quality, represented by reinforced concrete foundations and high-quality walls, was an emerging driver of adaptive capacity (Fig. 5). The Terai region's reliance on non-engineered, low-quality construction with low code compliance [69,70] has likely limited the improvements in adaptive capacity in these areas. Communication and internet access, yet another emerging factor (Fig. 5), have increased, especially in the mountains of Karnali and Koshi provinces [71,72] and thus strengthened adaptive capacity, yet many rural areas still suffer from inadequate electricity and communication infrastructure [73].

These socio-economic changes are unfolding in a context of intensifying climate extremes. Climate change has intensified temperature extremes in Nepal [74] and increased the frequency of erratic rainfall, prolonged dry periods, and reduced snow cover [75,76]. These climatic shifts have amplified hydrometeorological hazards, such as floods, landslides, glacial lake outbursts, heat waves, and cascading hazards [40,77]. Furthermore, major shocks such as the 2015 Gorkha Earthquake, COVID-19, and the Nepal Flood 2017 have reshaped communities' exposure and social vulnerability in the short-to long-term, for instance through displacement, livelihood disruption, change in building practices, and increased disaster experience. Given the evolving dynamics of demographic structure, migration, education, infrastructure, and housing quality, our study highlights the value of integrated and longitudinal analyses that capture the co-evolution of social vulnerability components over time.

5.3. Limitations of our study

Despite the relevance and broad applicability of our approach, several limitations should be acknowledged. We compiled indicators from census data, which lacked measures of economy, disaster experience, early warning systems, and ongoing disaster risk reduction efforts. Although the evolution of the census questionnaire in Nepal supported the inclusion of a few indicators on poverty and employment in 2021, we excluded them to maintain consistency with the 2011 census. Disaster experience, for instance, can shape an individual's preparedness, response, and coping capacity [78,79]. Major events such as the Gorkha Earthquake or COVID-19 may have influenced people's risk perception but are not reflected in our set of indicators. Future censuses should incorporate such information to better capture dynamics of social vulnerability to multi-hazards. On the other hand, increasing the number of indicators can also increase redundancy, multicollinearity, and hinder the interpretability of findings [80,81].

The influence of individual indicators on social vulnerability is context-dependent and often non-linear. Some indicators contribute to both sensitivity and adaptive capacity, with net effects varying spatially and across disaster phases. For instance, migration can reduce human resources for disaster preparedness and response and thus increase sensitivity, yet simultaneously increase remittance income and improve economic conditions, thus strengthening adaptive capacity. Likewise, urbanisation may increase sensitivity in dense settlements but can at the same time enhance adaptive capacity through rapid infrastructural development as well as improved access to resources and communication services. To make such trade-offs tractable, we assigned indicators to appropriate social vulnerability components by their predominant influence in specific disaster phases. This might underrepresent the heterogeneity of such indicators across space and time.

6. Conclusions

This study advances social vulnerability assessment to disasters by dissecting spatio-temporal transitions of social vulnerability through the interaction of its key components – sensitivity and adaptive capacity – aligning with recommendations by IPCC [9]. Our approach is applicable globally but particularly valuable in data-scarce areas, where censuses are often the only comprehensive nationwide information source on social vulnerability indicators [24].

Our case of Nepal provides critical insights into the evolutionary dynamics of social vulnerability and its spatial distribution over the past decade. Social vulnerability has decreased nationally overall, largely due to a strong, consistent increase in adaptive capacity, which was partly offset by increased sensitivity in many parts of the country. The spatial patterns reveal notable heterogeneity in shifts in social vulnerability components; for instance, in several municipalities in Madhesh province, a pronounced worsening in sensitivity coincided with moderate improvements in adaptive capacity, resulting in overall increases in social vulnerability levels. Such findings emphasize that improvements in adaptive capacity alone do not automatically translate into reduced social vulnerability, particularly where demographic and social sensitivity continue to intensify. By examining the temporal interaction and co-evolution of sensitivity and adaptive capacity, our framework offers a more dynamic understanding of social vulnerability transitions than what we see in conventional social vulnerability analyses. This provides actionable insights for the planning of future interventions targeting lower sensitivity and/or strengthened adaptive capacity.

The evolution of social vulnerability components is occurring alongside intensifying hazards from climate change and rising exposure driven by urbanization, infrastructure expansion, and population mobility. Future risks and impacts may worsen if improvements in social vulnerability – through reduced sensitivity and stronger adaptive capacity – do not keep pace. To further support disaster risk reduction efforts, social vulnerability assessments such as the one presented in this paper should be integrated with assessments of other risk components, i.e., hazard and exposure, as social vulnerability aspects are often underrepresented in traditional risk assessments [24]. Doing this within a comprehensive multi-hazard framework would enable prioritising vulnerability reduction efforts to those communities that face significant risks from multiple hazards, ultimately building long-term resilience.

CRediT authorship contribution statement

Anup Shrestha: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Josias Láng-Ritter:** Conceptualization, Formal analysis, Methodology, Supervision, Validation, Writing – review & editing. **Dipesh Chapagain:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Maija Taka:** Methodology, Supervision, Writing – review & editing. **Olli Varis:** Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

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

Acknowledgements

We express our sincere gratitude to Qiankun Niu and Sanish Bhochhibhoya for valuable discussions regarding the methodological approach used in this study. Additionally, we would like to acknowledge funding from Maa-ja vesitekniikan tuki ry (Anup Shrestha and Maija Taka), the Department of Built Environment of Aalto University (Anup Shrestha), Maj ja Tor Nesslingin Säätiö (Josias Láng-Ritter), the GloWater project (Global connections and collaborative solutions for sustainable water security) funded by the Research

Council of Finland (Josias Láng-Ritter), and the Ministry of Education and Culture of Finland through the Digital Waters (DIWA) Doctoral Education Pilot related to the DIWA Flagship (decision no. 359248) funded by the Research Council of Finland's Flagship Programme (Maija Taka and Josias Láng-Ritter). Aalto University's AI assistant was used for proofreading and refinement of the writing in this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2026.106306.

Data availability

The census data can be downloaded from the official webpage of the National Statistics Office, Nepal (https://censusnepal.cbs.gov.np/results). The Python code for all the analysis performed in this article is openly accessible on Zenodo (https://doi.org/10.5281/zenodo.20851459).

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