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Article

Vulnerability Assessment of Rural Human–Land–Industry Systems in the Plateau–Mountain–Basin Ecological Transition Zone: Evidence from 90 Counties in Sichuan, China

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Abstract

The plateau–mountain–basin ecological transition zone of Sichuan Province, China, concentrates national ecological barrier functions and severe rural development pressures along a steep basin–mountain–plateau gradient, and the vulnerability of its rural human–land–industry system constrains green rural revitalization. Existing vulnerability assessments focus on ecosystems or household livelihoods; few take the county as the unit and integrate people, land, and industry into a unified framework. This study constructed a 3×3 matrix framework crossing the three dimensions of exposure, sensitivity, and adaptive capacity with the three system elements of people, land, and industry, selected 16 indicators, and assessed 90 counties of Sichuan. Weights were assigned with the entropy weight method; a vulnerability index was synthesized as VI = EI + SI − AI; counties were classified into five levels with the Jenks natural breaks method; and an obstacle degree model diagnosed the dominant vulnerability-generating factors. Sensitivity carried the largest dimension weight (0.6103), whereas adaptive capacity accounted for only 0.0953, indicating that inadequate capacity is a universal regional deficiency. The mean VI of the 90 counties was 0.2400, rising from the Chengdu Plain (0.1878) through Panxi (0.2704) to Northwest Sichuan (0.2887). Of the 22 high-vulnerability counties, 15 lay in Northwest Sichuan, 6 in Panxi, and only one, Guanghan City, on the plain. The leading obstacle factors were the proportion of ethnic minority population (16.52%) and county-seat altitude (9.93%), and three vulnerability types were identified: alpine ecological–ethnic compound, mountain poverty–sensitivity compound, and plain high-density sensitivity. Reweighting with the coefficient-of-variation method yielded a Spearman rank correlation of 0.9041, confirming robustness. The framework supports county-specific adaptation strategies for green rural revitalization in ecological transition zones.

Keywords: Ecological Transition Zone; Rural Human–Land–Industry System; Vulnerability Assessment; Entropy Weight Method; Obstacle Degree Model; Rural Revitalization

1. Introduction

The terrain descending stepwise from the eastern margin of the Qinghai–Tibet Plateau through the Hengduan Mountains to the Sichuan Basin forms the steepest transitional segment between China's first and second topographic steps. The southern portion of the plateau's eastern boundary runs roughly along the Wenxian–Pingwu–Beichuan–Luding–

Shimian–Mianning–Yanyuan line; the plateau surface to the west of this line stands at 4000–4500 m, whereas the basin to the east falls mostly to 500–2000 m, and the maximum relief between the main ridge and the basin margin exceeds 7300 m [1]. Intense topographic undulation and vertical hydrothermal differentiation make this belt, referred to here as the plateau–mountain–basin ecological transition zone (hereafter "the transition zone"), one of the most complex geographic and ecological gradient regions in China. Alpine meadows, high-mountain gorges, mid-mountain forests, and basin hills replace one another completely along the elevation gradient, while ethnic composition, livelihood modes, and settlement forms shift in parallel. The zone also carries national ecological security functions. The Zoige wetland supplies approximately 29–45% of the incoming water to the upper reaches of the Yellow River; the Zoige National Park candidate area and the Giant Panda National Park are located within the region; and the National Planning Outline for the Protection of Ecologically Vulnerable Areas has designated the Hengduan Mountains as the southwest mountain farming–pastoral ecotone. Sichuan Province is therefore charged with a dual mission: consolidating the ecological barrier in the upper reaches of the Yangtze and Yellow Rivers and building a higher-level "Tianfu granary" for the new era, and the province's ecological civilization evaluation places the barrier function at the core of its indicator system [2]. The transition zone is the spatial carrier where these overlapping strategies intersect most deeply and where their tensions concentrate; the stability of its rural systems directly affects both the barrier function and the development of ethnic minority areas.

In proportion to this strategic status, rural areas of the transition zone have long borne survival-level pressures: disaster exposure is high, ecological background constraints are rigid, fiscal self-sufficiency is weak, and the tendency toward a single-industry structure is evident. The region lies in the middle segment of the North–South seismic belt, where the Longmenshan, Xianshuihe, and Anninghe fault zones converge, and seismic ground-motion intensity is high by national zonation standards. The 2008 Wenchuan M8.0 earthquake caused heavy casualties and economic losses; the 2013 Lushan M7.0, 2017 Jiuzhaigou M7.0, and 2022 Luding M6.8 earthquakes successively damaged the regional economy; and in 2024, a flash flood and debris flow in Malie Township, Hanyuan County, left 14 people dead and 25 missing, while a major debris flow in Guzan Town, Kangding City, killed 12 people and destroyed a bridge on the Ya'an–Kangding Expressway. Beyond hazards, counties in ethnic areas generally have low fiscal self-sufficiency and depend heavily on transfer payments for public services; industrial structures remain single, the modernization of farming and animal husbandry is limited, and ecological conservation policies impose rigid constraints on resource development. Existing studies indicate that the livelihood vulnerability of rural households in the ethnic areas of Western Sichuan is significantly influenced by education level, income structure, and cultivated land resources, and that the socio-ecological vulnerability of plateau counties is generally high with complex driving forces [3,4]. Under external disturbances, the three elements of people, land, and industry readily fall out of balance, and the vulnerability of the rural "human–land–industry" system has become a fundamental constraint on rural revitalization in the transition zone.

After the completion of poverty alleviation, most counties in the transition zone were designated as national- or provincial-level key counties for rural revitalization assistance. Evaluations of the linkage quality between consolidating poverty-alleviation gains and rural revitalization show that industry and talent remain the weakest links among the 50 key counties in Sichuan [5]. However, existing vulnerability assessments either focus on the ecosystem itself or descend to the household livelihood scale; few assessments take the county as the unit and integrate the three elements of people, land, and industry into a unified framework [6,7]. Constructing a vulnerability assessment framework for rural

human–land–industry systems oriented to ecological transition zones therefore has both theoretical and policy significance. At the theoretical level, it integrates the development-oriented research tradition on human–land–industry elements with the risk-oriented paradigm of vulnerability assessment into a single analytical logic. At the policy level, it can directly serve Sichuan in identifying vulnerability-generating factors and formulating differentiated adaptation strategies, thereby supporting the consolidation and extension of poverty-alleviation achievements and the promotion of green rural revitalization.

Accordingly, this study builds on social–ecological system theory, the sustainable livelihood framework, and the man–land relationship areal system theory. It decomposes the vulnerability of the rural human–land–industry system into three dimensions—exposure, sensitivity, and adaptive capacity—and constructs a two-dimensional matrix framework that crosses the dimension layer with the three system elements of people, land, and industry, forming a 3×3 matrix. Within this framework, people constitute the core subject, encompassing population scale, structure, migration, and livelihood capacity; land is the spatial carrier and resource-environment background, encompassing terrain, climate, land, and ecological conditions; and industry is the functional link that converts labor and resources into livelihood output and public finance. The three elements interact and constrain one another, and each cell of the matrix corresponds to a class of observable and quantifiable assessment content. The assessment units cover 90 counties (excluding municipal districts) across the three major economic zones of Sichuan Province: 40 counties (county-level cities) under the eight prefecture-level cities of the Chengdu Plain Economic Zone, 19 counties under Panzhihua City and Liangshan Yi Autonomous Prefecture in the Panxi Economic Zone, and 31 counties under Garze Tibetan Autonomous Prefecture and Aba Tibetan and Qiang Autonomous Prefecture in the Northwest Sichuan Ecological Demonstration Zone. Together these counties span the complete basin–mountain–plateau gradient from the basin interior to the plateau hinterland. Methodologically, we applied the entropy weight method for objective weighting, synthesized a vulnerability index as VI = EI + SI − AI, where EI, SI, and AI denote the exposure, sensitivity, and adaptive capacity indices, respectively, classified the 90 counties into five vulnerability levels using the Jenks natural breaks method, and diagnosed the dominant vulnerability-generating factors with an obstacle degree model. We further examined the robustness of the results by re-weighting the indicators with the coefficient of variation method. The analysis answers three sequential questions: where the transition zone is vulnerable, why it is vulnerable, and how it should respond.

This study makes four contributions. First, it develops, to our knowledge, the first integrated assessment framework that crosses the three vulnerability dimensions (exposure, sensitivity, adaptive capacity) with the three elements of the rural territorial system (people, land, industry) as a 3×3 matrix, providing a conceptual interface between the human–land–industry research tradition and vulnerability assessment. Second, it conducts a county-scale assessment of 90 counties that covers the full basin–mountain–plateau gradient, extending the unit of analysis beyond single ecosystems or household surveys to a regional system of counties. Third, it combines composite measurement with obstacle-degree attribution and robustness checks under alternative weighting, which moves the analysis from static mapping toward factor diagnosis. Fourth, it derives three vulnerability types and proposes zone-specific adaptation strategies, offering decision support for differentiated green revitalization in ecological transition zones.

The remainder of this paper is organized as follows. Section 2 reviews the literature and presents the theoretical framework; Section 3 describes the study area, indicator system, data sources, and methods; Section 4 reports the empirical results, including weights, zonal patterns, five-level grading, obstacle diagnosis, and robustness tests; Section 5 discusses the findings and their policy implications; and Section 6 concludes..

2. Literature Review and Theoretical Framework

2.1. Vulnerability Research: Concepts and Assessment Paradigms

Vulnerability research emerged at the intersection of ecology and disaster studies. Blaikie et al. [8] proposed the pressure and release (PAR) model, which treats a disaster as the product of a natural hazard intersecting with socially produced vulnerability, traced from root causes through dynamic pressures to unsafe conditions. The model relocated the explanation of disaster loss from natural processes to social structures, but it resists direct quantification and has mainly served as a conceptual foundation. A parallel tradition operationalized vulnerability through indicators. Cutter et al. [9] built the Social Vulnerability Index (SoVI) for United States counties, compressing dozens of socioeconomic variables into a small set of factors by principal component analysis and mapping place vulnerability as the overlap of biophysical risk and social susceptibility. Brooks et al. [10] extended this indicator–index tradition to the national level, screening eleven proxy variables that explain cross-national differences in disaster mortality. This line of work is replicable and well suited to cross-county comparison and mapping, although its results are sensitive to indicator selection and weighting. Adger [11] synthesized the disaster and livelihood traditions and posed two questions that any assessment must answer first: vulnerable to what, and who is vulnerable. These two questions remain the entry point of vulnerability analysis.

The rise of sustainability science expanded the object of analysis from the hazard-bearing entity to the coupled human–environment system. Turner et al. [12] defined vulnerability as a function of exposure, sensitivity, and coping and adaptive capacity, and stressed cross-scale linkages and system reorganization after disturbance. Gallopín [13] clarified the logical boundaries among vulnerability, resilience, and adaptive capacity, treating adaptive capacity as the property by which a system adjusts its own state to reduce vulnerability. Folke [14] added the notion of transformability from the resilience perspective. Smit and Wandel [15] argued from community-scale adaptation practice that adaptive capacity is an internal component of vulnerability rather than its opposite. Together these works consolidated the exposure–sensitivity–adaptive capacity structure that most subsequent empirical assessments have adopted.

The IPCC assessments gave this structure its most widely used formulation. The Fourth Assessment Report (AR4) defined vulnerability as the degree to which a system is susceptible to the adverse effects of climate change, expressed as a function of exposure, sensitivity, and adaptive capacity [16]. The Sixth Assessment Report (AR6) reframed the concept around risk, in which vulnerability denotes only the propensity to be adversely affected and exposure is moved outside it [17]. The revised definition has diffused slowly: a systematic review by Estoque et al. [18] found that the exposure–sensitivity–adaptive capacity (E–S–A) tripartition still dominates empirical vulnerability research. Critiques from the social–ecological systems (SES) literature hold that mainstream frameworks treat the social subsystem thinly; Berrouet et al. [19] therefore proposed distinguishing individual, social, and territorial layers when assessing SES vulnerability. The AR4 formulation continues to structure applied assessments. Sharma and Ravindranath [20] operationalized the IPCC framework for hazard-specific vulnerability assessment under climate change. Yu et al. [21] built a driver-based framework on the same tripartition to assess vulnerability in the poverty-stricken counties of the Funiu Mountain area. Ge et al. [22] used it to identify urban–rural differences in social vulnerability to natural hazards across China.

Three points of convergence matter for this study. Exposure and sensitivity raise vulnerability, whereas adaptive capacity lowers it. Vulnerability is a state attribute of the system, determined by internal conditions and manifested under specific disturbance contexts, which licenses cross-sectional measurement of vulnerability even where

disturbance events cannot be observed directly. The assessment unit can be legitimately set at the territorial system rather than the individual or household. The present study accordingly follows the Turner framework and the IPCC AR4 operational definition, with the SES correction that the object is a county-level territorial system.

2.2. Rural Human–Land–Industry System Research

The man–land relationship areal system theory provides the ontological basis for rural system research in Chinese geography. Wu [23] established the man–land relationship areal system as the research core of geography, holding that the discipline should study how human activities and the territorial environment interact within specific regions. Liu [24] extended this theory to rural issues: the rural regional system was characterized as a composite of interacting population, land, and industry elements, and urban–rural integration was proposed as the systemic pathway to rural revitalization in the new era. A fuller statement of human–earth system science then repositioned the man–land relationship as the analytical foundation for territorial governance and sustainability research [25].

Applied work developed along two lines. The first concerns land use and rural sustainability. Liu [26] introduced a research agenda linking land use transition to rural sustainability in China, arguing that land use change is both the mirror and the lever of rural restructuring. Liu et al. [27] set out the theory, technology, and management of rural revitalization, treating the restructuring of population, land, and industry elements as the core mechanism of rural development. Long et al. [28] showed how land consolidation supports rural vitalization by restructuring rural land use patterns and releasing the productive potential of idle and inefficient land. Yang and Liu [29] decoded China's targeted poverty alleviation campaign from a geography perspective, using the population–land–industry structure to explain how place-based interventions altered rural development trajectories and why poorly matched interventions failed.

The second line measures the coupling coordination of rural population, land, and industry. Cheng et al. [30] decomposed the rural regional system into the three subsystems and used a coupling coordination degree model to portray coordinated development patterns and their mechanism in the Huang–Huai–Hai area, a major grain-producing plain. Li et al. [31] scaled the analysis to rural China as a whole, mapping the national spatial pattern of population–land–industry coupling coordination and detecting its influencing factors with a geographical detector; coordination was found to decline from the eastern plains toward the western mountain and plateau regions. At the micro scale, Li et al. [32] analyzed the mutual feedback mechanism among human, land, and industry elements within rural regional systems, showing how the state of one element transmits to the others and how element imbalance feeds back into system degradation. Huang et al. [33] applied the same framework to the Loess Plateau and identified the spatio-temporal pattern and driving mechanism of coordinated human–land–industry development in an ecologically fragile setting.

Two observations follow. First, this literature is uniformly development-oriented: every study asks how well the elements coordinate, not how stable the system is under disturbance. High coordination does not imply low vulnerability, because tightly coupled elements can transmit shocks quickly under high exposure. Second, no conceptual interface has been built between the population–land–industry element structure and the E–S–A dimension structure; the element layer and the dimension layer remain in separate literatures that do not cite each other. Embedding the vulnerability dimensions into the human–land–industry element structure is the entry point of this study.

2.3. Vulnerability Research in Ecological Transition Zones and Western Sichuan

Vulnerability research in ecological transition zones has concentrated on the ecological subsystem. Qiao et al. [6] developed a comprehensive ecological vulnerability assessment method and applied it to the farming–forestry–pastoral ecotone of western Sichuan and northwestern Yunnan, a case area lying within the same transition belt from the Qinghai–Tibet Plateau to the Sichuan Basin examined here; their composite index combined ecological sensitivity, pressure, and resilience at the county scale. In the northern agro-pastoral ecotone, Li et al. [34] used the vulnerability scoping diagram (VSD) framework to assess the spatio-temporal evolution of drought vulnerability across 112 counties, providing a complete paradigm for county-group assessment within an ecotone and showing that drought vulnerability was shaped jointly by climate exposure and livelihood structure. Bai et al. [35] traced the transition of the northern agro-pastoral ecotone from a human–Earth system perspective, showing how the zone's boundary and internal states shift under coupled natural and social drivers rather than under climate forcing alone.

Empirical work on the social side of the transition zone has accumulated mainly at household and prefecture scales. Li et al. [36] applied a livelihood vulnerability index to rural households in Liangshan Yi Autonomous Prefecture, Sichuan, and revealed clear spatial differences tied to terrain and livelihood type, with pure farming households more vulnerable than households with off-farm income. Cao et al. [37] used a hierarchical linear model to show that household poverty vulnerability in Liangshan is jointly determined by village-level context and household livelihood assets, which suggests that poverty reduction in ethnic areas must intervene at both levels. At the county scale on the plateau, Bai et al. [38] mapped heat vulnerability of urban and rural residents across Tibetan counties, one of the few county-group vulnerability mappings on the Qinghai–Tibet Plateau, and found systematically higher vulnerability in rural than in urban counties.

Taken together, transition-zone studies either assess the ecological subsystem alone or stay at household and single-county scales. No study has treated the rural social–economic systems of an entire transition belt, spanning a complete basin–mountain–plateau gradient, as the object of county-group vulnerability assessment.

2.4. Research Gaps and the Two-Dimensional Matrix Framework

County-level vulnerability assessment has matured in recent years. Yang and Pan [7] built an evaluation theory of rural vulnerability and mapped its spatial patterns for Chinese counties, and Yu et al. [39] assessed the driving mechanism of rural vulnerability for 117 counties in Heilongjiang Province. In the Chinese-language literature, Li et al. [40] systematized vulnerability concepts and assessment methods, and Chen et al. [41] measured the evolution of social–ecological system vulnerability in semi-arid areas based on the VSD framework. From the social–ecological perspective, Li et al. [42] evaluated county-level rural territorial system vulnerability and proposed differentiated response strategies, and Xi et al. [43] classified the vulnerability of rural settlement systems in the alpine canyon area of Western Sichuan under geological hazard stress. Broader framings include the county-level socio-ecological-economic system assessment of Chongqing by Liu et al. [44] and the rural social–ecological system assessment of Yunnan by He et al. [45]. At finer scales, Zhang et al. [46] applied the livelihood vulnerability index to communities in an environmentally sensitive region of China. Liu et al. [47] measured how poverty alleviation resettlement reshaped household livelihood vulnerability in western mountainous areas, and Chen et al. [48] reviewed rural vulnerability, migration, and relocation in mountain areas of Western China, noting that relocated households can be more vulnerable than before relocation.

Three gaps remain. First, transition-zone studies stay within ecological assessment or at household and single-county scales; county-group assessment over a full basin-mountain-plateau gradient is absent. Second, the coupling coordination literature and the vulnerability literature have never been integrated: the former measures development

states, the latter measures risk states, and no framework crosses the two. Third, existing assessments rarely link dimensional attribution to spatial differentiation within a single analytical structure; obstacle-factor diagnosis and robustness testing are often added as separate steps rather than derived from the assessment framework itself.

Building on this literature, this study defines rural human–land–industry system vulnerability as a state attribute of the county-level rural territorial system: under external disturbance, the system is prone to loss and difficult to restore, as jointly determined by the inherent defects of its internal population, resource-environment, and industry structure and by its coping and recovery capacity. People are the core subject, covering population size, structure, mobility, and livelihood capability; land is the spatial carrier and resource-environment baseline; industry is the functional link that converts labor and resources into livelihood output and public revenue. Vulnerability forms through the coupling of three forces. External disturbance determines exposure: the study area lies where the middle segment of the North–South seismic belt meets the western Sichuan rain screen, and the intensity and frequency of earthquakes, secondary geological hazards, and mountain torrents set the degree of stress. Internal structure determines sensitivity: aging and working-age outflow weaken hazard-bearing potential, fragmented terrain amplifies disturbance transmission, and industrial monoculture removes economic buffering. Coping and recovery capacity constitutes adaptive capacity, covering household income, local finance, infrastructure, and public services. Exposure and sensitivity raise vulnerability, whereas adaptive capacity lowers it; following Smit and Wandel [15], adaptive capacity is an internal component of vulnerability rather than its opposite.

Combining the two lineages, this study constructs a two-dimensional matrix framework (Figure 1). The dimension layer comprises exposure, sensitivity, and adaptive capacity, following the IPCC AR4 paradigm [16]; the element layer comprises people, land, and industry, following the man–land relationship areal system theory [23,25]. The crossing yields nine cells, each corresponding to observable and quantifiable content: people exposure captures population outflow pressure under disturbance; land exposure captures seismic ground motion, geological hazard density, and the high-altitude alpine baseline; industry exposure denotes the exposure of livelihood production to hazard-prone terrain, conditioned mainly by the land-exposure context; people sensitivity covers population density, ethnic composition, aging, and rural population size; land sensitivity is expressed through forest cover as the ecological buffer; industry sensitivity covers primary-industry dependence and grain supply capacity; people adaptive capacity covers rural income, urbanization, and public service provision; land adaptive capacity is expressed through the ecological endowment that supports recovery, measured jointly with the land conditions; and industry adaptive capacity covers fiscal self-sufficiency and the overall economic level. The matrix ensures complete coverage of the vulnerability concept and balanced representation of the three elements; it forms the skeleton of the indicator design in Section 3.

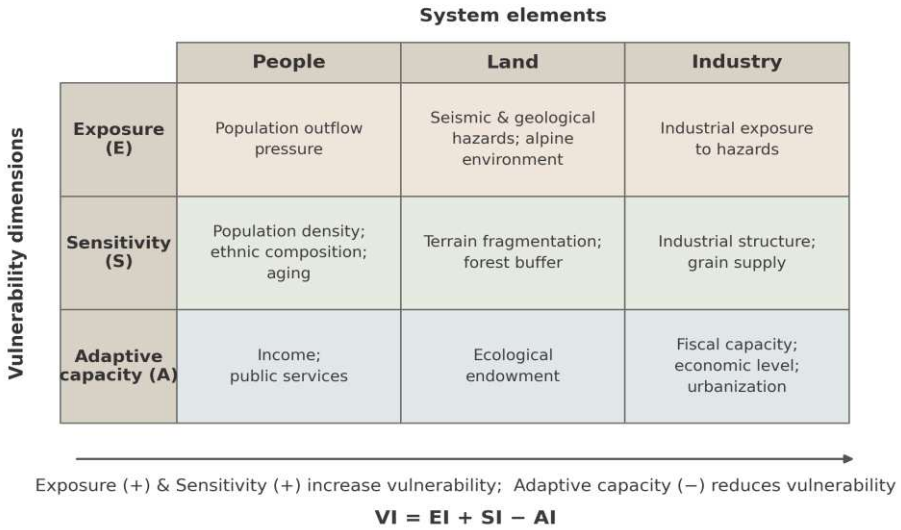


Figure 1. Theoretical framework for vulnerability assessment of rural human–land–industry systems in the plateau–mountain–basin ecological transition zone.

3. Materials and Methods

3.1. Study Area

The study area covers the complete basin–mountain–plateau transition gradient within Sichuan Province, China. Following the provincial economic zoning scheme, it comprises 90 county-level units, with municipal districts excluded. The Chengdu Plain Economic Zone contributes 40 counties and county-level cities administered by eight prefecture-level cities: Chengdu, Deyang, Mianyang, Suining, Ziyang, Meishan, Leshan, and Ya'an. The Panxi Economic Zone contributes 19 counties under Panzhihua City and Liangshan Yi Autonomous Prefecture. The Northwest Sichuan Ecological Demonstration Zone contributes 31 counties under Garze Tibetan Autonomous Prefecture and Aba Tibetan and Qiang Autonomous Prefecture. From southeast to northwest, the terrain shifts from basin hills and peri-basin mountains through alpine gorges to the plateau surface, and elevation rises from below 500 m to above 4000 m. The belt thus straddles both sides of the southern segment of the eastern boundary of the Qinghai–Tibet Plateau and captures the full geomorphic and ecological gradient of this boundary zone [1]. Figure 2 shows the location and composition of the study area.

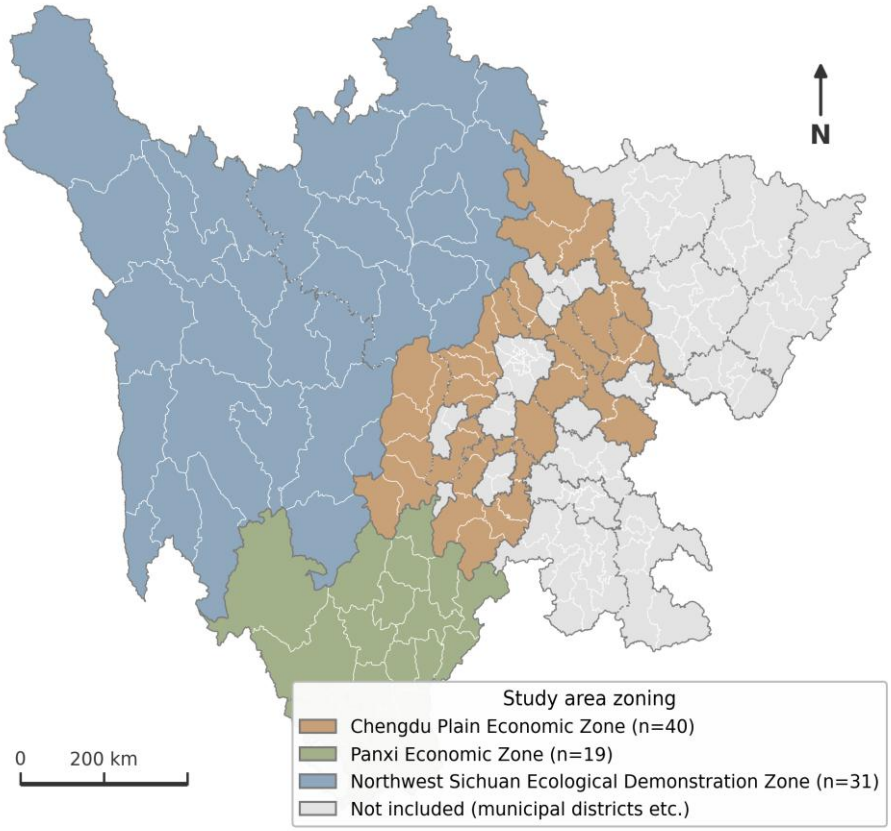


Figure 2. The study area: 90 counties in three economic zones of Sichuan Province, China.

The natural setting is characterized by concentrated hazard stress and steep ecological zonation. The region lies in the middle segment of the North–South seismic belt and within the Huaxi rain screen, where the Longmenshan, Xianshuihe, and Anninghe fault zones converge. Earthquakes, mountain floods, and debris flows occur frequently. Alpine meadow, alpine gorge, mid-mountain forest, and basin hills replace one another along the elevation gradient, forming a complete vertical spectrum of landscape types. The candidate area of Zoige National Park and the Giant Panda National Park are located within the study area, which performs water conservation and ecological barrier functions for the upper reaches of the Yangtze and Yellow Rivers.

Socioeconomic conditions contrast sharply across the three zones. The Chengdu Plain Economic Zone is densely populated and highly urbanized, and it carries the core production function of the Tianfu granary, the principal grain base of southwestern China. The Panxi Economic Zone enjoys favorable hydrothermal conditions, but dry-hot valleys coexist with concentrated ethnic minority settlement, and resource-based industries dominate the county economies. The Northwest Sichuan Ecological Demonstration Zone is sparsely populated, with a predominantly Tibetan population and generally weak fiscal self-sufficiency; most counties depend heavily on transfer payments. These systematic differences in the states of the people, land, and industry elements across the three zones provide a well-contrasted sample for assessing the vulnerability of rural human–land–industry systems and for diagnosing zone-specific weaknesses.

3.2. Indicator System and Data Sources

The indicator system takes the nine-cell framework constructed in Section 2 as its logical basis. That framework crosses three vulnerability dimensions (exposure, sensitivity, and adaptive capacity) with three rural territorial system elements (people, land, and industry), and each cell of the matrix corresponds to a class of observable system states. Indicator selection followed three principles: scientific soundness, data availability, and

regional relevance. Scientific soundness requires that each indicator has an explicit theoretical link to the dimension and element it represents. Data availability requires that values can be obtained from official statistical sources for all 90 counties. Regional relevance requires that the indicator captures the specific stresses of the transition zone, such as seismic hazard and population outflow.

Candidate indicators were screened one by one against data completeness across the 90 counties, and indicators with large caliber gaps were removed. In particular, the major disaster frequency indicator used in an early version was replaced by the density of registered geological hazard sites. Most counties had no public records of historical disaster counts, so the original indicator would have introduced systematic distortion rather than real differences in hazard exposure. After screening, the final system contains 3 dimensions and 16 indicators, as shown in Table 1.

Table 1. Indicator system for vulnerability assessment of rural human–land–industry systems.

Dimension	Code	Indicator	Direction	Unit	Data source
Exposure	E1	Seismic peak ground acceleration	+	g	GB 18306-2015 Seismic Ground Motion Parameters Zonation Map of China [49]
Exposure	E2	Density of registered geological hazard sites	+	sites/100 km²	2025 public lists of geological hazard sites and county-level prevention plans of each prefecture
Exposure	E3	Net population outflow rate	+	%	Seventh National Population Census county bulletins and county statistical bulletins
Exposure	E4	Altitude of county seat	+	m	Official county profiles and statistical bulletins
Sensitivity	S1	Population density	+	persons/km²	Seventh National Population Census county bulletins
Sensitivity	S2	Proportion of ethnic minority population	+	%	Seventh National Population Census county bulletins
Sensitivity	S3	Share of primary industry	+	%	2023 county statistical bulletins
Sensitivity	S4	Forest coverage rate	−	%	2023 county statistical bulletins and forestry authorities
Sensitivity	S5	Rural population size	+	10,000 persons	Seventh National Population Census county bulletins and county statistical bulletins
Sensitivity	S6	Proportion of population aged 65 and above	+	%	Seventh National Population Census county bulletins
Sensitivity	S7	Per capita grain output	−	kg/person	2023 county statistical bulletins
Adaptive capacity	A1	Fiscal self-sufficiency rate	−	%	2023 county statistical bulletins
Adaptive capacity	A2	Urbanization rate	−	%	2023 county statistical bulletins
Adaptive capacity	A3	Hospital beds per 10,000 people	−	beds	2023 county statistical bulletins

Dimension	Code	Indicator	Direction	Unit	Data source
Adaptive capacity	A4	Per capita GDP	−	yuan	2023 county statistical bulletins
Adaptive capacity	A5	Per capita disposable income of rural residents	−	yuan	2023 county statistical bulletins

The exposure dimension describes the intensity of external disturbances acting on the county rural system. Seismic peak ground acceleration (E1) measures the seismic design intensity assigned to each county under the national standard [49], reflecting long-run seismic exposure rather than single events. The density of registered geological hazard sites (E2) captures the prevalence of landslide, collapse, and debris-flow hazards. The net population outflow rate (E3) reflects the erosion of local labor and the depth of demographic stress. The altitude of the county seat (E4) proxies the severity of terrain and climatic constraints on production and daily life. The sensitivity dimension describes internal structural attributes that amplify losses. Population density (S1) and rural population size (S5) measure the scale of the exposed population; the proportions of ethnic minority population (S2) and of population aged 65 and above (S6) capture structural fragility in human capital and social support; the share of primary industry (S3) reflects dependence on agriculture; forest coverage rate (S4) and per capita grain output (S7) act in the opposite direction, since higher ecological endowment and grain security reduce sensitivity. The adaptive capacity dimension measures the resources available for response and recovery: fiscal self-sufficiency rate (A1), urbanization rate (A2), hospital beds per 10,000 people (A3), per capita GDP (A4), and per capita disposable income of rural residents (A5).

Data came mainly from the 2023 county statistical bulletins on national economic and social development. Population-structure indicators were drawn from the county bulletins of the Seventh National Population Census. Seismic parameters were taken from the national standard zonation map [49]. Geological hazard sites used the pre-flood-season registered caliber published in the 2025 public lists of each prefecture. Where individual indicators differed in reference year or statistical caliber, three rules were applied: values from the nearest-year official bulletin were used as substitutes; hazard site density was uniformly converted from the identified or registered caliber published by each county, without subjective estimation; and when multiple sources reported different values for the same indicator, the statistical bulletin value was preferred. All exposure and sensitivity indicators point in the vulnerability-increasing direction. Adaptive capacity indicators are constructed so that larger values mean stronger capacity; a higher adaptive capacity index (AI) therefore indicates stronger adaptive capacity.

3.3. Methods

The assessment proceeded in four steps: range standardization, entropy weighting, vulnerability index synthesis and grading, and obstacle degree diagnosis.

First, to eliminate dimensional differences, all raw indicators were standardized by the range method in the vulnerability-increasing space. For a positive indicator, whose larger raw value implies higher vulnerability, the standardized value is given in Equation (1):

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

For a negative indicator, the transformation is reversed (Equation (2)):

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

where x_ij is the raw value of indicator j for county i, x'_ij is the standardized value in [0,1], and min(x_j) and max(x_j) are the minimum and maximum of indicator j across the 90 counties. The five adaptive capacity indicators (A1–A5) were standardized in the capacity direction, so that larger standardized values mean stronger capacity, and then aggregated into the adaptive capacity index AI, which enters the vulnerability index as a subtraction term.

Second, indicator weights were determined by the entropy weight method [50–52]. The method uses the dispersion of indicator values across evaluation units as a measure of information content: an indicator that varies more among counties carries more discriminating information and receives a larger weight. For each indicator, the proportion of county i under indicator j is given in Equation (3):

$$p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \quad (3)$$

The information entropy of indicator j is given in Equation (4):

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad k = \frac{1}{\ln n} \quad (4)$$

where n=90 is the number of counties. The degree of divergence is g_j=1-e_j, and the weight is obtained by normalization, as shown in Equation (5):

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \quad (5)$$

where m=16 is the number of indicators. The entropy method derives weights entirely from the data and involves no subjective judgment, which suits the multi-unit comparison of 90 counties in this study. It should be noted, however, that a low entropy weight does not imply that an indicator is conceptually unimportant; it only means that the indicator varies little across the 90 counties and therefore carries limited discriminating information. This caveat is particularly relevant for the adaptive capacity indicators, whose low weights are interpreted in Section 4.1 as evidence of a region-wide capacity deficiency rather than as a sign of irrelevance.

Third, the vulnerability index was synthesized and graded. Following the IPCC conceptual paradigm of vulnerability and county-level assessment practice [53], the vulnerability index of county i is defined in Equation (6):

$$VI_i = EI_i + SI_i - AI_i \quad (6)$$

where EI_i, SI_i, and AI_i are the exposure, sensitivity, and adaptive capacity indices, each computed as the weighted sum of the standardized indicators within the corresponding dimension. A larger VI_i indicates higher vulnerability. The 90 counties were then classified into five vulnerability levels (low, relatively low, medium, relatively high, and high) using the Jenks natural breaks method [54], which determines class breakpoints by minimizing within-class variance, so that counties within a level are as similar as possible and differences between levels are maximized.

Fourth, an obstacle degree model [55–57] was used to diagnose the factors that constrain each county. The diagnosis was performed in the vulnerability-increasing space. For the adaptive capacity indicators, the capacity-deficit direction was used, that is, one

minus the capacity-standardized value, so that a weak endowment of capacity appears as a large obstacle contribution. The obstacle degree of indicator j for county i is given in Equation (7):

$$M_{ij} = \frac{w_j x'_{ij}}{\sum_{j=1}^{m} w_j x'_{ij}} \times 100\% \quad (7)$$

where M_ij measures the constraining strength of indicator j on the vulnerability of county i, and x'_ij is taken in the vulnerability-increasing space as described above. For each county, the leading factors were extracted by ranking M_ij, and the common vulnerability drivers and differentiated weaknesses were summarized at the regional and zonal levels.

To test whether the results depend on the weighting scheme, the coefficient of variation method was applied as an alternative objective weighting approach in a robustness check. The resulting vulnerability rankings were compared with the entropy-weighted rankings using the Spearman rank correlation coefficient, and the zonal gradient and the composition of the highest-vulnerability counties were examined for consistency between the two weighting schemes. The robustness results are reported in Section 4.

4. Results

4.1. Indicator Weights

Applying the entropy weight method to the range-standardized indicator matrix of the 90 counties yielded the weights reported in Table 2.

Table 2. Entropy weights of the 16 indicators.

Code	Indicator	Direction	Weight
E1	Seismic peak ground acceleration	+	0.0727
E2	Density of registered geological hazard sites	+	0.0870
E3	Net population outflow rate	+	0.0192
E4	Altitude of county seat	+	0.1157
S1	Population density	+	0.1890
S2	Proportion of ethnic minority population	+	0.1393
S3	Share of primary industry	+	0.0440
S4	Forest coverage rate	−	0.0335
S5	Rural population size	+	0.1214
S6	Proportion of population aged 65 and above	+	0.0647
S7	Per capita grain output	−	0.0184
A1	Fiscal self-sufficiency rate	−	0.0100
A2	Urbanization rate	−	0.0196
A3	Hospital beds per 10,000 people	−	0.0119
A4	Per capita GDP	−	0.0239
A5	Per capita disposable income of rural residents	−	0.0299

At the dimension level, sensitivity carried the largest aggregate weight at 0.6103, followed by exposure at 0.2945; adaptive capacity accounted for only 0.0953. At the indicator level, the four largest single weights all belonged to population-structure indicators: population density (S1, 0.1890), the proportion of ethnic minority population (S2, 0.1393), rural

population size (S5, 0.1214), and the altitude of the county seat (E4, 0.1157), the last being closely tied to where population concentrates in this terrain.

These weights require a specific interpretation because the entropy method assigns weight according to the dispersion of an indicator across evaluation units rather than to any judgment of importance. An indicator that varies strongly among counties carries more discriminating information and therefore receives more weight. The dominance of population-structure indicators thus indicates that the 90 counties differ most sharply in how population is concentrated, in ethnic composition, and in the scale of the rural population. This pattern is consistent with the geography of the transition zone, where densely settled basin counties and sparsely settled, ethnically distinct plateau counties lie within short distances of one another.

The low weight of adaptive capacity requires an equally careful reading. It does not mean that adaptive capacity is unimportant for vulnerability; rather, it means that adaptive capacity was uniformly weak across the sample. Fiscal self-sufficiency, rural income, and public service provision were low in nearly all 90 counties and varied little among them, so these indicators carried little discriminating information. Inadequate adaptive capacity is therefore a common deficiency of the whole region rather than a factor that differentiates one county from another. This reading is consistent with the fiscal reality of the transition zone, where most counties, including the relatively better-off plain counties, depend on transfer payments to fund basic public services. The differentiation of county-level vulnerability was driven by conditions at the exposure and sensitivity ends, a structure that the obstacle-degree diagnosis in Section 4.4 confirms from a different angle.

Two features of the weight structure stand out. First, the weight ranking already foreshadows the factor diagnosis: the indicators with the largest weights (S1, S2, S5, E4) reappear among the leading obstacle factors in Section 4.4, which suggests that the same population-structure and natural-background conditions both differentiate counties and constrain them. Second, the dimension weights depart sharply from an equal allocation. Had the 16 indicators been weighted equally, the sensitivity dimension, which contains seven indicators, would have dominated the composite index purely through block size; the entropy weights instead let the data determine the dimensional balance, and they still assign sensitivity the largest share. The weight results thus support the framework design, in which vulnerability differentiation in the transition zone is expected to run primarily through the internal structure of the population–industry system and only secondarily through capacity gaps.

4.2. Zonal Statistical Characteristics

Weighted aggregation of the standardized indicators produced the exposure index (EI), sensitivity index (SI), and adaptive capacity index (AI) for each county, from which the vulnerability index (VI) was synthesized as VI = EI + SI − AI. Table 3 reports the zonal means of the four indices, and Figure 3 compares them across the three economic zones.

Table 3. Mean vulnerability indices of the three economic zones.

Economic zone	Counties	EI	SI	AI	VI
Chengdu Plain Economic Zone	40	0.0533	0.1824	0.0479	0.1878
Panxi Economic Zone	19	0.1069	0.1891	0.0256	0.2704
Northwest Sichuan Ecological Demonstration Zone	31	0.1259	0.1885	0.0257	0.2887

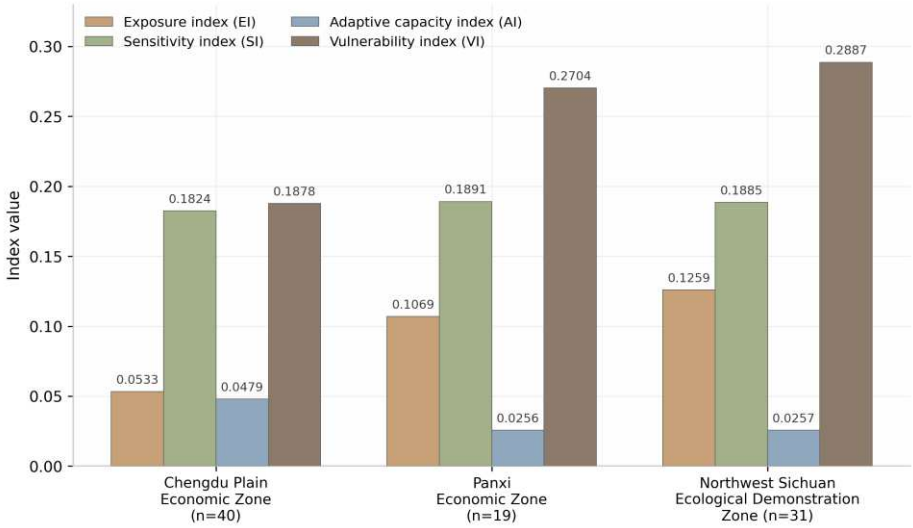


Figure 3. Comparison of vulnerability indices across the three economic zones.

Vulnerability displayed a clear gradient along the basin–mountain–plateau transition. The Northwest Sichuan Ecological Demonstration Zone recorded the highest mean VI (0.2887), the Panxi Economic Zone ranked second (0.2704), and the Chengdu Plain Economic Zone was far lower (0.1878). The gap between the plateau zone and the plain zone was therefore substantial, exceeding half of the plain zone's own value.

Decomposition by dimension shows where this gradient originates. Exposure exhibited the steepest zonal contrast: EI averaged 0.1259 in Northwest Sichuan, 0.1069 in Panxi, and only 0.0533 on the Chengdu Plain, a difference of more than twofold between the extremes. Differences in alpine altitude and in the hazard-forming environment along the seismic fault zones thus constitute the primary factor separating the three zones. Sensitivity, by contrast, was nearly equal across zones, with SI means ranging only from 0.1824 to 0.1891. The similarity in level conceals a difference in composition. In plain counties, sensitivity arose mainly from population density and rural population size; in Northwest Sichuan and Panxi, it arose mainly from ethnic composition and dependence on agriculture. Adaptive capacity diverged sharply again: the Chengdu Plain averaged 0.0479, about twice the values of Northwest Sichuan (0.0257) and Panxi (0.0256). Because AI enters the vulnerability index as a subtraction term, this twofold capacity gap widened the vulnerability gap that exposure and sensitivity had already created.

The combination of dimensions is itself informative. Plain counties had the lowest EI but an SI close to that of the other two zones, which indicates that their vulnerability stemmed mainly from a sensitive population–industry structure rather than from hazard exposure. Counties in Northwest Sichuan and Panxi faced the simultaneous stacking of high exposure, high sensitivity, and low adaptive capacity, with each dimension adding to, rather than offsetting, the others. This contrast has direct implications for intervention. In plain counties, measures that relax population–land tension and adjust the industrial structure address the binding constraint, whereas in plateau counties no single-dimension measure can suffice because exposure, sensitivity, and capacity deficits overlap. The zonal results therefore suggest that the spatial pattern of rural vulnerability in the transition zone was governed primarily by the exposure gradient and was further amplified by the adaptive capacity gap.

4.3. Five-Level Spatial Pattern of Vulnerability

Across the 90 counties, VI ranged from a maximum of 0.3708 in Butuo County to a minimum of 0.0963 in Yingjing County, with a mean of 0.2400 and a median of 0.2491. The Jenks natural breaks method [54] identified four breakpoints, 0.1560, 0.2047, 0.2532, and

0.2985, which divided the counties into five levels: low, relatively low, medium, relatively high, and high vulnerability. Table 4 cross-tabulates the five levels against the three economic zones, Figure 4 maps the resulting spatial pattern, and Table 5 lists the 22 high-vulnerability counties in descending order of VI.

Table 4. Distribution of counties by vulnerability level and economic zone.

Vulnerability level	Chengdu Plain	Panxi	Northwest Sichuan	Total
Low	11	2	0	13
Relatively low	19	2	1	22
Medium	4	3	8	15
Relatively high	5	6	7	18
High	1	6	15	22

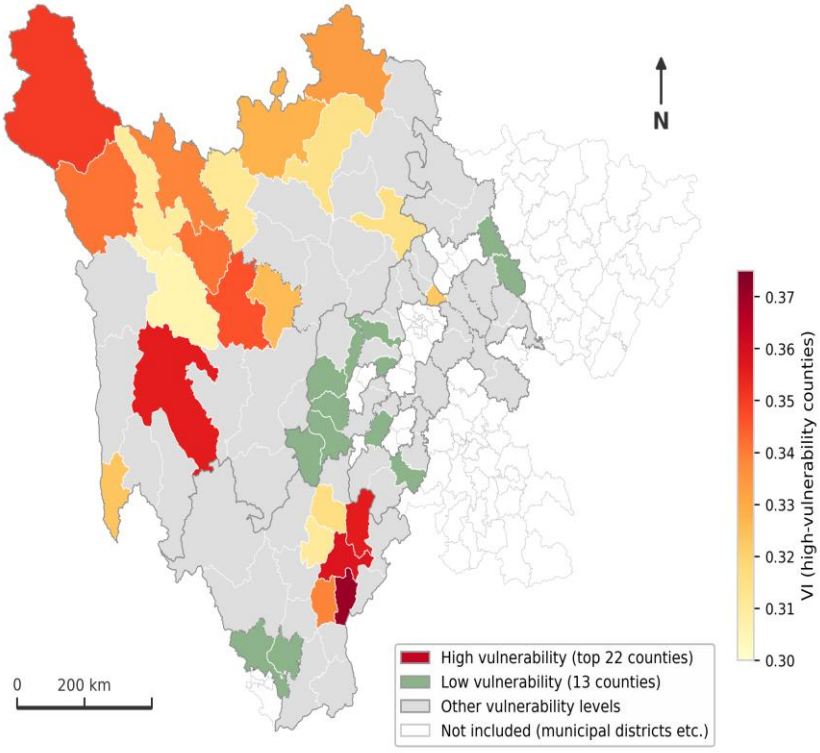


Figure 4. Five-level classification of rural human–land–industry system vulnerability across the 90 counties.

Table 5. The 22 high-vulnerability counties, ranked by VI.

No.	County	Prefecture	VI
1	Butuo County	Liangshan Yi Autonomous Prefecture	0.3708
2	Zhaojue County	Liangshan Yi Autonomous Prefecture	0.3580
3	Meigu County	Liangshan Yi Autonomous Prefecture	0.3557
4	Litang County	Garze Tibetan Autonomous Prefecture	0.3557
5	Shiqu County	Garze Tibetan Autonomous Prefecture	0.3502
6	Daofu County	Garze Tibetan Autonomous Prefecture	0.3463
7	Dege County	Garze Tibetan Autonomous Prefecture	0.3413
8	Luhuo County	Garze Tibetan Autonomous Prefecture	0.3411
9	Puge County	Liangshan Yi Autonomous Prefecture	0.3387

No.	County	Prefecture	VI
10	Seda County	Garze Tibetan Autonomous Prefecture	0.3385
11	Zoige County	Aba Tibetan and Qiang Autonomous Prefecture	0.3335
12	Aba County	Aba Tibetan and Qiang Autonomous Prefecture	0.3281
13	Danba County	Garze Tibetan Autonomous Prefecture	0.3260
14	Derong County	Garze Tibetan Autonomous Prefecture	0.3235
15	Guanghan City	Deyang City	0.3231
16	Yuexi County	Liangshan Yi Autonomous Prefecture	0.3159
17	Maoxian County	Aba Tibetan and Qiang Autonomous Prefecture	0.3150
18	Hongyuan County	Aba Tibetan and Qiang Autonomous Prefecture	0.3146
19	Rangtang County	Aba Tibetan and Qiang Autonomous Prefecture	0.3115
20	Xide County	Liangshan Yi Autonomous Prefecture	0.3106
21	Garze County	Garze Tibetan Autonomous Prefecture	0.3101
22	Xinlong County	Garze Tibetan Autonomous Prefecture	0.3059

The five-level pattern clustered strongly toward high-altitude ethnic areas. In Northwest Sichuan, 22 of 31 counties fell into the relatively high or high levels, a combined share of 71.0%, and no county in this zone qualified for the low level. The corresponding share in Panxi was 63.2% (12 of 19 counties). On the Chengdu Plain, only 6 of 40 counties, or 15.0%, reached the relatively high level or above, and 30 of the 40 plain counties were classified as low or relatively low. The distribution in Table 4 is also asymmetric within zones: the medium level was the modal category in Northwest Sichuan only in combination with the higher levels, whereas the plain zone's counts declined monotonically from the relatively low level upward. The 13 low-vulnerability counties, namely Yingjing, Tianquan, Shimian, Emeishan, Muchuan, Miyi, Lushan, Zitong, Yanbian, Hanyuan, Yanting, Dayi, and Pujiang, concentrated in the basin-rim mountains and along the western margin of the Chengdu Plain, where the ecological background is favorable and population pressure is low. Of the 22 high-vulnerability counties, 15 lay in Northwest Sichuan and 6 in Panxi, and 21 were ethnic-area counties of Garze, Aba, or Liangshan prefectures. Guanghan City was the only high-vulnerability county on the plain.

The rank order within the high-vulnerability list reinforces the same reading. The three highest-VI counties, Butuo (0.3708), Zhaojue (0.3580), and Meigu (0.3557), are all Yi-area counties of Liangshan, and the plateau counties of Garze and Aba occupy most of the remaining positions. Guanghan City, ranked 15th at 0.3231, is the only plain county in this list, which indicates that a sufficiently extreme sensitivity structure can elevate vulnerability to the highest level even where exposure is moderate and adaptive capacity comparatively strong.

Dimensional extremes corroborated the mechanisms behind this pattern. EI peaked in Danba (0.1654), Luhuo (0.1595), and Litang (0.1539), all alpine-gorge or high-cold plateau counties. SI peaked in Guanghan (0.3236), Anyue (0.2789), and Renshou (0.2784), all populous hilly counties. AI was highest in Dujiangyan (0.0719), Pengzhou (0.0704), and Shifang (0.0703), and lowest in Meigu (0.0021), Butuo (0.0046), and Puge (0.0070). The spatial correspondence was exact: adaptive capacity highs coincided with vulnerability lows, and adaptive capacity lows with vulnerability highs.

Two further observations place the results in a broader context. First, the pattern is consistent with county-level findings at the national scale, where high rural vulnerability concentrates in both alpine ecological counties and densely populated agricultural counties [7]. Both causal pathways coexisted within the Sichuan transition zone: a high-

exposure, low-capacity pathway in the plateau counties and a high-sensitivity pathway in the crowded plain counties. Second, a counterpoint case qualifies the role of hazard exposure alone. Pingwu and Beichuan counties, although located in the epicentral area of the 2008 Wenchuan earthquake, ranked only at the relatively low vulnerability level, a position that can be partly explained by their low population density and high forest coverage. Hazard exposure appears to convert into high vulnerability mainly when it is overlaid with a sensitive population–industry structure.

4.4. Obstacle Degree Diagnosis

The obstacle degree model [57] quantified the constraining strength of each indicator on county vulnerability. Figure 5 ranks the average obstacle degree of the 16 indicators across all 90 counties, and Table 6 reports the top five obstacle factors for each economic zone.

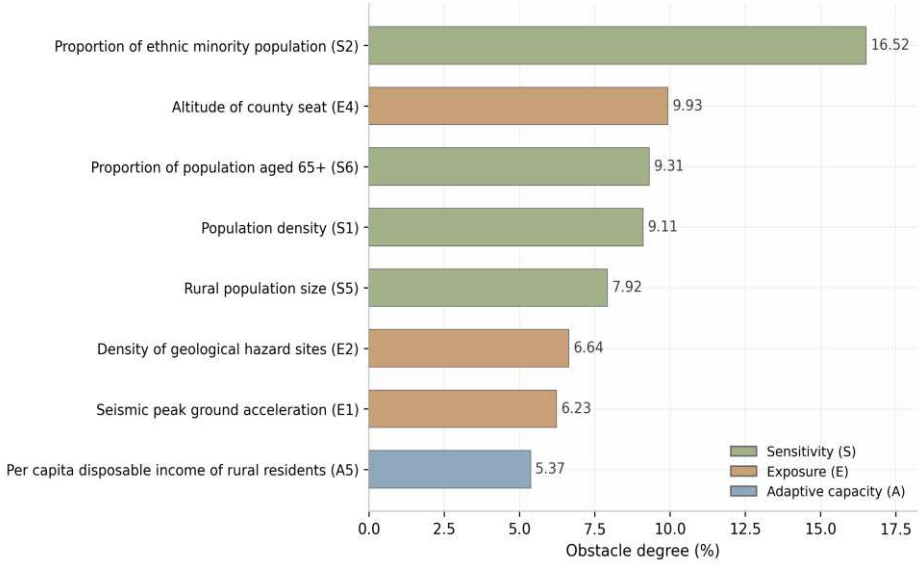


Figure 5. Ranking of average obstacle degree of indicators across the 90 counties.

Table 6. Top five obstacle factors and their obstacle degrees (%) by economic zone.

Economic zone	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Chengdu Plain	S1 Population density (18.14)	S6 Population aged 65+ (16.16)	S5 Rural population size (13.14)	E2 Hazard site density (7.78)	A5 Rural income (4.90)
Panxi	S2 Ethnic minority share (22.10)	E4 Altitude of county seat (11.11)	E1 Seismic PGA (8.71)	S5 Rural population size (8.06)	S3 Primary industry share (6.46)
Northwest Sichuan	S2 Ethnic minority share (30.22)	E4 Altitude of county seat (18.91)	E1 Seismic PGA (6.49)	A5 Rural income (5.81)	E2 Hazard site density (5.28)

At the regional scale, the proportion of ethnic minority population ranked first, with an average obstacle degree of 16.52%. The altitude of the county seat followed at 9.93%, then the proportion of population aged 65 and above at 9.31%, population density at 9.11%, and rural population size at 7.92%. Three of the top five factors were therefore population-structure indicators. The density of geological hazard sites (6.64%), seismic peak ground acceleration (6.23%), and per capita disposable income of rural residents (5.37%) occupied ranks six through eight, indicating that hazard exposure and the income shortfall also constrained counties materially. The fiscal self-sufficiency rate ranked last at only 2.33%. Because fiscal self-sufficiency was low in nearly every county and differed little among them, its dispersion and hence its obstacle degree were small, a mechanism consistent with the low entropy weight of the adaptive capacity dimension in Section 4.1.

The zonal obstacle structures diverged in an interpretable way. On the Chengdu Plain, population density was the leading obstacle (18.14%), followed by aging (16.16%) and rural population size (13.14%), indicating that the principal tension there lay in the human–land relationship under dense settlement combined with demographic aging. In both Panxi and Northwest Sichuan, the ethnic minority share ranked first (22.10% and 30.22%, respectively) and the altitude of the county seat ranked second (11.11% and 18.91%), so that ethnic social structure and the high-cold environmental background acted as paired constraints. The obstacle values in Northwest Sichuan were markedly higher than in Panxi for both factors, mirroring its higher vulnerability level.

County-level profiles reveal the microstructure of these mechanisms. In Litang County, the obstacle degree of the ethnic minority share reached 29.6% and that of altitude 24.6%; in Shiqu County, the corresponding values were 30.6% and 26.0%. Butuo County combined an ethnic-share obstacle of 29.3% with extremely weak adaptive capacity. Maoxian County showed an ethnic-share obstacle of 32.0% together with a hazard-site density obstacle of 14.7%. Guanghan City, the only high-vulnerability plain county, had a population-density obstacle of 45.2%, with rural population size and aging contributing 10.5% and 10.2%. In Xichang, seismic peak ground acceleration was the leading factor at 18.7%. Even at the medium vulnerability level, the same plain-type structure appeared: in Jintang County, the obstacle degrees of population density, rural population size, and aging reached 35.5%, 20.1%, and 11.3%, suggesting that the high-density sensitivity structure is general among populous plain counties rather than specific to Guanghan.

On this basis, three vulnerability types can be distinguished. The first is the alpine ecological–ethnic compound type, represented by Litang and Shiqu, in which an ethnic-structure obstacle of about 30% and an altitude obstacle of about 25% overlap, locking counties between a high-cold environmental background and a distinctive social structure. The second is the mountain poverty–sensitivity compound type, represented by Butuo, Zhaojue, and Meigu, in which an ethnic-share obstacle of about 29% combines with an AI below 0.01, so that high sensitivity and severely inadequate adaptive capacity reinforce each other. The third is the plain high-density sensitivity type, represented by Guanghan, in which a single population-density obstacle of 45.2% dominates. The typology shows that a common regional outcome, high vulnerability, was produced by at least three distinct factor combinations, so a uniform regional response would mistarget most counties. The three types instead point to different policy targets: ecological compensation and livelihood transition for alpine counties, remediation of income and public service deficits for mountain counties, and spatial optimization of settlements for high-density plain counties.

4.5. Robustness Checks

Three checks assessed whether the results depend on specific methodological choices.

First, we tested sensitivity to the weighting method. Re-weighting the indicators with the coefficient-of-variation method produced a VI series whose Spearman rank correlation with the entropy-weight VI was 0.9041 ($p = 3.06 \times 10^{-34}$). The zonal gradient under the alternative weights was identical in ordering: Northwest Sichuan (0.2612) remained above Panxi (0.2499), which remained above the Chengdu Plain (0.1763). Seven of the ten highest-vulnerability counties were shared between the two weighting schemes. The ranking results were therefore not sensitive to the choice between these two objective weighting methods.

Second, we considered the choice of weighting benchmark. Equal weighting was not used as a benchmark because it is biased by block size: the sensitivity dimension contains seven indicators, whereas exposure contains four and adaptive capacity five, so equal weights would let the sensitivity block dominate the composite index by construction. Entropy weighting, which assigns weights according to the information content of each

indicator, avoids this block-size artifact and is more defensible for a multi-unit comparison of this kind.

Third, we verified the validity of the indicator replacement made during indicator system construction. Before replacement, the exposure dimension measured hazard history through the frequency of major disasters; under this specification, the indicator received a distorted weight of 0.266 and the zonal gradient in vulnerability vanished. After replacement with the density of registered geological hazard sites, the weight returned to 0.0870 and the zonal gradient re-emerged. The replacement decision was therefore empirically justified rather than cosmetic.

The three checks address different sources of uncertainty: the first concerns the weighting algorithm, the second the benchmark against which weights are interpreted, and the third the construction of the indicator set itself. Taken together, they indicate that the main conclusions, namely the zonal gradient from the Chengdu Plain through Panxi to Northwest Sichuan, the composition of the 22-county high-vulnerability list, and the obstacle-degree diagnosis, are robust to alternative weighting schemes and to the specification of the hazard indicator. Residual uncertainty attaches mainly to data caliber rather than to method, and is discussed with other limitations in Section 5.

5. Conclusions

5.1. Interpretation in the Context of Prior Work

The dominant role of population-structure and natural-background factors is broadly consistent with county-level evidence at the national scale. Yang and Pan [7] identified two types of high-vulnerability counties in China: alpine ecological counties constrained by harsh environments, and densely populated agricultural counties under acute population-land tension. Both pathways appear in the Sichuan transition zone. However, our county-level obstacle diagnosis reveals a more specific pattern than this national typology: the plateau group is not simply "high-exposure, low-capacity" but is jointly locked by ethnic composition and high-cold altitude, while the plain group is not simply "high-sensitivity" but is dominated by a single population-density obstacle that can reach 45.2\%45.2%. The transition zone therefore compresses the two national pathways into one region, but the obstacle structure within each pathway differs from what the national-scale typology alone would predict. This difference suggests that county-level factor diagnosis adds information that national-scale mapping cannot provide.

The county-level obstacle structure also mirrors household-level evidence from Liangshan and the Western Sichuan ethnic areas. Field surveys in these areas repeatedly identify a profile of low income, low education, low livelihood diversification, and heavy dependence on a single farming or pastoral livelihood as the core of household vulnerability [3,37,58]. Our diagnosis at the county scale converges on the same structure from the opposite direction of aggregation: the ethnic minority share ranked first among obstacle factors both region-wide (16.52%) and in Panxi and Northwest Sichuan (22.10% and 30.22%), and rural per capita income entered the top five obstacles in all three zones. The convergence of the two scales suggests that the county-level indicators do not merely proxy administrative conditions but capture the aggregate expression of livelihood constraints that household surveys observe directly. Cao et al. [37] showed with hierarchical models that village context and household assets jointly determine poverty vulnerability in Liangshan; our results are consistent with that two-level reading, in that counties where ethnic composition and altitude jointly constrain livelihoods are precisely those where household adaptive capacity is lowest.

The counterpoint of Pingwu and Beichuan counties qualifies the role of hazard exposure. Although both counties lay in the epicentral area of the 2008 Wenchuan earthquake, they ranked only at the relatively low vulnerability level, a position that can be partly

explained by low population density and high forest coverage. Hazard exposure converted into high vulnerability mainly where it overlaid a sensitive population–industry structure, as in Maoxian County, where an ethnic-share obstacle of 32.0% combined with a hazard-site density obstacle of 14.7%. This finding echoes relocation and migration studies in western mountain areas, which show that post-disaster outcomes depend on livelihood structure rather than on hazard intensity alone, and that relocated households can end up more vulnerable than before if livelihood reconstruction fails [48]. Exposure is therefore best read as a necessary but not sufficient condition of high vulnerability in this region.

The county-group gradient from the Chengdu Plain through Panxi to Northwest Sichuan extends prior county-level rural vulnerability work, which has focused on single provinces or plains regions, such as the 117-county analysis of Heilongjiang [39]. Where that work examined spatial–temporal patterns within a largely homogeneous agricultural setting, the present design compared three economic zones that together span a full basin–mountain–plateau transition. The result that exposure exhibited the steepest zonal contrast (EI from 0.0533 to 0.1259) while sensitivity remained nearly level across zones (SI from 0.1824 to 0.1891) could only emerge from a cross-gradient sample, and it indicates that the spatial pattern of vulnerability in transition zones is governed primarily by the exposure gradient and amplified by the adaptive capacity gap. The three-type typology adds a further layer to this comparison. Prior county-level studies typically rank counties and map clusters; the obstacle-degree diagnosis here shows that a common outcome, high vulnerability, was produced by at least three distinct factor combinations. Typology-based differentiation is therefore not a descriptive convenience but a precondition for effective intervention, because measures that relax the binding constraint of one type leave the constraints of the other two untouched.

Finally, the low weight of the adaptive capacity dimension (0.0953) requires a careful reading. Because the entropy method weights indicators by their dispersion across counties, the low weight indicates that fiscal self-sufficiency, rural income, and public service provision were uniformly weak and varied little among the 90 counties, not that capacity is unimportant. The fiscal self-sufficiency rate, with the lowest single weight (0.0100) and the lowest obstacle degree (2.33%), was low in nearly every county. Inadequate adaptive capacity is therefore a common deficiency of the whole region rather than a factor that differentiates counties. The practical implication is that capacity building is a universal task in the transition zone: it will not reorder the vulnerability ranking by itself, but no county can reduce vulnerability durably without it. This distinction between differentiating factors and common deficiencies matters for how assessment results are used. Differentiating factors identify where to target zone-specific measures, whereas common deficiencies define the baseline investments that every county requires regardless of rank. Confusing the two would lead either to neglect of fiscal and income support, because it does not move the ranking, or to indiscriminate equalization programs that ignore the exposure and sensitivity structures that actually separate counties.

5.2. Policy Implications

The three vulnerability types identified in Section 4.4 point to zone-specific adaptation strategies, and the obstacle diagnosis supplies the specific targets within each zone.

In the Northwest Sichuan Ecological Demonstration Zone, where 22 of 31 counties reached the relatively high or high vulnerability level and the paired obstacles of ethnic composition (30.22%) and county-seat altitude (18.91%) dominate, policy should focus on cultivating ecological-compensation-based fiscal capacity and sustainable livelihoods. The creation of Zoige National Park and the grassland ecological subsidy and reward mechanism offer institutional channels through which the principle that protectors benefit can be formalized and converted into a stable autonomous revenue source for counties

that currently depend almost entirely on transfer payments. On the industry side, improving the quality and efficiency of the yak and Tibetan sheep industries, through breeding, forage supply, and processing, addresses the dependence on a single pastoral livelihood that household-level studies identify as the core livelihood risk [3,58]. These measures together aim to break the lock-in between alpine sensitivity and adaptive deficit that characterizes the alpine ecological–ethnic compound type.

In the Panxi Economic Zone, where seismic exposure is prominent, agricultural dependence is high, and six counties fall in the high-vulnerability level, policy should combine disaster prevention engineering with industrial diversification. Registered geological hazard sites should be monitored and treated at higher density, and households on high-risk sites should be relocated with attention to livelihood reconstruction, since relocation without follow-up support can leave households more vulnerable than before [48]. Extending specialty agriculture and clean-energy value chains can buffer the local economy against disturbances and reduce the share of primary industry, which ranked fifth among Panxi obstacle factors (6.46%). For the mountain poverty–sensitivity compound counties of Liangshan, where adaptive capacity indices fell below 0.01 in Butuo, Meigu, and Puge, remediation of income and public service deficits is the binding constraint and should take precedence.

In the Chengdu Plain Economic Zone, where vulnerability stems mainly from a high-density sensitivity structure, with population density (18.14%), aging (16.16%), and rural population size (13.14%) as the leading obstacles, policy should optimize the spatial layout of settlements and the allocation of public services. Population and industry should be guided to concentrate in an orderly way in key towns away from geological hazard zones, and medical and elderly-care resources should be allocated according to the resident population rather than the registered population, in response to the aging pressure that ranks second among the zone's obstacles. These adjustments also serve the construction of the higher-level Tianfu granary, for which the plain counties are the core carriers, by easing the population–land tension that the sensitivity indicators register.

Three cross-cutting considerations apply. First, the zonal strategies should be coordinated with the policy of linking consolidated poverty-alleviation achievements with rural revitalization, because most high-vulnerability counties are national or provincial key rural revitalization assistance counties in which industry and talent remain the weakest links. Second, the three strategies are complementary rather than substitutable: ecological compensation in Northwest Sichuan, hazard engineering in Panxi, and settlement optimization on the plain each address a different binding constraint, and a uniform regional program would mistarget most counties. Third, the vulnerability dimension should be incorporated into Sichuan's ecological civilization evaluation, so that ecological barrier building and green rural revitalization reinforce each other instead of being assessed as separate agendas. Given that inadequate adaptive capacity is a region-wide condition, capacity-building investments in fiscal strength, income, and public services should run through all three strategies as a common foundation rather than as a zone-specific measure.

5.3. Limitations and Future Research

Four limitations qualify the results, and each defines a direction for future work.

First, the assessment rests on a single-year cross-section, mainly 2023 statistical yearbook data supplemented by the seventh population census. A cross-section can locate vulnerability in space but cannot capture its trajectory, so the results say nothing about whether the zonal gap is narrowing or widening. Future work should construct a multi-period county panel, analyze the dynamics of the three dimensions separately, and conduct scenario simulation to test how vulnerability responds to policy or climate shocks.

Second, the county scale cannot reveal livelihood differences among households within a county. The convergence between our obstacle structure and household-survey findings in the same region [37,58] is suggestive, but it is not a validation. Household micro-surveys in representative counties of each vulnerability type would allow two-scale cross-validation and would clarify which county-level conditions transmit to household-level outcomes.

Third, all 16 indicators derive from official statistics, which constrains both precision and timeliness; statistical yearbooks appear with a lag, and county-level reporting quality varies. Introducing spatialized indicators, such as the Normalized Difference Vegetation Index (NDVI) for ecological background and nighttime light data for economic activity, would improve spatial precision and permit more frequent updating between census rounds.

Fourth, caliber differences remain among data sources. The density of registered geological hazard sites, in particular, depends on the disclosure calibers of different prefectures, and indicators drawn from county statistical communiques are not fully standardized. Once statistical calibers are unified, a consistency re-check of the affected indicators should be conducted to strengthen inter-county comparability. These limitations concern data rather than method; the robustness checks in Section 4.5 indicate that the main conclusions are stable under alternative weighting and indicator specifications.

6. Conclusions

(1) The 3×3 matrix framework and the 16-indicator system proved feasible for county-scale vulnerability assessment. Crossing the three dimensions of exposure, sensitivity, and adaptive capacity with the three elements of people, land, and industry aligned the conceptual structure of vulnerability with the element structure of the rural territorial system, so that each matrix cell corresponds to a class of observable assessment content. The entropy weights revealed a strongly uneven dimensional structure: sensitivity ranked first at 0.6103, exposure followed at 0.2945, and adaptive capacity accounted for only 0.0953. The four largest indicator weights were population density (0.1890), the proportion of ethnic minority population (0.1393), rural population size (0.1214), and the altitude of the county seat (0.1157). Adaptive capacity was uniformly weak across the 90 counties, so capacity deficiency is a universal condition of the region rather than a factor that differentiates counties; vulnerability differentiation was driven mainly by population structure and natural background. The framework design therefore matches the dominant structure of regional differentiation.

(2) Vulnerability rose significantly along the basin–mountain–plateau gradient. The mean VI of the 90 counties was 0.2400; the Northwest Sichuan Ecological Demonstration Zone averaged 0.2887, the Panxi Economic Zone 0.2704, and the Chengdu Plain Economic Zone 0.1878. Exposure exhibited the steepest zonal gradient (0.1259, 0.1069, and 0.0533, respectively); sensitivity was nearly equal across zones but differed in composition; and adaptive capacity on the Chengdu Plain was about twice that of the other two zones. Under the Jenks five-level classification, counties at the high and relatively high levels accounted for 71.0% of Northwest Sichuan and 63.2% of Panxi, but only 15.0% of the Chengdu Plain. Of the 22 high-vulnerability counties, 15 lay in Northwest Sichuan and 6 in Panxi, and Guanghan City was the only high-vulnerability county on the plain.

(3) Three causal types of vulnerability can be distinguished. The alpine ecological–ethnic compound type, represented by Litang and Shiqu counties, is jointly locked by ethnic composition and high-cold altitude. The mountain poverty–sensitivity compound type, represented by Butuo, Zhaojue, and Meigu counties, combines high sensitivity with severely inadequate adaptive capacity, so that the two deficits reinforce each other. The plain high-density sensitivity type, represented by Guanghan City, is dominated by a

single population-density obstacle of 45.2%. At the regional scale, the leading obstacle factors were the proportion of ethnic minority population (16.52%), the altitude of the county seat (9.93%), and the proportion of population aged 65 and above (9.31%), indicating that population structure and natural background constitute the most widespread vulnerability-generating mechanism. This pattern is consistent with national-scale findings that high rural vulnerability concentrates in both alpine ecological counties and densely populated agricultural counties [7], and with evaluations of key rural-revitalization assistance counties that identify industry and talent as the weakest links.

(4) The assessment results are robust. Re-weighting the indicators with the coefficient-of-variation method produced a VI ranking whose Spearman rank correlation with the entropy-weight ranking reached 0.9041; the zonal gradient was identical in ordering, and 7 of the top-10 high-vulnerability counties were shared between the two weighting schemes. Replacing the disaster-frequency indicator with the density of registered geological hazard sites restored a normal weight and re-established the zonal gradient, which verifies the validity of the indicator replacement. The main conclusions therefore do not depend on a specific weighting scheme.

The central message of this study is that the 3×3 matrix framework converts a regional vulnerability map into county-specific factor diagnoses, thereby supporting differentiated adaptation strategies for green rural revitalization in the ecological transition zone.

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