International Journal of Geo-Information

Article

Socio-Ecological Vulnerability in Aba Prefecture, Western Sichuan Plateau: Evaluation, Driving Forces and Scenario Simulation

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Abstract: With the social and economic development in recent years, human activities have been more extensive and intensified. As a result, ecosystems are damaged to varying degrees, and regional ecological environments tend to be weaker. The socio-ecological system in Aba Prefecture, Western Sichuan Plateau, China, the researched area, also faces increasingly serious problems. To advance ecological civilization development in a coordinated way across the country, the national government and the competent authorities have launched a series of new strategies. Research on socio-ecological vulnerability, a major part of the ecosystem protection and restoration program, is provided with powerful spatial data observation and analysis tools thanks to the invention and development of remote sensing and geographic information system technologies. This study was based on the vulnerability scoping diagram (VSD) framework. Multi-source data such as digital elevation model (DEM), geographical data such as land use types, soil and geological disasters, remote sensing image data, meteorological data and social statistics data from 2005 to 2019 were used to construct the temporal social-ecosystem vulnerability evaluation index database of Aba Prefecture, Western Sichuan Plateau. The spatial principal component analysis (SPCA) is applied to evaluating the socio-ecological vulnerability and analyzing its spatial-temporal variation in Aba Prefecture, Western Sichuan Plateau. To probe into the driving effects of various impact factors on the socio-ecological vulnerability, the Geodetector is used to analyze the driving factors. The ordered weighted average (OWA) method is applied to the multi-scenario analysis of socio-ecological vulnerability in the researched area. The conclusions of this study are as follows: (1) from 2005 to 2019, the spatial distribution characteristics of exposure and sensitivity in Aba Prefecture were higher in the southeast and lower in the northwest, and the overall spatial distribution characteristics of socio-ecological system vulnerability showed that the degree of vulnerability increased from the north to the southeast. (2) Extreme natural climate conditions play a leading role in the driving of socio-ecosystem vulnerability, followed by human production activities and geological hazards. (3) The degree of social-ecosystem vulnerability in Aba Prefecture will increase with the increase of decision risk coefficient. The results of social-ecosystem vulnerability under the status quo scenario are similar to those in 2010 and 2019, indicating that the selected evaluation factors can reflect the actual social-ecosystem vulnerability. In the sustainable guided scenario and the unsustainable guided scenario, the proportion of the area of the social-ecosystem severe vulnerability level was at the minimum value and the maximum value, respectively.

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Citation: Yang, X.; Dai, X.; Li, W.; Lu, H.; Liu, C.; Li, N.; Yang, Z.; He, Y.; Li, W.; Fu, X.; et al. Socio-Ecological Vulnerability in Aba Prefecture, Western Sichuan Plateau: Evaluation, Driving Forces and Scenario Simulation. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 524. https://doi.org/10.3390/ijgi11100524

Academic Editor: Wolfgang Kainz

Received: 27 July 2022
Accepted: 14 October 2022
Published: 17 October 2022

Keywords: spatial analysis; socio-ecological system vulnerability; vulnerability scoping diagram framework; geodetector; scenario simulation; Aba Prefecture

1. Introduction

With the social and economic development in recent years, human activities have been more extensive and intensified. As a result, ecosystems are damaged to varying degrees, and regional ecological environments tend to be weaker. The socio-ecological system in Aba Prefecture, Western Sichuan Plateau, also faces increasingly serious problems. Research on socio-ecological vulnerability are a major part of the ecosystem protection and restoration program. Thanks to the invention and development of remote sensing and geographic information system technologies, powerful data observation and analysis tools are available for high-precision and large-scale socio-ecological vulnerability research with high spatial-temporal resolution.

Since the beginning of the 21st century, scholars across the globe have been probing into the man–earth interaction and its combined impact on socio-ecological systems from perspectives of environmental science, geographical science and ecology, and with population, resources, environment, society and economy as the main evaluation factors [1–6]. Their research could be a scientific basis for ecological resource protection and reasonable economic development in local places. Many scientific research institutions have carried out scientific research on this issue. They often use multi-source datasets on physical geography and humanistic society with an impact on socio-ecological vulnerability as the evaluation factors to build socio-ecological vulnerability evaluation models applicable to the researched areas, thus evaluating the contribution of individual factors to socio-ecological vulnerability [7–11].

At present, the research on socio-ecosystem vulnerability is rich and diverse, and the research fields tend to be global, diverse and novel. Mafi-Gholami, et al., employed Fuzzy Approaches to evaluating the socio-ecological vulnerability in the Persian Gulf and the mangrove forest in the northern bay, the Gulf of Oman, in order to provide key index data for making living conditions management strategies and adaptation plans [12]. Chang et al., established a framework of socio-ecological-technological vulnerability to evaluate the ecological vulnerability to floods in six American cities, providing decision-making support for mitigating risks [13]. Wu et al., carried out large-scale remote-sensing research on the ecological vulnerability index in areas along the China–Pakistan Economic Corridor [14]. They analyzed the spatial-temporal variation in such vulnerability and its impact factors, providing key decision-making support for ecological, environmental protection and economic development. Jiang et al., used grid-level prototype models to build a framework simulating the ecological vulnerability in the Bangladesh–China–India–Myanmar Economic Corridor for spatial recognition and spatial-temporal analysis [15,16]. In China, the focus is still on the evaluation of ecological vulnerability in the upper reaches of the Minjiang River [17], the analysis of spatial-temporal change and pattern of ecological vulnerability in the Qinghai–Tibet Plateau [18,19], the evaluation of management measures to the ecological environment vulnerability in urban wetlands [20,21], etc. From a socio-ecological perspective, Shi et al., followed the principle of "collaborative tolerance, collaborative constraint, collaborative amplification and collaborative diversification" to elaborate on the resisting mechanisms of ecosystems to risks [22]. Geng et al., analyzed and studied the evolution features of the resilience of socio-ecologically-productive landscapes in areas along the main stream of the Yellow River within Henan Province, based on which they provided decision-making support for social production and ecological environment governance and defense in areas along the Yellow River, facilitating the improvement of ecological environment, economic development and human life [23]. In terms of models and frameworks for socio-ecological vulnerability evaluation, different researchers have different research perspectives and follow different screening standards for index

factors, thus building vulnerability evaluation models and frameworks based on different index systems [24–27]. At present, the mainstream frameworks for socio-ecological vulnerability research are: vulnerability scoping diagram (VSD) [28–33], press state response (PSR) [15,27,34–38], pressure conduction potential (PCP), driving force pressure state influence response management (DPSIRM) [10,39,40], etc. Given the different features, purposes and requirements for different researched areas, different models could be chosen to build applicable index systems.

The multi-scenario simulation of socio-ecological vulnerability is a research method by which the best-matched scenario is identified based on the different levels of impact of different evaluation indexes on vulnerability (the different levels of impact would lead to a difference in social and ecological risks in different development scenarios) [41,42]. A large number of scholars have carried out much research in urban spatial planning, infrastructure support, regional energy application, and urban disaster prevention [35,43–47]. The multi-scenario simulation research method has been widely applied to various research fields and researched areas. The researched areas are mostly places prioritized in national policies [48], yet there are only a few studies on plateaus and mountainous areas, especially in the Western Sichuan Plateau, China. This plateau is an important part of the "two screens and three belts" national ecological security strategic pattern of China, and Aba Prefecture on the plateau is an autonomous prefecture for ethnic minorities. Thus this place has its unique cultural and regional features. Under the national poverty alleviation and rural revitalization strategies, understanding the variation in socio-ecological vulnerability in different scenarios in this place could assist it in cultural and ecological environmental governance, in creating a pleasant living environment, which is the basic requirement under the rural revitalization strategy, and in making further progress in rural revitalization in an all-round way [5,49–51].

Although research across the globe is paying increasing attention to socio-ecological vulnerability, problems such as the lack of clearly-defined concepts and analysis frameworks remain unsolved [52]; most existing research is focused on the impact of climate [53–58], natural disasters and other natural factors on ecosystems [12,18,24,59–62], as well as social vulnerability. There is a lack of combined research on social-ecological systems, especially on vulnerability caused by human factors like urbanization, tourism development, environment pollution and public security. Therefore, efforts should be made to define the concept of socio-ecological vulnerability, build certain analysis frameworks for the impact of core factors, especially human factors, and carry out research on socio-ecological systems, thus obtaining research findings in socio-ecological vulnerability on multiple scales and under the impact of various factors.

The study area of this paper is located in the western Sichuan Plateau. Given its abundant natural resources, frequent geological hazards [63], extreme climate [64], and human activities intensified by tourism development, the VSD could better reflect the impact of natural factors (especially climatic factors) and human factors on the socio-ecological system [65]. Given that, in this paper, the VSD is selected to build the index system reflecting factors impacting the socio-ecological vulnerability in Aba Prefecture and study the long-time-series vulnerability variation. To probe into the driving force of various impact factors on the socio-ecological vulnerability in the Aba Prefecture, the ordered weighted average (OWA) method is used to carry out the multi-scenario simulation of the socio-ecological vulnerability in the researched area.

2. Data Sources

2.1. Overview of Study Area

Within the researched area are three main mountains: the Minshan Mountains in the northeast, the Longmen Mountains in the southeast, and the Qionglai Mountains in the south. The area is on the Mulangsi Town and Longmenshan fault zones, which is the main reason for the frequent earthquakes here. Situated on the Western Sichuan Plateau, this prefecture is home to numerous high mountains and steep gorges, with an average

elevation of 3500–4000 m. In its south, mountains are towering and precipitous, and in its north, there are low hills. The large elevation drop gives rise to numerous river valleys in this prefecture, and these are where people gather and ecologically vulnerable areas are located. This prefecture has a diverse landform, covering flatland, mesa, hilly country and highland, offering various types of landscape. The location of the study area is shown in Figure 1.

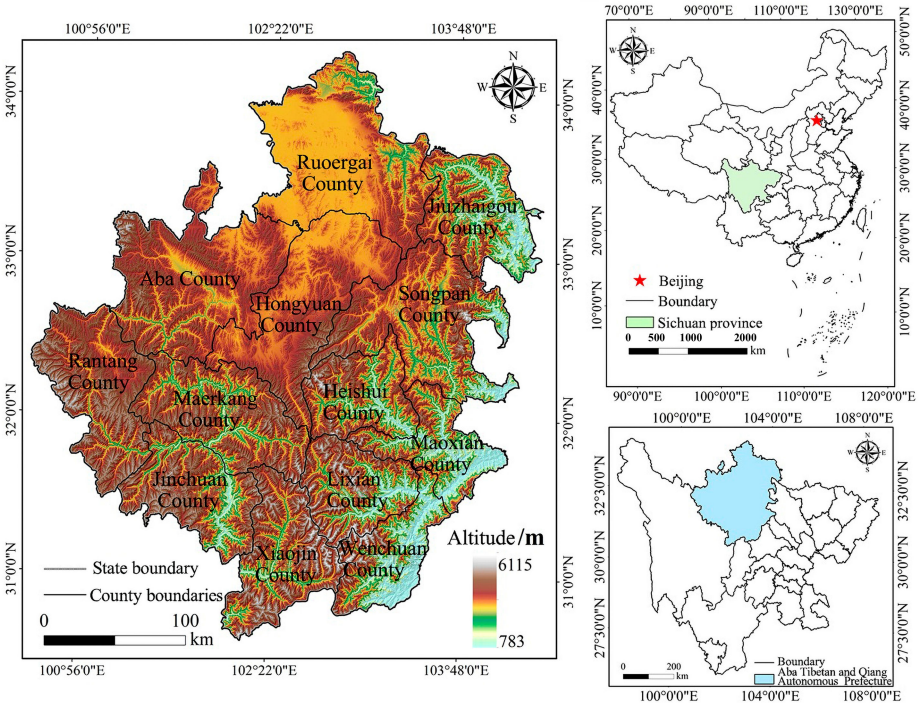


Figure 1. Map of the researched area.

2.2. Data Sources

In this study, the indexes of natural climate, terrain elevation, vegetation cover, land use and human society were selected. Data sources, types and resolutions are detailed in Table 1. Because of the different data sources, to ensure the accuracy of research data, projection transformation and resampling are made to pretreat all data. The spatial resolutions are coordinated to be 30 × 30 m, and spatial reference: CGCS2000_3_Degree_CK_CM_102E.

Table 1. Data sources.

Item	Type	Spatial Resolution	Time	Source
DEM	Raster	30m	/	Geospatial Data Cloud (http://www.gscloud.cn, accessed on 10 January 2021)
Administrative division	Vector	/	2019	Resource and Environment Science and Data Center, Chinese Academy of Sciences (http://www.resdc.cn, accessed on 10 January 2021)
Landform	Raster	30 m	2019	National Geomatics Center of China (http://www.globallandcover.com, accessed on 10 January 2021)
Geological hazard location	/	/	2005–2019	Sichuan Research Institute for Ecological Restoration of Territorial Space and Geological hazard Prevention and Control

Table 1. *Cont.*

Item	Type	Spatial Resolution	Time	Source
Soil erodibility factor	Raster	30 m	/	National Science and Technology Infrastructure—National Earth System Science Data Center (http://www.geodata.cn, accessed on 10 January 2021)
Daily precipitation and temperature	/	/	2000–2019	National Meteorological Science Data Center(http://data.cma.cn, accessed on 15 January 2021)
Vegetation coverage	Raster	250 m	2005–2019	Resource and Environment Science and Data Center, Chinese Academy of Sciences (http://www.resdc.cn, accessed on 15 January 2021)
Socioeconomic statistics	/	/	2005–2019	Statistics Bureau of Aba Tibetan and Qiang Autonomous Prefecture(http://tjj.abazhou.gov.cn, accessed on 10 January 2021)

3. Methods

The technical roadmap of this paper is shown in Figure 2. Based on multi-source data such as remote sensing, geographical, meteorological and statistical data, the VSD framework was used to establish a time-series social-ecosystem vulnerability evaluation database in Aba Prefecture of Western Sichuan Plateau. The vulnerability evaluation results are obtained by SPCA, and spatio-temporal variation characteristics are analyzed from various aspects, perspectives and methods. Based on the vulnerability analysis results, we used the Geodetector to analyze the driving force of impact factors and study how index factors impact the socio-ecological vulnerability in the researched area and the spatial distribution features in a quantitative way. The OWA method is used to build multiple scenarios to simulate the socio-ecological vulnerability in the researched area.

3.1. VSD Framework and Evaluation Indexes

The VSD extracts index factors on exposure, sensitivity and adaptability of ecosystems and builds evaluation index systems, ensuring a clear hierarchy in the socio-ecological vulnerability evaluation for the researched area and a progressive evaluation process. Exposure reflects the level of stress or impact on natural ecosystems by external factors. Sensitivity is the level of human society and natural ecosystems being disturbed and impacted by the change in the external environment. Adaptability is the ability of the natural ecosystem in the researched area to adapt to, resist and recover from negative impacts [66].

3.1.1. Exposure Indexes

The exposure sources of Aba Prefecture are mainly reflected in the socio-ecological system under the influence of environmental changes, which are reflected in geological disasters, extreme climate and human activities, etc. The main evaluation indicators include geological disaster density, population density, extreme climate index, etc. The World Meteorological Organization has defined 27 extreme climate indexes, including 16 temperature indexes and 11 precipitation indexes [62]. Considering the data representativeness and completeness of all meteorological stations in Aba Prefecture, the researched area, we have selected six index factors for an extreme climate to analyze the extreme climate features in the area, and chosen 3 of those indexes based on the significance test results as the evaluation factors for follow-up vulnerability research in the researched area. The extraction results of all the index factors are shown in Figure 3. Given the significant test results of the said six extreme climate evaluation factors (SU25: the number of days in which the daily maximum temperature is >25 °C in the year, FD0: the number of days

in which the daily minimum temperature is <0 °C in the year, TXx: monthly maximum of daily maximum temperature in each month of the year, TNx: monthly maximum of daily minimum temperature in each month of the year, TXn: monthly minimum of daily maximum temperature in each month of the year and TNn: monthly minimum of daily minimum temperature for each month of the year), three indexes (SU25 (A5), FD0 (A6), TNx (A7)) are selected as the follow-up evaluation factors for socio-ecological vulnerability in Aba Prefecture. Table 2 shows the calculation method of exposure indexes.

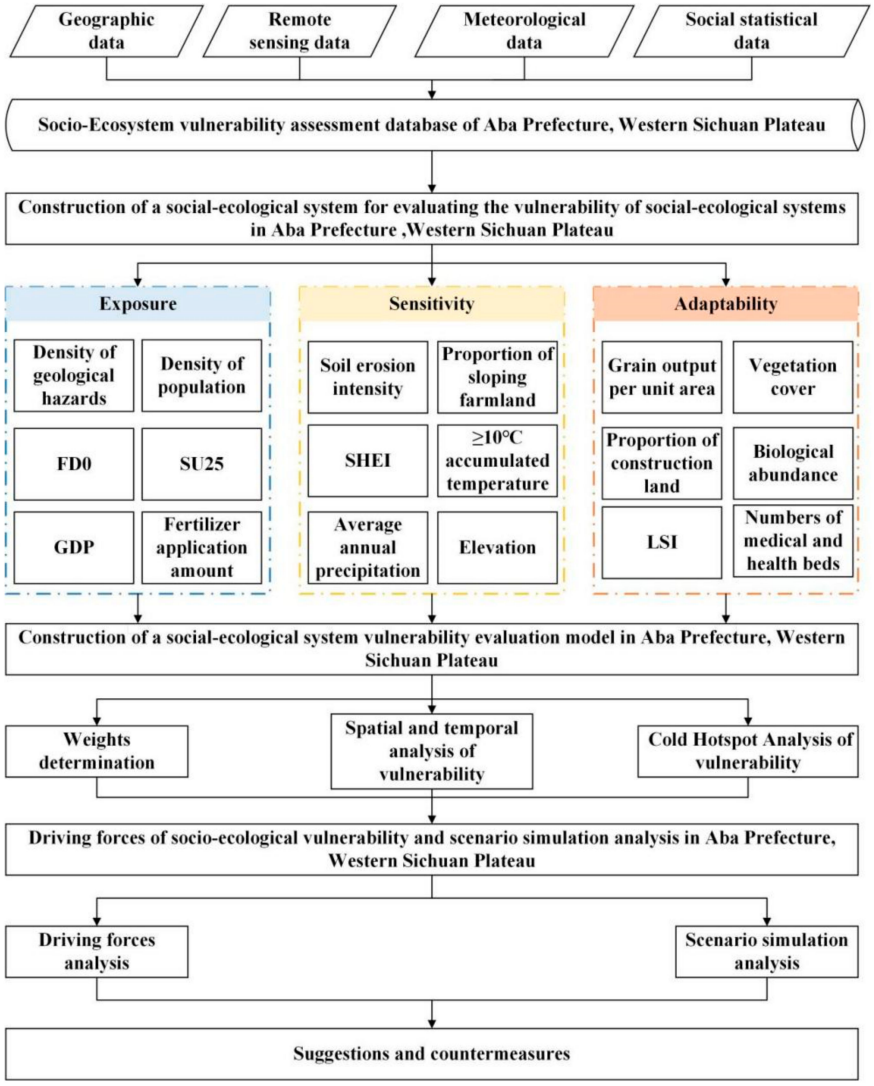


Figure 2. Research technology roadmap.

3.1.2. Sensitivity Indexes

The sensitivity of the study area is mainly reflected in natural resources, topography, climate and other conditions, which can be reflected by the proportion of sloping farmland, landscape pattern index, elevation, slope, conventional meteorological conditions, etc. Table 3 shows the calculation method of sensitivity indexes.

3.1.3. Adaptability Indexes

The adaptive capacity is reflected in the response made by the socio-ecological system under the influence of environmental change, which can be reflected by the level of social and economic development, education level and medical and health security, such as vegetation cover, grain yield per unit area, construction land proportion, and the

number of beds in medical and health institutions. Table 4 shows the calculation method of adaptability indexes.

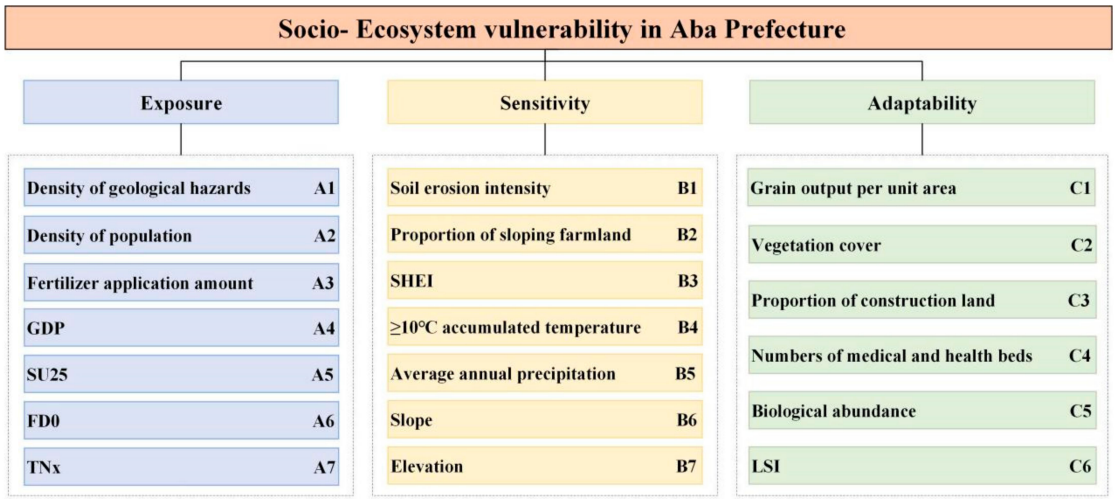


Figure 3. Index system for socio-ecological vulnerability evaluation.

Table 2. Calculation method of exposure indexes.

Exposure Indexes	
Name of Index	**Calculation Method**
Density of geological hazards (A1)	Based on the statistical data of geological disaster points in Aba Prefecture over the years, the density of geological disasters per unit area was obtained by using ArcGIS kernel density tool
Density of population (A2)	A2 = N/S, where N is the total population at the end of the year, S is the land area of the administrative region
Fertilizer application amount (A3)	A3 = Q/T, where Q is the amount of fertilizer applied, and T is the actual cultivated land area at the end of the year
Per capita gross domestic product (A4)	A4 = P/N, where P is gross domestic product, N is total population
Extreme climate index (A5, A6 and A7)	In this study, SU25 (A5), FD0 (A6), and TNx (A7) were selected as the subsequent assessment indexes of socio-ecological vulnerability based on the significance detection results of extreme climate assessment indicators

Table 3. Calculation method of sensitivity indexes.

Sensitivity Indexes	
Name of Index	**Calculation Method**
Soil erosion intensity (B1)	$B1 = R * K * L * S * F$, where $B1$ is soil erosion intensity, R is rainfall factor, K is soil erodibility factor, L is slope length factor, S is slope factor, and F is vegetation coverage.
Proportion of sloping farmland (B2)	B2 = S1/S2, S1 is the area of sloping farmland greater than 15°, S2 is the total area of cultivated land in the region
Shannon's Evenness Index, SHEI (B3)	$SHEI = \frac{-\sum_{i=1}^{m}(P_i \ln P_i)}{\ln m}$, where Pi is the proportion of landscape occupied by patch type (category) i, m is the number of patches in the landscape type, and the range is $0 \leq \text{SHEI} \leq 1$
The accumulated temperature is greater than or equal to 10 degrees (B4)	Based on the temperature data of the study area, interpolation in the ArcGIS
Average annual precipitation (B5)	Based on meteorological station data in the study area, interpolation in the ArcGIS
Topographical factor (B6 and B7)	Generated based on DEM data in the study area

Table 4. Calculation method of adaptability indexes.

Adaptability Indexes	
Name of Index	**Calculation Method**
Grain output per unit area (C1)	$C1 = N/S$, where N is the total grain output of the region, and S is the area of cultivated land at the end of the year
Fractional vegetation cover, FVC (C2)	$C2 = (NDVI - NDVI_{soil})/(NDVI_{veg} - NDVI_{soil})$, where $NDVI_{soil}$ is the $NDVI$ value of raster cells with uncovered vegetation. $NDVI_{veg}$ is the $NDVI$ value of raster cells completely covered with vegetation
The proportion of construction land (C3)	$C3 = S1/S2$, where $S1$ is the construction land area of the township, $S2$ is the total area of the township
Number of beds in medical and health institutions per 1000 people (C4)	Based on the statistics of medical and health institutions in the study area, interpolation in the ArcGIS
Biological abundance index (C5)	$C5 = \begin{pmatrix} 0.35 \times A_{forest} + 0.21 \times A_{grassland} + 0.28 \times A_{water} \\ +0.11 \times A_{plough} + 0.04 \times A_{build} + 0.01 \times A_{unuesd} \end{pmatrix} / A$, where A is the total area of the township area, A_{forest} is the area of woodland, $A_{grassland}$ is the area of grassland, A_{water} is the area of water, A_{plough} is the area of cultivated land, A_{build} is the area of building land and A_{unused} is the area of unused land
Landscape shapei, LSI (C6)	$LSI = \frac{0.25E}{\sqrt{A}}$, where E is the total length of all patch boundaries in the landscape, and A is the total landscape area

3.2. Evaluation Indexes Weight Assignment

3.2.1. Normalization of Evaluation Indexes

To remove the dimensional effect among evaluation indexes and ensure the accuracy of index weight assigned in the following steps, all the indexes are normalized. Among them, indexes with whose increase the socio-ecological vulnerability worsens are defined as positive indexes, and indexes with whose increase the socio-ecological vulnerability improves are determined as negative indexes.

Formula for positive index normalization:

$$Z_{ij} = \frac{X_{ij} - Min(X_j)}{Max(X_j) - Min(X_j)} \tag{1}$$

Formula for negative index normalization:

$$Z_{ij} = \frac{Max(X_j) - X_{ij}}{Max(X_j) - Min(X_j)} \tag{2}$$

where, Z_{ij} is the normalized result ($0 \leq Z_{ij} \geq 1$), X_{ij} is the original data, and i and j are the ordinal number of years and indexes, respectively.

3.2.2. Indexes Weight Assignment

In natural and human ecosystems, different indexes have different impacts on society and the ecosystem, and their contribution degrees are also different. Therefore, the weight should be used to objectively reflect the vulnerability of each index relative to the study area. The method of spatial principal component analysis (SPCA) is objective, uses less data processing and is more comprehensive. Therefore, The SPCA method was used to complete the weight assignment of vulnerability assessment indexes. The basic idea of SPCA is to replace many original N influencing factors with a few comprehensive factors, that is, assuming that the initial evaluation index ($X1, X2, \ldots, Xp$) and the comprehensive index can be obtained by the linear combination of multiple groups of variables to replace the original evaluation index.

In this paper, the weight of each index assignment mainly uses the SPCA of ArcGIS software tool. The operating principle of the tool is to convert the data in the input band into a new multivariate attribute space that rotates the axis relative to the original space, elimi-

nates the data redundancy to achieve the effect of data dimensionality reduction, and multiple variables are transformed into principal component factors for index weight assignment.

3.3. Vulnerability Index Model

The vulnerability index represents the specific vulnerability level of socio-ecological system in the researched area. In this research, the Synthetical Index Method is used to calculate the socio-ecological vulnerability index in Aba Prefecture, the researched area. The calculation formula is:

$$EI = \sum_{i=1}^{n} W_i \times X_i \tag{3}$$

where EI is the index of exposure, i is the number of exposure indexes, and X_i and W_i are the values and weights of the indexes, respectively.

$$SI = \sum_{j=1}^{n} W_j \times Y_j \tag{4}$$

where SI is the index of sensitivity, j is the number of sensitivity indexes, Y_j is the value of sensitivity indexes, and W_i is the weight of sensitivity indexes.

$$ACI = \sum_{k=1}^{n} W_k \times Z_k \tag{5}$$

where ACI is the index of adaptability, k is the number of adaptability indexes, Z_k stands for the value of adaptability indexes and W_i represents the weight of adaptability indexes.

The socio-ecological vulnerability index (SVI) is calculated as follows in Formula (6).

$$SVI = EI + SI - ACI \tag{6}$$

3.4. Geodetector

Geodetector can test the spatial differentiation of univariate and also detect the possible causal relationship between two variables by testing the coupling of the spatial distribution of two variables. In the research, the factor detector and interactive detector are employed to analyze the socio-ecological vulnerability and its spatial change rules under the impact factors during the 2005–2019 periods in Aba Prefecture. Among them, the factor detector could evaluate the contribution of certain impact factors to the socio-ecological vulnerability [67]. See Formula (7).

$$Q_{D,H} = 1 - \frac{1}{N\sigma^2} \sum_{h-1}^{L} N_h \sigma_h^2 \tag{7}$$

where D is a certain impact factor, H represents the socio-ecological vulnerability index, and Q stands for the contribution by certain impact factors to socio-ecological vulnerability, with a value range of [0, 1]. N and σ^2 are the sample size and its variance, respectively. h is the number of sample layers, and L is the number of types of impact factors. The higher the value of Q is, the greater its contribution to socio-ecological vulnerability is.

3.5. Scenario Simulation

3.5.1. Ordered Weighted Average Method

In this paper, the OWA method is adopted for the scenario simulation of the socio-ecological vulnerability in the Aba Prefecture to explore the development trend of such vulnerability in different scenarios and provide a decision-making basis for ecological environment protection. The OWA was first proposed by Yager, et al., which ranks each evaluation factor according to its importance [68,69]. Factors at different order places have different order weights, and the layers are overlaid when factors have the same weight.

At present, multiple OWA weight determination methods have been developed, among which the monotone increasing rule is the easiest one to understand and work with, and the order weight could be expressed as:

$$w_i = Q_{RIM}\left(\frac{i}{m}\right) - Q_{RIM}\left(\frac{i-1}{m}\right), \quad i = 1, 2, \ldots, m \tag{8}$$

$$Q_{RIM}(c) = c^a \tag{9}$$

where, i is the evaluation order, w_i stands for order weights, and m is the total number of evaluation factors. c is the independent variable, and a is the risk factor. When $a = 1$, the weights at all places are equal, meaning the vulnerability prefers no individual factor. When $a < 1$, the more important the factor is, the higher its order weight is, and the evaluator is negative and pessimistic about vulnerability.

3.5.2. Scenario Indicator Setting

To ensure the effectiveness and simplicity of scenario simulations, the 10 evaluation factors (B4, A6, C1, A5, A7, A2, B2, A1, C5 and A4) with the greatest contribution to social-ecosystem vulnerability in the geographic detector were used as the influencing factors in the scenario simulation. The analytic hierarchy process (AHP) is used to weigh the evaluation factors, and the order weight of each evaluation factor is calculated according to Equation (8).

Scenario simulation is realized by the OWA function of IDRISI software. After setting the factor weights and order weights, scenarios under different risk coefficients can be simulated so as to explore the impact of different decisions on the development of socio-ecosystem. Table 5 shows the order weights under different risk coefficients and simulates different decision-making scenarios. The more optimistic the evaluator is, the lower the risk of the socio-ecosystem in the study area is, the stronger the adaptability of the socio-ecosystem is, and the more it will not affect the stable development of the socio-ecosystem. The more pessimistic the evaluator is, the higher the risk of the socio-ecosystem in the study area is, the worse the adaptability of the socio-ecosystem is, and the more susceptible the sustainable development of the socio-ecosystem is. It is worth noting that when $a = 1000$ and $a = 10$, the risk of the socio-ecological system in the study area is overestimated, resulting in almost severe vulnerability in the study area. When $a = 0.0001$ and $a = 0.1$, the risk of the socio-ecological system in the study area will be over underestimated, and the vulnerability level of the study area will be mainly potential vulnerability. The above two types of scenarios are obviously not in line with the actual situation. Therefore, this paper comprehensively considers the previous research results and chooses $a = 1.2$, $a = 1$ and $a = 0.8$ to simulate the unsustainable guide, status quo and sustainable guide, respectively.

Table 5. Order weight calculation results.

		B4	A6	C1	A5	A7	A2	B2	A1	C5	A4
No preference	w (a = 1)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Be optimistic about	w (a = 0.1)	0.79	0.06	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.01
Optimism	w (a = 0.5)	0.32	0.13	0.10	0.09	0.08	0.07	0.06	0.06	0.05	0.05
The most optimistic	w (a = 0.0001)	1	0	0	0	0	0	0	0	0	0
Be pessimism about	w (a = 2)	0.01	0.03	0.05	0.07	0.09	0.11	0.13	0.15	0.17	0.19
Pessimism	w (a = 10)	0	0	0	0	0.01	0.01	0.02	0.08	0.24	0.65
The most pessimism	w (a = 1000)	0	0	0	0	0	0	0	0	0	1

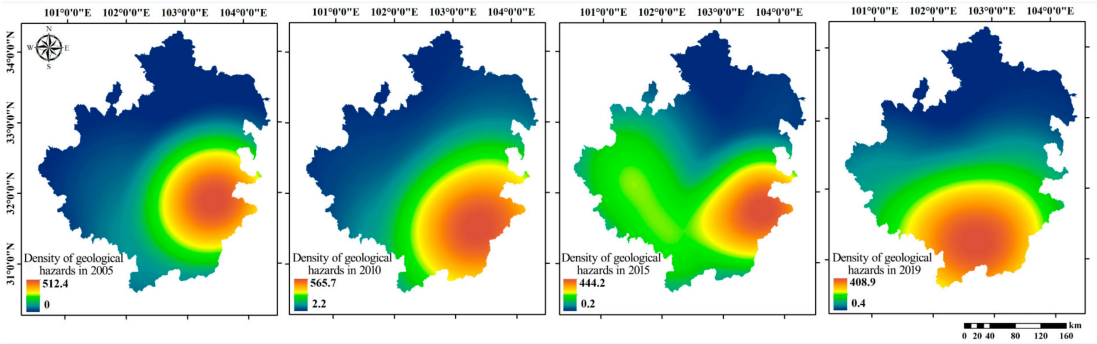
4. Results

4.1. Index Factor Extraction

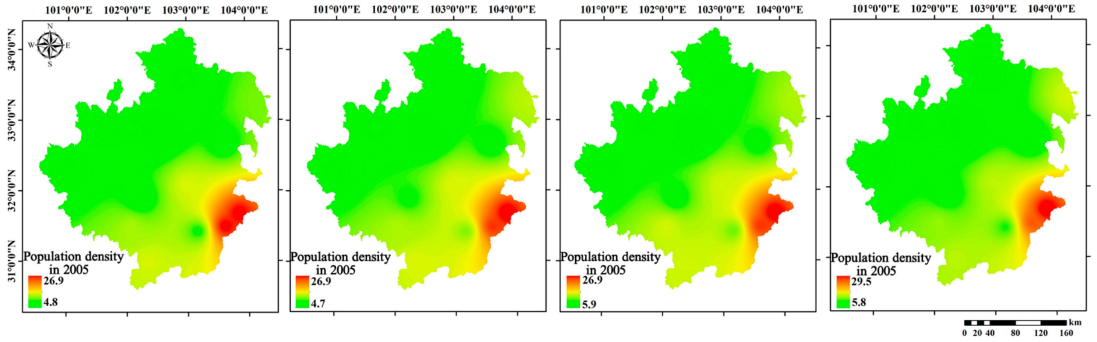
On the basis of multi-source data types, with the VSD and following evaluation index selection principles, 20 impact factors, including soil erosion intensity, extreme climate index, vegetation cover, biological abundance and health care level are selected

on three dimensions: exposure, sensitivity and adaptability. Thus the index system for socio-ecological vulnerability evaluation in the researched area is built (Figure 3).

Based on the calculation method described in Section 3.1.1, the spatial distribution of the exposure indexes were obtained, and Figure 4 shows the calculated spatial distribution map of exposure indexes.



(**a**)



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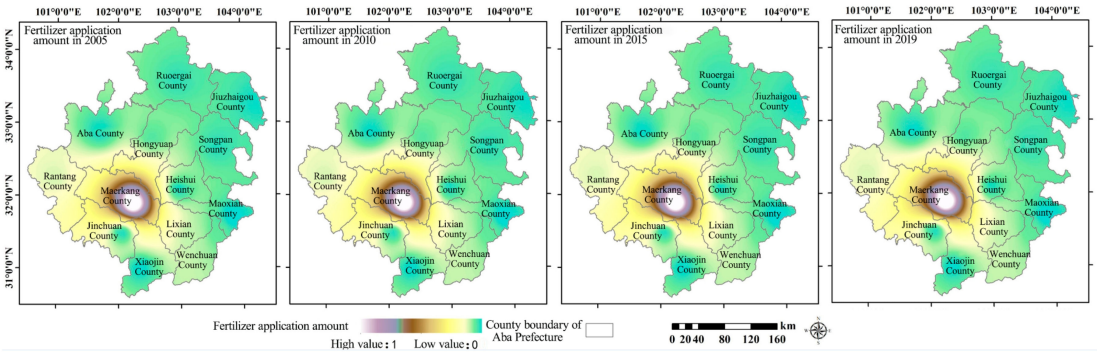
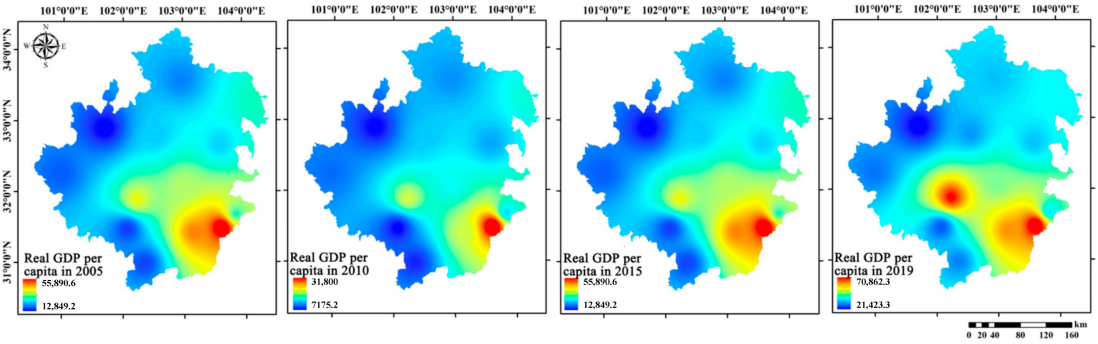
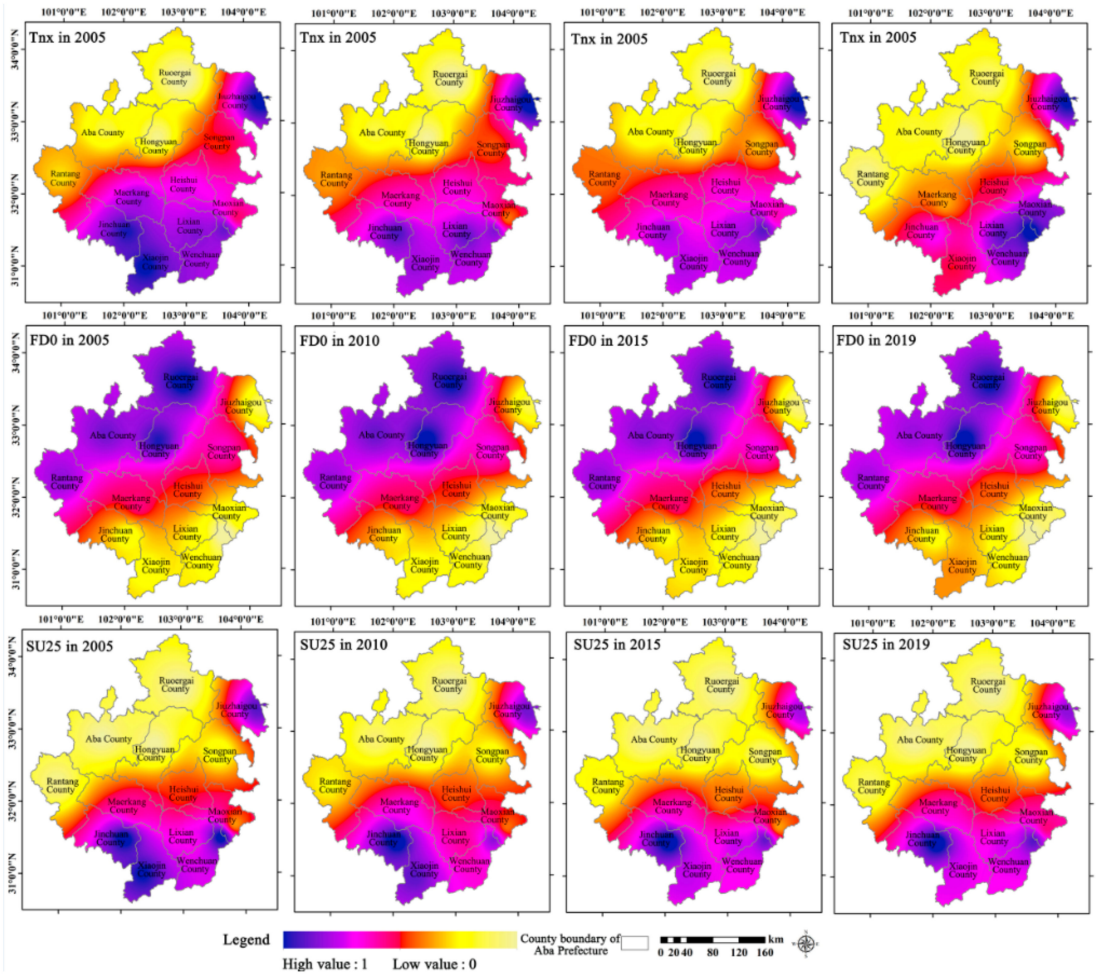


(**c**)



(**d**)

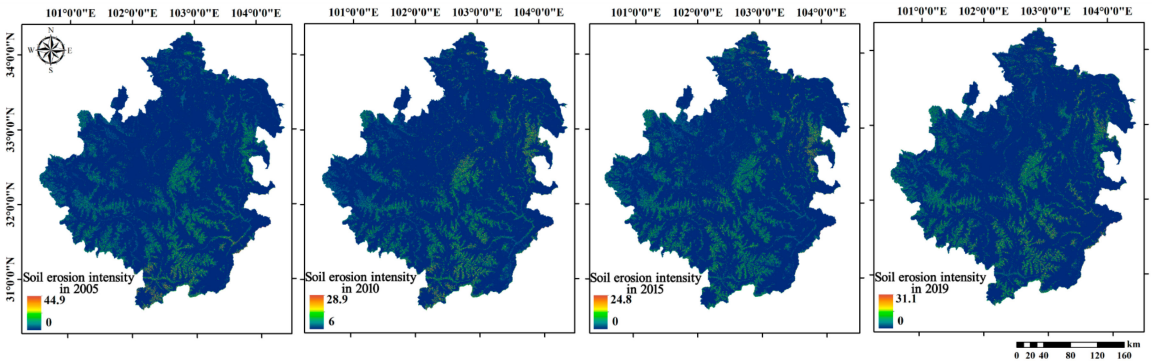
Figure 4. *Cont.*



(**e**)

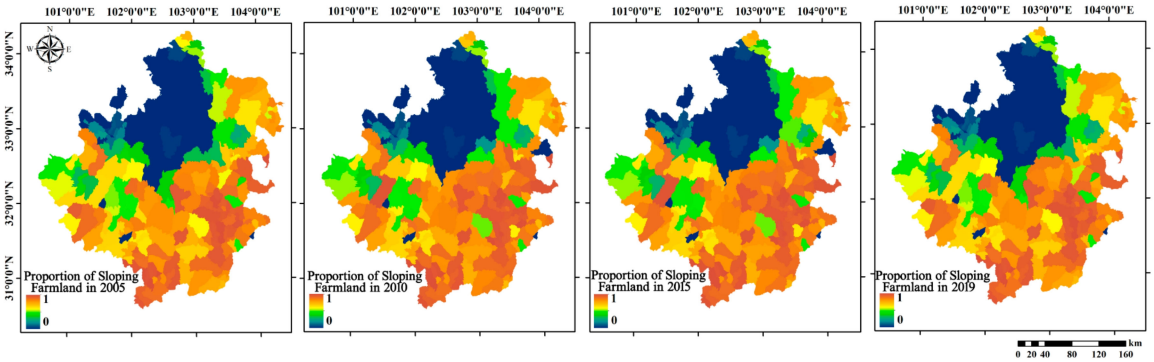
Figure 4. Spatial distribution map of exposure indexes. (**a**) density of geological hazards, (**b**) density of population, (**c**) fertilizer application amount, (**d**) per capita gross domestic product, and (**e**) extreme climate index.

Based on the calculation method described in Section 3.1.2, the spatial distribution of the sensitivity indexes were obtained, and Figure 5 shows the calculated spatial distribution map of sensitivity indexes.



(**a**)

Figure 5. *Cont.*



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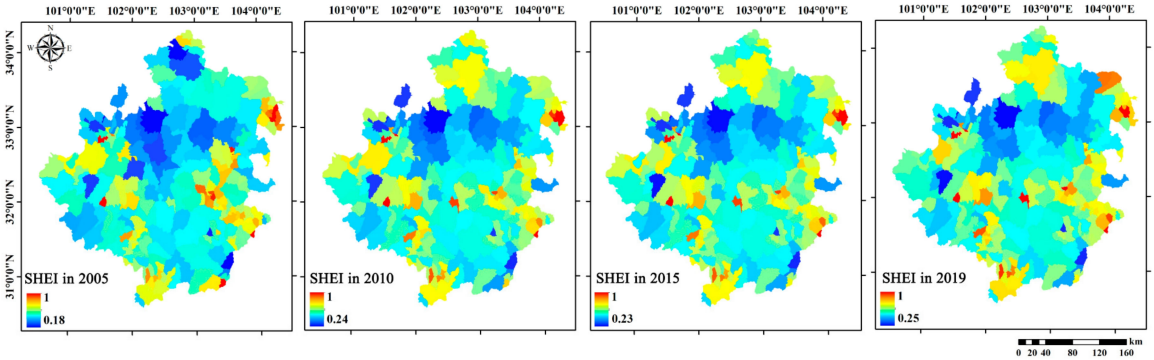

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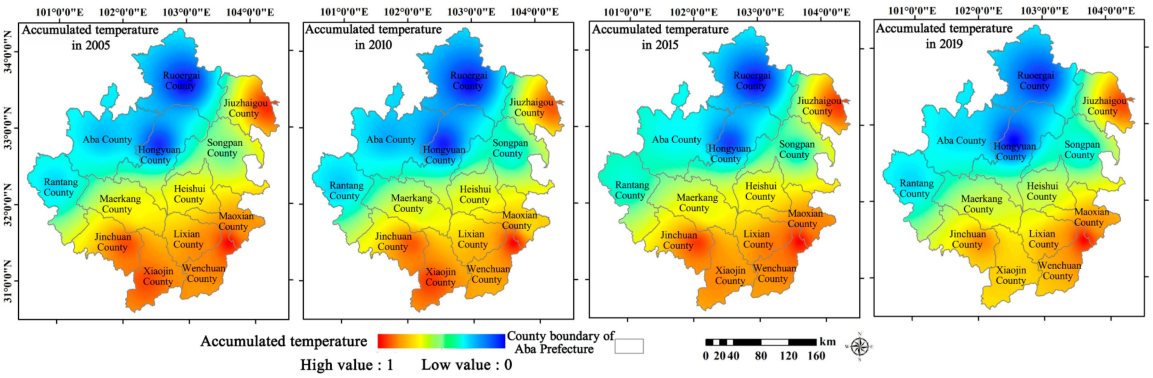

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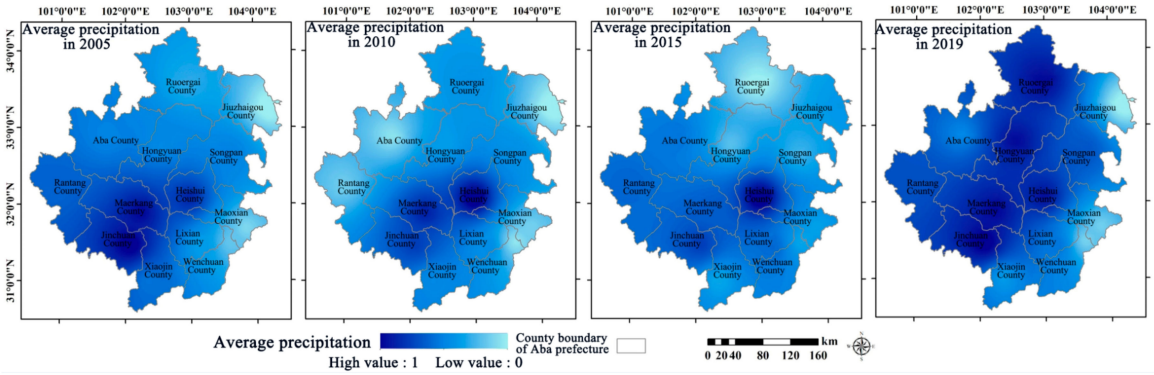

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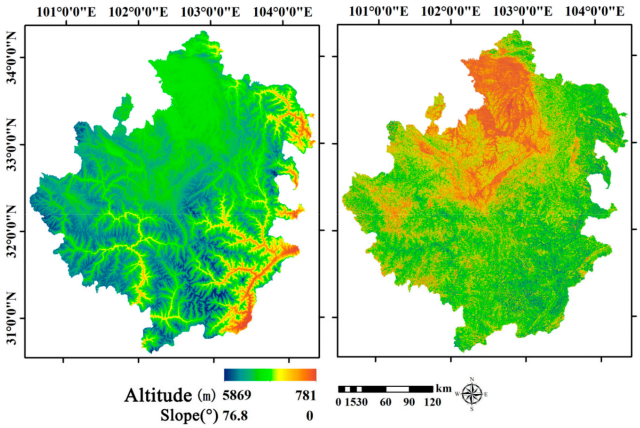
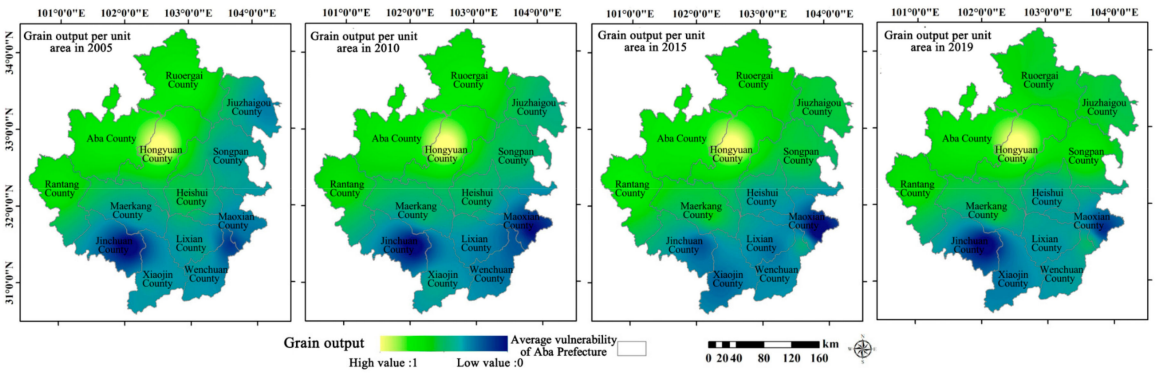
Figure 5. *Cont.*



(**f**)

Figure 5. Spatial distribution map of sensitivity indexes. (**a**) soil erosion intensity, (**b**) proportion of sloping farmland, (**c**) SHEI, (**d**) the accumulated temperature is greater than or equal to 10 degrees, (**e**) average annual precipitation, and (**f**) topographical factor.

Based on the calculation method described in Section 3.1.3, the spatial distribution of the adaptability indexes were obtained, and Figure 6 shows the calculated spatial distribution map of adaptability indexes.



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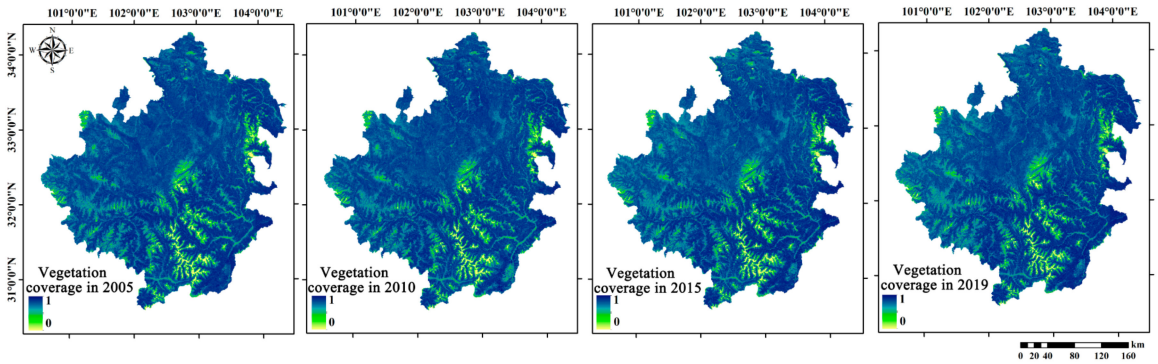

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Figure 6. *Cont.*

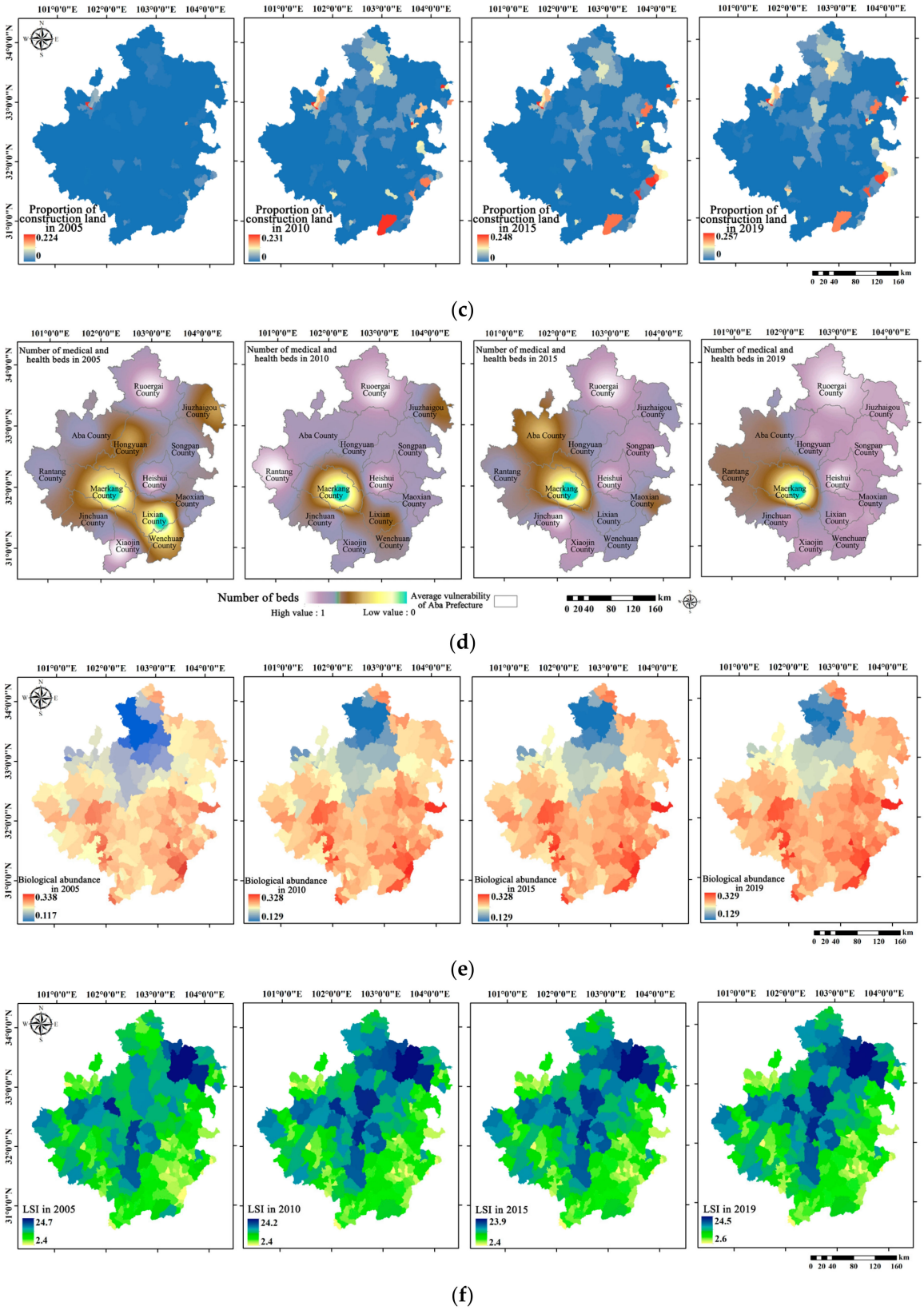

Figure 6. Spatial distribution map of adaptability indexes. (**a**) grain output per unit area, (**b**) FVC, (**c**) the proportion of construction land, (**d**) the number of beds in medical and health institutions per 1000 people, (**e**) biological abundance index, and (**f**) LSI.

4.2. Spatial-Temporal Analysis of Socio-Ecological Vulnerability in Aba Prefecture

Index data are normalized. The spatial principal component analysis is applied to analyzing the 20 index factors. And weight coefficients and accumulated contribution rates of the principal components, exposure, sensitivity and adaptability, in Aba Prefecture in 2005, 2010, 2015 and 2019 are obtained, as detailed in Table 6.

Table 6. Principal component weight coefficients and accumulated contribution rates in Aba Prefecture in different time periods.

Year	Principal Component	Exposure		Sensitivity		Adaptability	
		Weight Coefficient	Accumulated Contribution Rate (%)	Weight Coefficient	Accumulated Contribution Rate (%)	Weight Coefficient	Accumulated Contribution Rate (%)
2005	PC1	0.72	72.35	0.71	70.58	0.45	44.89
	PC2	0.19	90.89	0.15	85.35	0.27	71.76
	PC3	\	\	\	\	0.15	86.49
2010	PC1	0.76	76.17	0.71	71.18	0.56	56.39
	PC2	0.14	90.53	0.12	83.32	0.22	78.37
	PC3	\	\	0.09	92.43	0.12	89.96
2015	PC1	0.74	74.13	0.74	74.36	0.51	51.38
	PC2	0.12	85.97	0.10	83.96	0.22	73.01
	PC3	\	\	0.09	92.86	0.15	88.16
2019	PC1	0.78	78.00	0.72	71.58	0.52	52.31
	PC2	0.12	90.35	0.14	85.30	0.22	74.12
	PC3	\	\	\	\	0.14	88.29

According to the results in the table above, indexes with accumulated contribution rates above 85% are defined as principal component factors, which are used to calculate the vulnerability indexes EI, SI and ACI corresponding to exposure, sensitivity and adaptability in Aba Prefecture in 2005, 2010, 2015 and 2019. For the socio-ecological vulnerability aggregative index, the natural breaks method is used to divide the vulnerability index into 5 grades: potential vulnerability ($0 \leq SVI \leq 0.248$), micro-degree vulnerability ($0.248 < SVI \leq 0.428$), light vulnerability ($0.428 < SVI \leq 0.602$), moderate vulnerability ($0.602 < SVI \leq 0.758$) and severe vulnerability ($0.758 < SVI \leq 1$). See Table 3 for the grading standards (Table 7).

Table 7. Grading standards for socio-ecological vulnerability index in Aba Prefecture.

Grade	Potential Vulnerability	Micro-Degree Vulnerability	Light Vulnerability	Moderate Vulnerability	Severe Vulnerability
Range	[0, 0.248]	(0.248, 0.428]	(0.428, 0.602]	(0.602, 0.758]	(0.758, 1]

4.2.1. Analysis of Spatial-Temporal Change in Socio-Ecological Vulnerability in Aba Prefecture

The socio-ecological vulnerability indexes in Aba Prefecture in 2005, 2010, 2015 and 2019 are calculated based on the aggregative index mentioned above. The vulnerability indexes are reclassified following the said grading standards, based on which the spatial distribution of socio-ecological vulnerability in the researched area over the 2005–2019 period is worked out (Figure 7). The Spatial Analyst tool in the software ArcGIS is adopted to work out the area proportions of the socio-ecological vulnerability grades in Aba Prefecture in different time periods (Table 8).

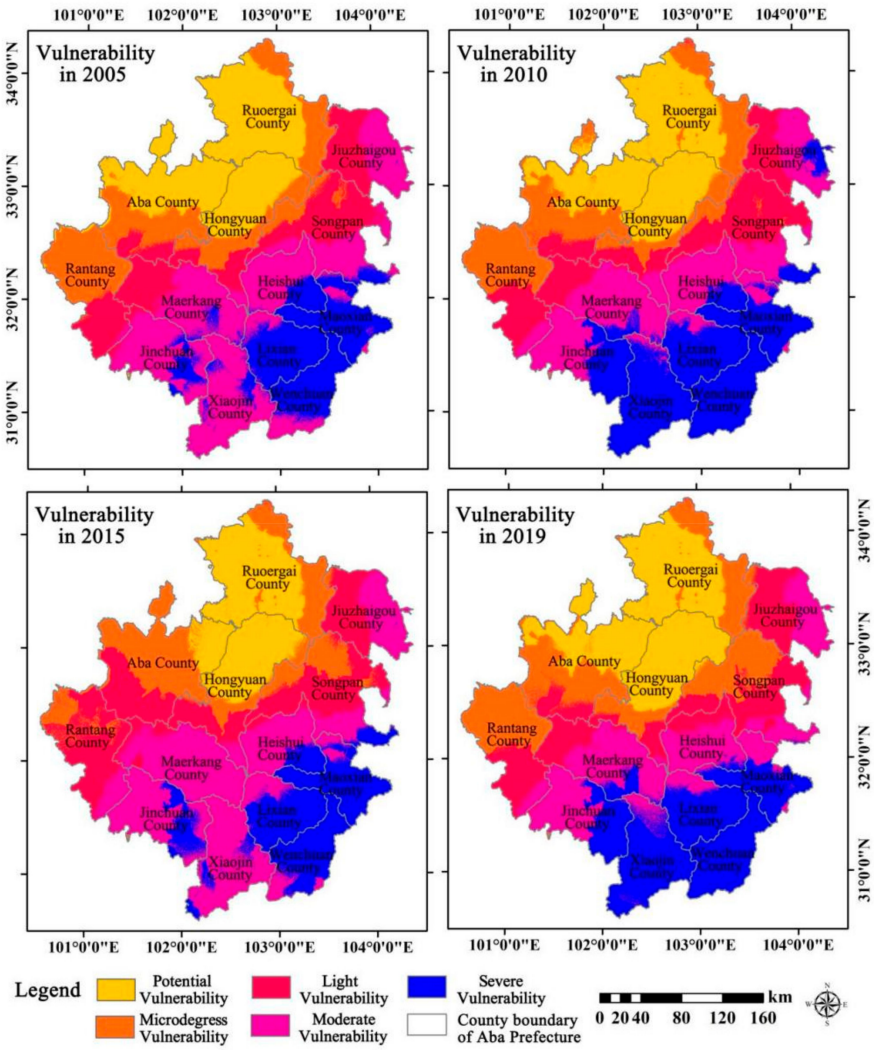

Figure 7. Spatial distribution of socio-ecological vulnerability in Aba Prefecture, 2005–2019.

Table 8. Areas and proportions of the socio-ecological vulnerability grades in Aba Prefecture, 2005–2019.

Vulnerability Grade	2005		2010		2015		2019	
	Area km^2	Proportion (%)	Area km^2	Proportion (%)	Area km^2	Proportion (%)	Areakm^2	Proportion (%)
Potential vulnerability	18,059.3	21.76	17,187.6	20.71	14,034.0	16.91	18,524.2	22.32
Micro-degree vulnerability	14,103.1	16.99	14,132.6	17.03	14,885.8	17.93	16,681.3	20.10
Light vulnerability	13,299.4	16.02	14,056.8	16.93	16,283.7	19.62	13,754.6	16.57
Moderate vulnerability	23,599.5	28.43	17,546.4	21.14	24,620.8	29.66	16,394.8	19.75
Severe vulnerability	13,945.8	16.80	20,083.8	24.20	13,184.6	15.88	17,654.2	21.27

The socio-ecological vulnerability in Aba Prefecture in 2005, 2010, 2015 and 2019 is analyzed based on Table 4 and Figure 4. As is shown, moderate vulnerability accounted for the largest area, 23,599.5 km^2 (28.43%), in Aba Prefecture in 2005, mainly involving Jinchuan County in the west, Xiaojin County in the South, Maerkang City and Heishui County in the middle, and Jiuzhaigou County and Songpan County in the east. It is followed by potential vulnerability, which accounted for 21.76% of the total area and was seen in Ruoergai County, Aba County and Hongyuan County in the north part of this prefecture. In those counties, the socio-ecological vulnerability index was low, vegetation coverage was high, and population density was lower. Among them, Ruoergai County, which is

home to the most beautiful alpine wetland grassland of China, enjoys vast grasslands, and is implementing effective ecological environment construction and protection measures. It is a pilot county in China for comprehensive ecological compensation.

Compared with 2005, the area proportions of potential vulnerability and moderate vulnerability in 2010 declined to 20.71% and 21.14%, respectively. Instead, area proportions of micro-degree vulnerability and light vulnerability rose to 17.03% and 16.93%, respectively. Severe vulnerability accounted for a much larger area. It is also the vulnerability grade involving the largest area in Aba Prefecture at that time—20,083.8 km^2 (24.2%), mainly seen in Xiaojin County, Wenchuan County, Lixian County, Jinchuan County and Maoxian County in the southern part of Aba Prefecture. Those counties had higher socio-ecological vulnerability indexes and higher density of geological hazards and population. Yingxiu Town, the epicenter of the 2008 Wenchuan Earthquake, is among them. After the earthquake, both social and ecological systems of Wenchuan County were damaged, leading to a higher socio-ecological vulnerability index than in 2005.

Compared with the results in 2005 and 2010, the area proportions of potential vulnerability and severe vulnerability declined in 2015 to 16.91% and 15.88%, respectively. The area proportions of micro-degree vulnerability and light vulnerability were 17.93% and 19.62%, respectively, with only minor changes. In that period, moderate vulnerability had the largest area proportion—29.66% (24,620.8 km^2), and mainly involved Jinchuan and Xiaojin counties in the southern part, Maerkang City and Heishui County in the middle, and part of Jiuzhaigou County in the northwestern part of Aba Prefecture. In those counties and regions, socio-ecological vulnerability indexes were higher and human activities were more active. As the capital of this prefecture, Maerkang is developed in transportation infrastructure and abundant in natural resources. Tourist attractions in this city include the Kesha Folk Houses, Songgang Zhibo Ancient Blockhouse, Dazang Temple and Chage Temple, etc. The tertiary industry contributes as high as 86.4% of its total revenue. Therefore, Maerkang City faces more socio-ecological system problems caused by human life and production activities.

In 2019, socio-ecological vulnerability was high in the north and low in the south of Aba Prefecture. The indexes in the southern part of this prefecture were all high, mainly covering areas with severe vulnerability (21.28% of the total area) and moderate vulnerability (19.74% of the total area). To be specific, Xiaojin, Wenchuan, Lixian, Maoxian and Jinchuan (southeast) counties in the south of Aba Prefecture suffered severe vulnerability. Those counties are developed in tourism and are high in human factor indexes like population density and fertilizer consumption and natural factor indexes like geological hazard density and extreme climate; they suffer more damage from natural disasters and human life and production activities. The socio-ecological system in the north of the researched area is stable. This region mainly consisted of areas of potential vulnerability (22.32%), micro-degree vulnerability (20.09%) and light vulnerability (16.58%). Among them, the area of potential vulnerability was the largest, being 18,525 km^2, mainly covering the western part of Ruoergai County in the north of Aba Prefecture, most parts of Hongyuan County and most parts of the north of this prefecture. This area is less frequent in geological hazards and low in population density. Socio-ecological damage by natural disasters or human life or activities are fewer, and the socio-ecological system management and protection policies in these areas are effective.

According to surveys, the ecological environment management and governance in all those counties/city is done by themselves. Therefore, in this research, the socio-ecological vulnerability evaluation is carried out to the 13 administrative counties/city of Aba Prefecture. The Spatial Analyst tool in the software ArcGIS is used to work out the average areas and proportions of the socio-ecological vulnerability grades in the counties/city in Aba Prefecture over the 2005–2019 period (Table 9).

Table 9. Area proportions of socio-ecological vulnerability grades in administrative regions, Aba Prefecture.

Administrative Region	Potential Vulnerability		Micro-Degree Vulnerability		Light Vulnerability		Moderate Vulnerability		Severe Vulnerability	
	Area km²	Proportion (%)	Area km²	Proportion (%)	Area km²	Proportion (%)	Area km²	Proportion (%)	Area km²	Proportion (%)
Jinchuan County	6.6	0.1	18.4	0.3	94.1	1.8	3499.2	65.2	1752.7	32.6
Hongyuan County	5018.9	60.2	1675.1	20.1	1299.5	15.6	348.9	4.2	0	0
Heishui County	0.1	0.1	2.2	0.1	347.6	8.4	3027.5	73.5	743.7	18.1
Aba County	4282.1	42.3	4332.3	42.8	1506.0	14.9	0	0	0	0
Maerkang City	0.1	0.1	9.9	0.2	1668.5	25.2	4530.0	68.5	406.5	6.2
Ruoergai County	7336.9	71.0	2960.5	28.7	36.2	0.4	0	0	0	0
Wenchuan County	1.9	0.1	6.5	0.2	0	0	364.1	8.9	3708.7	90.9
Jiuzhaigou County	8.5	0.2	163.1	3.1	2570.4	48.7	2389.2	45.3	147.1	2.8
Lixian County	0.2	0.1	0.5	0.1	0	0	725.9	16.7	3615.1	83.3
Songpan County	27.9	0.3	1978.1	23.8	4153.5	49.9	1768.8	21.3	396.3	4.8
Maoxian County	2.9	0.1	9.6	0.3	0.2	0.1	662.7	17.1	3206.6	82.6
Xiaojin County	5.1	0.1	13.7	0.3	0	0	2682.3	48.3	2857.0	51.4
Rangtang County	35.0	0.5	3471.0	52.3	2641.7	39.8	491.7	7.4	0	0

4.2.2. Analysis of Socio-Ecological Vulnerability in Major Counties/City in Aba Prefecture

Among the counties/city, Wenchuan County was hit the most in the 2008 earthquake, Maerkang City has attained marked achievements in the city-wide characteristic economy, and Ruoergai County protects wetland and develops ecological tourism, having a positive effect on ecosystems. Therefore, this paper focuses on the three counties/city, and analyzes the changing trend of their socio-ecological vulnerability and the impact factors.

1. Analysis of socio-ecological vulnerability results in Wenchuan County

The socio-ecological vulnerability index in Wenchuan County remained high over the 2005–2019 period. It rose first and tended to be stable then. This high index is related to the frequent geological hazards here. In particular, the 2008 Wenchuan Earthquake had seriously damaged its ecosystems, leading to the quick rise of its ecological vulnerability index in the following period. Figure 8 shows the spatial distribution of geological hazards taking place in Wenchuan from 2005 to 2019. As is shown, there were severe geological hazards occurring in different time periods, which concentrated in the northeast, southeast and central area of this county. The years 2010 and 2019 saw the most frequent geological hazards. In 2010, the numbers of severe disasters and minor disasters were equal. In 2019, severe disasters outnumbered minor disasters. Thanks to the ecological development path adopted by the local government, since 2010, the ecological vulnerability index in Wenchuan County has been stable and even dropping slightly. In recent years, Wenchuan has devoted active efforts to post-disaster reconstruction and adhered to the general plan of "cultivating forests in the south, building orchards in the north, and developing green industries and all-for-one tourism (health maintenance services)". On the basis of properly handling relations between ecosystem and development, between ecosystem and livelihood, and between ecosystem and stability, it takes the lead in building prefecture-level demonstration zones of ecological health maintenance and tourism, which has both improved the local production and economy and contributed to ecological balance and sustainable development.

2. Analysis of socio-ecological vulnerability results in Maerkang City

The socio-ecological vulnerability index in Maerkang City (Figure 9) remained high but balanced. It rose in 2015 but was back to the previous level in 2019. Despite its low population density, its per capita GDP accounted for a larger part of the total of Aba Prefecture. In 2019, its per capita GDP was in the second place in the prefecture. It offers better medical services. In particular, in 2015–2019, its medical institution beds per 1000 persons were far more than those in other counties within the prefecture. While maintaining the stable development of ecosystems, Maerkang has attained economic and production development, which is the result of its unique regional characteristic economic development mode. The local government earnestly implements the sustainable development strategy, and actively promotes the characteristic economic industries in local places. In recent years, Maerkang City has kept optimizing its rural industrial structure, promoting green vegetables, fruits and other agricultural products, and building characteristic agricultural production basis.

Thanks to those efforts, the economic benefits of agricultural products have been improved, and pesticide and fertilizer consumption has dropped. Furthermore, local places are vigorously developing clean energy. They follow the principles of "keeping raw ore within the prefecture, preventing funds from flowing out, and abiding by the basic security and environmental protection rules". Thus they have both ensured energy for production and reduced damage to ecosystems. In addition, innovative efforts are made to develop the tertiary industry, such as ecological tourism based on local culture and e-commerce. While ensuring sustainable development of the local ecosystem, those efforts have effectively driven economic development.

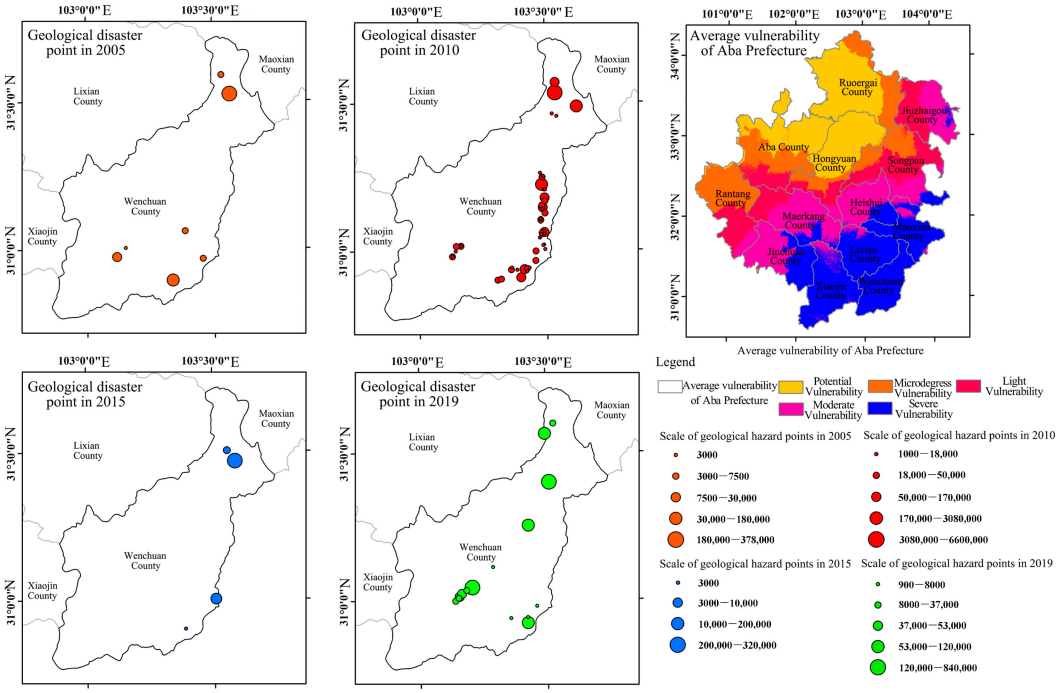

Figure 8. Spatial distribution of socio-ecological vulnerability in Wenchuan County, 2005–2019.

3. Analysis on socio-ecological vulnerability results in Ruoergai County

The socio-ecological vulnerability index (Figure 10) in Ruoergai County remained the lowest in the prefecture over the 2005–2019 period, and has been dropping and tending to be stable recently. This county has high vegetation coverage and low population density, and suffers from less geological hazards, ensuring good conditions for the stable development of ecosystems and creating significant economic development potential. The Ruoergai Grassland is hailed as the "most beautiful alpine wetland grassland in China", and enjoys high biodiversity. The local government has implemented policies pursuing both environmental protection and economic development. First, efforts are made to improve the ecological environment in the Ruoergai Wetland Reserve, advance the construction of ecological civilization demonstration zones, and implement ecological restoration plans. Vigorous efforts are made to return grazing land to grassland and afforest marginal farmland. Grazing banning, rotational grazing and other environmental protection and governance projects have been implemented in grasslands. As a result, Ruoergai has seen an improved environment and sustainable development of the animal husbandry economy. In addition, desertification governance is carried out along with water and land conservation. The importance of wildlife protection is promoted among local residents. All contribute to the maintenance of excellent ecological environment in this county. Second, ecological tourism is developed on the basis of advantageous natural resources in local places, which both create jobs for local residents and better promotelocal agricultural products. Thus this county has transformed from traditional husbandry to

tertiary industry. While achieving economic development, it adheres to the sustainable development principle of "lucid waters and lush mountains are invaluable assets".

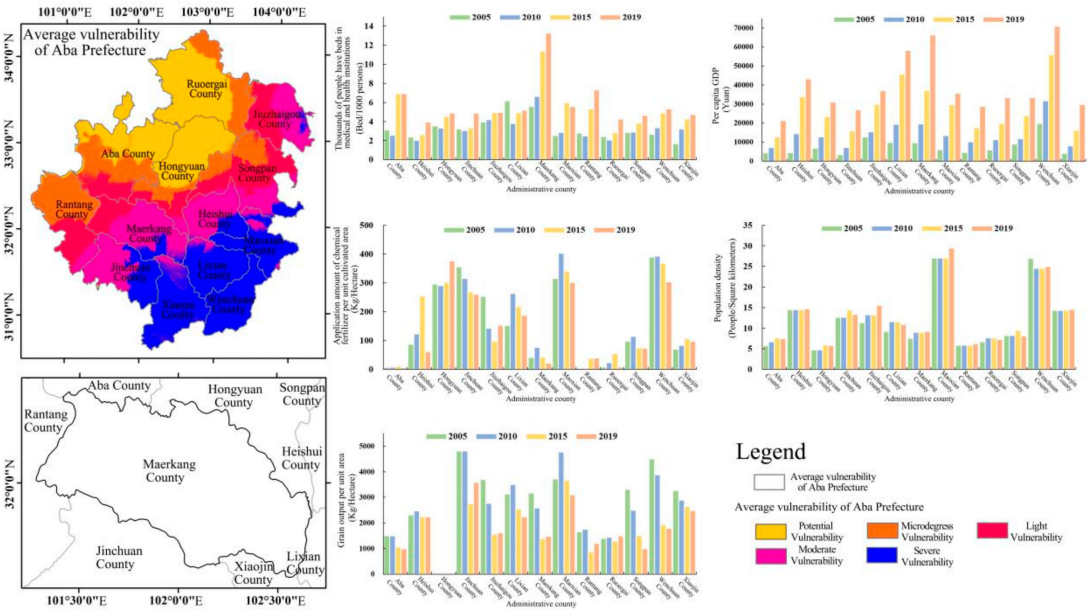

Figure 9. Spatial distribution of socio-ecological vulnerability in Maerkang City, 2005–2019.

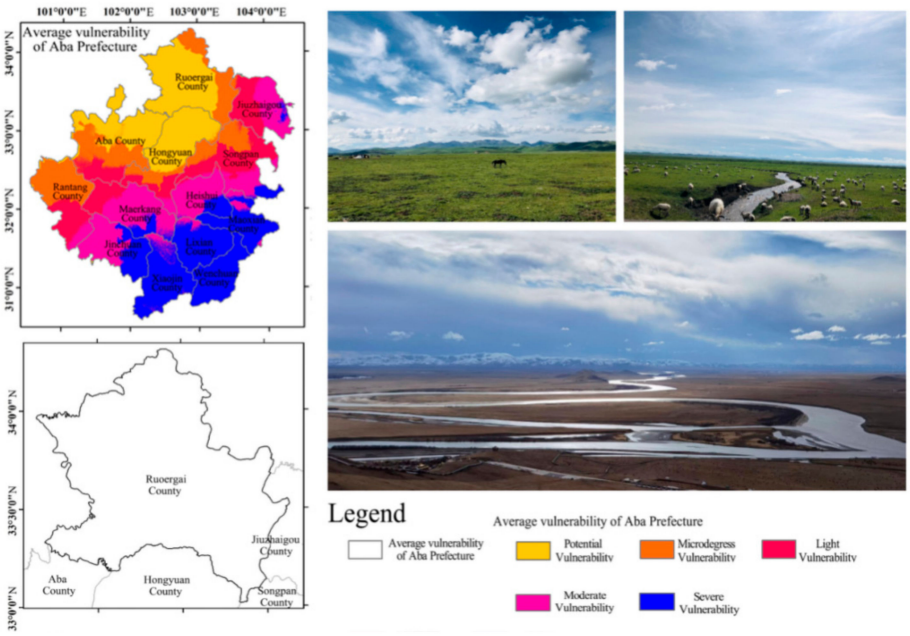

Figure 10. Spatial distribution of socio-ecological vulnerability in Ruoergai County, 2005–2019.

4.3. Analysis of Driving Forces

In this paper, the socio-ecological vulnerability index over 2005–2019 is taken as a dependent variable, and 20 impact factors, including the proportion of construction, grain output per unit area, average annual precipitation and proportion of sloping farmland are selected as the independent variables. The data of the socio-ecological vulnerability index and impact factors in the researched area are extracted. The impact factors are divided into 5 grades using the Natural Breaks method.

Table 10 shows the Q values of the 20 impact factors obtained with the factor detector. Factors with greater contribution to the socio-ecological vulnerability in Aba Prefecture

include the ≥10 °C accumulated temperature (0.888), per capita grain availability (0.846), FD0 (0.871), SU25 (0.840), TNx (0.780), population density (0.750), proportion of arable land (0.727), geological hazards (0.716), biological abundance (0.581), and GDP (0.227). Factors with less contribution to the socio-ecological vulnerability in Aba Prefecture include the soil erosion type (0.009), fertilizer application amount per unit area (0.063), medical institution beds per 1000 persons (0.081), and proportion of construction land (0.083). On such basis, we could see that in this prefecture, the socio-ecological vulnerability is dominated by extreme natural climate conditions, then human activities and geological hazards. The Q values of the three impact factors are ranked: (1) on the exposure dimension: FD0 > SU25 > TNx > population density > density of geological hazards > per capita GDP > fertilizer application amount per unit area; (2) on the sensitivity dimension: ≥10 °C accumulated temperature > proportion of sloping farmland > slope > average annual precipitation > elevation > SHEI > soil erosion type; (3) on the adaptability dimension: grain output per unit area > biological abundance > LSI > proportion of construction land > medical institution beds per 1000 persons > FVC.

Table 10. Statistical table of driving factors for the socio-ecological vulnerability index in Aba Prefecture.

Impact Factor	A1	A2	A3	A4	A5	A6	A7	B1	B2	B3
Q value	0.716	0.750	0.063	0.444	0.840	0.871	0.780	0.009	0.727	0.147
Impact value	B4	B5	B6	B7	C1	C2	C3	C4	C5	C6
Q vale	0.888	0.257	0.246	0.286	0.846	0.066	0.084	0.081	0.581	0.227

Note: A1: density of geological hazards; A2: population density; A3: fertilizer application amount per unit area; A4: GDP; A5: SU25; A6: FD0; A7: TNx; B1: soil erosion type; B2: proportion of sloping farmland; B3: SHEI; B4: ≥10 °C accumulated temperature; B5: average annual precipitation; B6: elevation; B7: slope; C1: grain output per unit area; C2: vegetation cover; C3: proportion of construction land; C4: medical institution beds per 1000 persons; C5: biological abundance; C6: LSI.

In the real environment, a geographical phenomenon is often determined by the complex interaction among multiple impact factors. To study the contribution of multifactorial interactions to the socio-ecological vulnerability in Aba Prefecture, in this paper, the Q value of the impact of pairwise interactions among the 20 impact factors on socio-ecological vulnerability in Aba Prefecture is calculated. As is shown in Table 7, all the 20 impact factors are enhanced after the pairwise interaction, and the Q values after interaction are higher than those of individual factors. Interactions with the greatest impact on socio-ecological vulnerability: interaction between grain output per unit area (on one side) and average annual precipitation, the proportion of sloping farmland, biological abundance, ≥10 °C accumulated temperature, and density of geological hazards (on the other side); interaction between average annual precipitation and ≥10 °C accumulated temperature; interaction between the proportion of sloping farmland (on one side) and ≥10 °C accumulated temperature, FD0 and SU25; interaction between biological abundance and ≥10 °C accumulated temperature; interaction between ≥10 °C accumulated temperature (on one side) and GDP, LSI, proportion of construction land, density of geological hazards and fertilizer application amount per unit area (on the other side); interaction between FD0 (on one side) and density of geological hazards and fertilizer application amount per unit area (on the other side); interaction between SU25 and density of geological hazards. The Q values of those interactions are higher than 0.9. Among them, ≥10 °C accumulated temperature has the highest frequency in terms of Q value greater than 0.9 after interaction with another factor. Considering both Tables 10 and 11, the contribution of extreme climate conditions, human activities and geological hazards are enhanced after the interaction with each other since they themselves have a greater contribution to the socio-ecological vulnerability in Aba Prefecture. Their interaction would worsen the socio-ecological vulnerability. Therefore, to protect the socio-ecological stability, local climate conditions should be considered, and protection plans based on local conditions should be implemented. In addition, at-

tention should be paid to protecting ecosystems during production activities. Excess land reclamation and overgrazing shall be avoided.

Table 11. Interactions among driving factors to socio-ecological vulnerability in Aba Prefecture.

Q Value of Interaction	C3	C1	B5	B7	B2	A2	C5	B4	B1	C4
C3	0.084									
C1	0.858	0.846								
B5	0.330	0.904	0.257							
B7	0.319	0.865	0.469	0.286						
B2	0.739	0.921	0.814	0.739	0.727					
A2	0.765	0.873	0.848	0.785	0.875	0.750				
C5	0.599	0.904	0.669	0.607	0.764	0.850	0.581			
B4	0.892	0.907	0.900	0.898	0.941	0.895	0.928	0.888		
B1	0.092	0.847	0.271	0.299	0.729	0.751	0.586	0.888	0.009	
C4	0.159	0.873	0.340	0.333	0.772	0.831	0.612	0.891	0.092	0.081
A6	0.879	0.898	0.902	0.887	0.935	0.874	0.925	0.896	0.872	0.888
C2	0.145	0.850	0.313	0.333	0.738	0.755	0.606	0.888	0.073	0.151
A4	0.505	0.893	0.642	0.566	0.816	0.809	0.721	0.903	0.456	0.615
C6	0.311	0.855	0.550	0.407	0.818	0.774	0.676	0.905	0.237	0.376
B3	0.299	0.875	0.393	0.375	0.765	0.787	0.645	0.910	0.154	0.326
A5	0.846	0.897	0.864	0.857	0.921	0.880	0.896	0.898	0.841	0.855
A7	0.794	0.861	0.866	0.805	0.887	0.803	0.870	0.890	0.781	0.825
A1	0.742	0.904	0.853	0.775	0.878	0.872	0.832	0.929	0.717	0.762
B6	0.307	0.866	0.471	0.458	0.755	0.779	0.640	0.893	0.254	0.332
A3	0.135	0.890	0.266	0.348	0.771	0.843	0.617	0.902	0.073	0.108
Q Value of Interaction	A6	C2	A4	C6	B3	A5	A7	A1	B6	A3
A6	0.871									
C2	0.873	0.066								
A4	0.896	0.477	0.444							
C6	0.886	0.283	0.544	0.227						
B3	0.892	0.200	0.536	0.394	0.147					
A5	0.895	0.842	0.880	0.865	0.867	0.840				
A7	0.875	0.784	0.841	0.806	0.820	0.871	0.780			
A1	0.921	0.724	0.833	0.761	0.772	0.924	0.892	0.716		
B6	0.882	0.294	0.568	0.395	0.352	0.856	0.802	0.787	0.246	
A3	0.900	0.131	0.549	0.352	0.214	0.860	0.848	0.742	0.328	0.063

4.4. Analysis of Scenario Simulation Results

Three scenarios are simulated in this paper, and the Natural Breaks method is used to grade the simulation results. On such basis, the spatial distribution, areas and proportions of the vulnerability grades in the researched area are worked out (Table 12 and Figure 11). Among them, in the status quo type scenario, the results are close to the proportions of socio-ecological vulnerability grades in Aba Prefecture in 2010 and 2019, showing that evaluation factors used in the scenario simulation are reliable. In the Sustainable Guide scenario, the area proportion of severe socio-ecological vulnerability in this prefecture is the smallest (4.71%), and the area proportions of the potential vulnerability and micro-degree vulnerability are the biggest. In such a scenario, the risk factor is less than 1, and the general socio-ecological vulnerability is lower than when the risk factor is 1. Therefore, during the vulnerability grade evaluation, more attention should be paid to the proportion of sloping farmland, the density of geological hazards, biological abundance, and per capita GDP. In the unsustainable guide scenario, the area proportion of severe socio-ecological vulnerability in Aba Prefecture is the largest (28.62%), and the area proportion of moderate vulnerability is the smallest. In such a scenario, the risk factor is greater than 1. Therefore, during the vulnerability grade evaluation, more attention should be paid

to ≥10 °C accumulated temperature, FD0, grain output per unit area and SU25. The general socio-ecological vulnerability is higher than when the risk factor is 1.

Table 12. Scenario simulation results of different socio-ecological vulnerability grades in Aba Prefecture, Western Sichuan Plateau.

Grade	Status Quo Type		Sustainable Guide		Unsustainable Guide	
	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%
Potential vulnerability	15,337.38	18.48	20,428.90	24.61	16,993.62	20.47
Micro-degree vulnerability	16,040.39	19.32	23,247.50	28.01	13,365.42	16.10
Light vulnerability	13,709.80	16.52	18,040.81	21.73	11,973.05	14.42
Moderate vulnerability	16,504.21	19.88	17,382.44	20.94	16,916.79	20.38
Severe vulnerability	21,414.96	25.80	3907.09	4.71	23,757.87	28.62

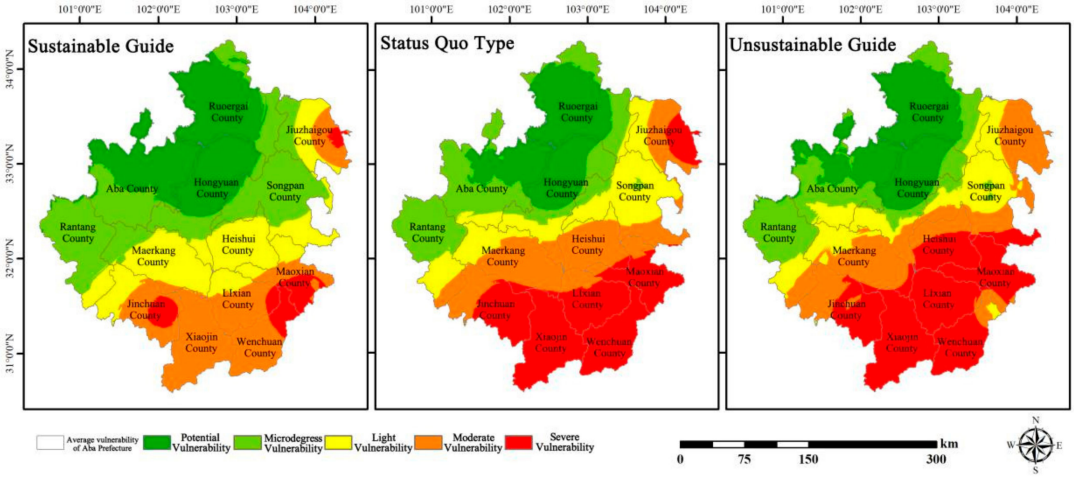

Figure 11. Spatial distribution of socio-ecological vulnerability in Aba Prefecture in different simulation scenarios.

According to the simulation results, risks arising from different decisions would drive the socio-ecological vulnerability in different directions. Notably, the scenarios above may not necessarily be the only best solutions for decision-making. These three scenarios are only for reference, and development strategies should be made based on the development needs in local places in different time periods. Then, the evaluation factors in the scenario simulation are selected based on the experience of the evaluator, which is another source of uncertainty in the simulation results.

5. Discussion

(1) Proper evaluation factors should be used. Evaluation factors are mainly selected according to the experience and knowledge of researchers presently. It is difficult to establish a set of selection standards applicable to different regions and on different spatial scales. In this paper, on the basis of multi-source data types with the VSD, and following the evaluation index selection principles, 20 impact factors, including soil erosion intensity, extreme climate index, vegetation cover, biological abundance and health care level, are selected on three dimensions: exposure, sensitivity and adaptability. Thus the index system for socio-ecological vulnerability evaluation in the researched area is built. When selecting evaluation factors, we should consider related principles of ecology, climatology and geology to select impact factors with a contribution to local socio-ecological systems. Notably, the spatial scale of evaluation

factors selected in this paper is county level. It could improve the spatial resolution of socio-ecological vulnerability if more specific data at the county level could be obtained.

(2) The changing trends of climate with elevation in Aba Prefecture are not the same. Strong wind is common in spring and winter, but it is dry and extreme meteorological events like droughts, frost, snow, low temperature and heavy snow are often seen. The climate types in this prefecture could be classified by elevation. It is the alpine climate at higher elevations, highland climate at the junction between mountains and highland, and the alpine valley climate in valleys, the three typical plateau monsoon climates. As pointed out in the Sixth Assessment Report by the UN Intergovernmental Panel on Climate Change, with global warming speeding up, the intensity and frequency of extreme weather events such as high-temperature weather, floods, agro-ecological droughts and strong typhoons will increase [64]. The World Meteorological Organization has defined 27 extreme climate indexes, including 16 temperature indexes and 11 precipitation indexes [70]. Considering the data representativeness and completeness of all meteorological stations in Aba Prefecture, the researched area, we have selected six index factors for the extreme climate to analyze the extreme climate features in the area. This research adopts Sen's Slope Estimation method to work out the inter-annual variance of extreme climate indexes in Aba Prefecture [71]. Three extreme climate indexes with greater inter-annual variance are selected. The abrupt change test method of Mann–Kendall is used to analyze the abrupt change features over 20 years in the researched area. Given the significance test results, three indexes are selected as the follow-up vulnerability evaluation factors for the researched area.

(3) The spatial distribution of socio-ecological vulnerability is not determined by individual geographic, climate or human factors but by the interaction of various factors. Factors having a greater contribution will determine the actual spatial distribution rule. When analyzing driving factors, we should first compare different driving factor analysis methods to assess their applicability to the researched area. Thus we could select the most applicable method and avoid the uncertainty arising from wrong analysis method selection. The Geodetector method works for both numeric data and qualitative descriptions. When analyzing different types of data, it could work out the actual contribution of individual impact factors to socio-ecological vulnerability, and identify the common effect of two factors with interactive effect on the vulnerability, to analyze the contribution of the interaction to ecological vulnerability. Yet, the Geodetector method can't identify the more specific interaction between factors. Therefore, this method should be improved and further developed in the future, to make it able to unveil the relation between impact factors and socio-ecological systems more accurately and at more levels.

6. Conclusions

In this paper, the multi-source spatial-temporal data in Aba Prefecture over the 2005–2019 period and the VSD are used to build a socio-ecological vulnerability evaluation system on three dimensions: exposure, sensitivity and adaptability. The Principal Component Analysis method is employed to obtain the weight coefficient and accumulated contribution rates of the principal component, exposure, sensitivity and adaptability in 2005, 2010, 2015 and 2019. The synthetical index method is used to calculate the socio-ecological vulnerability index in the Aba Prefecture. Mean values of the socio-ecological vulnerability index are adopted for hotspot clustering to probe into the spatial distribution of socio-ecological vulnerability in the place. In the end, to analyze driving factors for socio-ecological vulnerability in the place, we use the geodetector to analyze their contribution rates. The ordered weighted average and the analytic hierarchy process are used to build multiple scenarios to simulate the socio-ecological vulnerability in the researched area, in order to give suggestions on the protection and development of the socio-ecological systems in the place. Here are the main research findings of this paper:

(1) The spatial distribution feature of exposure and sensitivity in Aba Prefecture from 2005 to 2019: high in the southeast and low in the northwest. To be specific, Wenchuan, Maoxian, Lixian, Xiaojin and Heishui counties had higher indexes. These counties are high in population density, the density of geological hazards, the proportion of sloping farmland, SHEI, and soil erosion intensity. The spatial distribution feature of the adaptability index is high in the northwest and low in the south. Ruoergai, Aba and Hongyuan counties had higher adaptability indexes. These counties are high in vegetation cover, biological abundance and landscape shape indexes. The changing trend of exposure and adaptability: dropping first and then rising. The changing trend of sensitivity: rising first and then dropping. Among them, the exposure index changed the most from 2005 to 2010 (dropping by 4.27%); the sensitivity index changed the most over the 2015–2019 period (dropping by 9.04%); the adaptability index changed the most over the 2015–2019 period (up 9.25%).

(2) Features of the general spatial distribution of socio-ecological vulnerability in Aba Prefecture from 2005 to 2019: worsening from the north to the southeast. The area proportion of severe vulnerability rose, dropped and rose again over the 2005–2010, 2010–2015 and 2015–2019 periods. It rose to 21.27% in 2019, the largest proportion ever. Behind this change, the 2008 Wenchuan Earthquake was a major cause of the variation in socio-ecological vulnerability in the southeast of Aba Prefecture in that period. From 2015 to 2019, the rising population density and worsening soil erosion there also drove the socio-ecological vulnerability to go up quickly.

(3) According to the driving force analysis, extreme natural climate conditions are the dominant factors impacting the socio-ecological vulnerability in Aba Prefecture. Then it is human activities and geological hazards. Among individual factors, $\geq$10 °C accumulated temperature, per capita grain availability, FD0, SU25, TNx, population density, the proportion of sloping farmland and density of geological hazards have a greater driving effect on the socio-ecological vulnerability in Aba Prefecture. After the pairwise interaction among them, all factors see growing driving effects, especially the grain output per unit area interacted with the average annual precipitation, proportion of sloping farmland, biological abundance, $\geq$10 °C accumulated temperature and density of geological hazards. In addition, $\geq$10 °C accumulated temperature is the factor with the strongest effect after interaction with other impact factors. Therefore, it is very important for maintaining socio-ecological stability to take cold-resistant measures.

(4) According to the scenario simulation results, as the decision-making risk factor rises, the socio-ecological vulnerability in Aba Prefecture worsens. In the status quo type scenario, the socio-ecological vulnerability is similar to the results in 2010 and 2019, indicating that the selected evaluation factors could reflect the actual socio-ecological vulnerability. In the sustainable guide and unsustainable guide scenarios, the area proportions of severe vulnerability are the smallest and largest, respectively. The simulation results could be a reference for decision makers, but they should also consider local conditions when making decisions. Different social and ecological environment development strategies should be used based on the different development needs of local places in different time periods.

Author Contributions: Xingping Yang and Heng Lu drafted the manuscript and were responsible for the research design, experiment, and analysis. Chao Liu, Naiwen Li, Weile Li and Lei Ma reviewed and edited the manuscript. Xiaoai Dai, Zhengli Yang, Yuxin He, Wenyu Li, Xiao Fu, Yunfeng Shan and Youlin Wang supported the data preparation and the interpretation of the results. All of the authors contributed to editing and reviewing the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Key R & D Program of China (2019YFC1510700), the National Natural Science Foundation of China (41701499), the Sichuan Science and Technology Program (2018GZ0265), the Geomatics Technology and Application Key Laboratory of Qinghai

Province, China (QHDX-2018-07), the Major Scientific and Technological Special Program of Sichuan Province, China (2018SZDZX0027), and the Key Laboratory of the Evaluation and Monitoring of Southwest Land Resources (Ministry of Education), China(TDSYS202104).

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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