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Vulnerability Assessment and Spatiotemporal Evolution of Grassland Social–Ecological Systems in Xinjiang

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Abstract

Xinjiang grasslands are major ecological barriers and pastoral bases exposed to climate variability, grazing, land-use change, and socioeconomic pressures. This study assessed the vulnerability of grassland social–ecological systems in 81 counties from 2001 to 2020. A driver–pressure–state–impact–response (DPSIR) framework was integrated with CRITIC weighting and the TOPSIS model. Sen's slope estimator and the Mann–Kendall test were used to detect temporal trends, and the obstacle degree model identified key constraints. The mean vulnerability index declined from 55.82 to 50.27, accompanied by a marked increase in counties with low or relatively low vulnerability. Vulnerability was highest in southern Xinjiang, where highly vulnerable counties were concentrated in densely populated oasis agricultural areas. Significant declines occurred in 80 of the 81 counties. The response, state, and pressure dimensions showed the highest obstacle degrees. Fiscal self-sufficiency, agricultural machinery power, the grassland–cropland ratio, economic density, and the remote sensing ecological index were the main obstacles. Declining vulnerability was associated with lower grazing intensity, a smaller bare land proportion, and increases in economic density, rural disposable income, and total agricultural machinery power, whereas the comparatively high vulnerability in southern Xinjiang was associated with limited fiscal capacity, lower ecological quality, and arid conditions. These findings support region-specific grassland conservation and differentiated county-level governance.

Keywords: grassland social–ecological system; vulnerability assessment; DPSIR framework; CRITIC–TOPSIS; obstacle degree model; arid region

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1. Introduction

Xinjiang grasslands serve both as ecological barriers and as bases for pastoral production, and they are an important component of social–ecological systems in arid regions [1,2]. Under conditions of low precipitation, intense evaporation, and pronounced interannual climate variability, these grasslands are highly sensitive to warming, precipitation change, grazing pressure, and land-use change [3,4]. In recent years, vegetation cover decline, bare land expansion, and weakened ecological functions have occurred in some areas, further affecting livestock carrying capacity, pastoral household income, and the stability of pastoral development [5,6]. Assessing the vulnerability of grasslands' social–ecological systems in Xinjiang at the county scale is therefore necessary for identifying regional differences in grassland pressure, ecological state, and social support capacity.

Previous grassland assessments have focused primarily on ecological conditions. Indicators such as the Normalized Difference Vegetation Index (NDVI), aboveground biomass, and net primary productivity (NPP) are commonly used to characterize vegetation growth and productivity, whereas grassland degradation indices are used to assess degradation status [7–10]. These indicators can effectively reflect grassland ecological processes, but they provide limited information on social factors such as population agglomeration, dependence on animal husbandry, economic coping capacity, and governance response. In this study, the vulnerability of grassland social–ecological systems is defined as the extent to which grassland ecological structure, production functions, and social support capacity are affected by climate variability, grazing, land-use change, and variation in social response capacity. A social–ecological systems perspective emphasizes the interdependence of ecological processes, human activities, and governance responses and is therefore suited to examining interactions among grassland use, ecological change, and socioeconomic development in pastoral areas [11–13]. Because counties in Xinjiang differ substantially in hydrothermal conditions, grassland distribution, dependence on animal husbandry, and socioeconomic foundations, a continuous county-level assessment can help reveal temporal changes, spatial differentiation, and the main limiting factors of vulnerability.

Social–ecological system assessments commonly use methods such as the Pressure–State–Response (PSR) framework, the Driver–Pressure–State–Impact–Response (DPSIR) framework, coupling coordination degree models, structural equation modeling, and spatial analysis. Among these methods, the DPSIR framework organizes socioeconomic activities, resource-use pressures, ecological state changes, ecological and social impacts, and governance responses across the five dimensions of driver, pressure, state, impact, and response, and has been widely used in ecological environment assessment and sustainable resource-use studies [14–16]. For grassland social–ecological systems, the DPSIR framework can incorporate population and economic drivers, climate and grazing pressures, grassland ecological state, livelihood and ecological function impacts, and county-level response capacity into a unified assessment system, making it suitable for county-level vulnerability measurement.

In integrated assessment, indicator weights and evaluation models directly affect the comparability and stability of the results. The Criteria Importance Through Intercriteria Correlation (CRITIC) method determines objective weights based on indicator variability and inter-indicator conflict, while the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) evaluates each sample according to its relative distance from the ideal solutions [17,18]. Their combination provides a consistent basis for comparing multiple counties and years within the same indicator system.

For grassland social–ecological systems in Xinjiang, two assessment needs remain insufficiently addressed. First, assessments centered mainly on ecological conditions cannot fully represent county-level differences in livelihood conditions, economic support, and governance response. Second, temporal change, spatial differentiation, and the factors contributing most to vulnerability need to be examined within a unified county-level framework. The scientific contribution of this study lies in constructing a long-term DPSIR-based assessment for 81 counties and linking comprehensive vulnerability measurement with trend testing and obstacle-factor diagnosis. This framework enables ecological and socioeconomic components to be assessed together and identifies the main constraints on county-level grassland social–ecological systems.

Accordingly, this study aims to assess the spatiotemporal evolution and main limiting factors of grassland social–ecological system vulnerability in Xinjiang from 2001 to 2020. The specific objectives are to: (1) construct a county-level indicator system covering the driver, pressure, state, impact, and response dimensions; (2) quantify annual vulnerability and

characterize its temporal, spatial, and grade changes; (3) test county-level vulnerability trends and their statistical significance; and (4) identify the main obstacle dimensions and indicators to support differentiated grassland management and county-level decision-making.

2. Materials and Methods

2.1. Study Area

Xinjiang Uygur Autonomous Region is located in northwestern China and in the hinterland of the Eurasian continent, extending approximately from 73°40′ to 96°18′ E and from 34°25′ to 48°10′ N. It covers approximately 1,664,900 km^2, accounting for about one-sixth of China's land area [19]. Xinjiang has a geomorphic pattern commonly described as "three mountain ranges enclosing two basins": the Altai Mountains in the north, the Tianshan Mountains in the central part, and the Kunlun Mountains in the south, with the Junggar Basin and Tarim Basin distributed between these mountain systems. Based on geographic location and physiographic characteristics, Xinjiang is commonly divided into northern, southern, and eastern regions. Northern Xinjiang lies mainly north of the Tianshan Mountains, southern Xinjiang lies mainly to the south and includes extensive oasis agricultural areas, and eastern Xinjiang comprises Turpan and Hami, where arid deserts and mountain grasslands are interspersed (Figure 1). Owing to its inland location, distance from the ocean, and mountain barriers, Xinjiang has a typical temperate continental arid climate, characterized by low precipitation, strong evaporation, and uneven spatiotemporal distribution of water resources. Natural grasslands are widely distributed in Xinjiang, mainly across the Altai Mountains, Tianshan Mountains, Kunlun Mountains, and the margins of the two major basins. The spatial distribution of grasslands is strongly influenced by hydrothermal conditions, topography, and land-use patterns [2,20]. The spatial distribution of grasslands in Xinjiang is shown in Figure 2. This study uses 81 counties in Xinjiang as evaluation units, excluding the Xinjiang Production and Construction Corps and county-level cities directly administered by the autonomous region, to ensure consistency among socioeconomic statistical data, administrative boundaries, and remote sensing indicators at the spatial-unit level. The 81 county-level evaluation units were grouped into northern Xinjiang, southern Xinjiang, and eastern Xinjiang, as shown in Appendix A, Table A1.

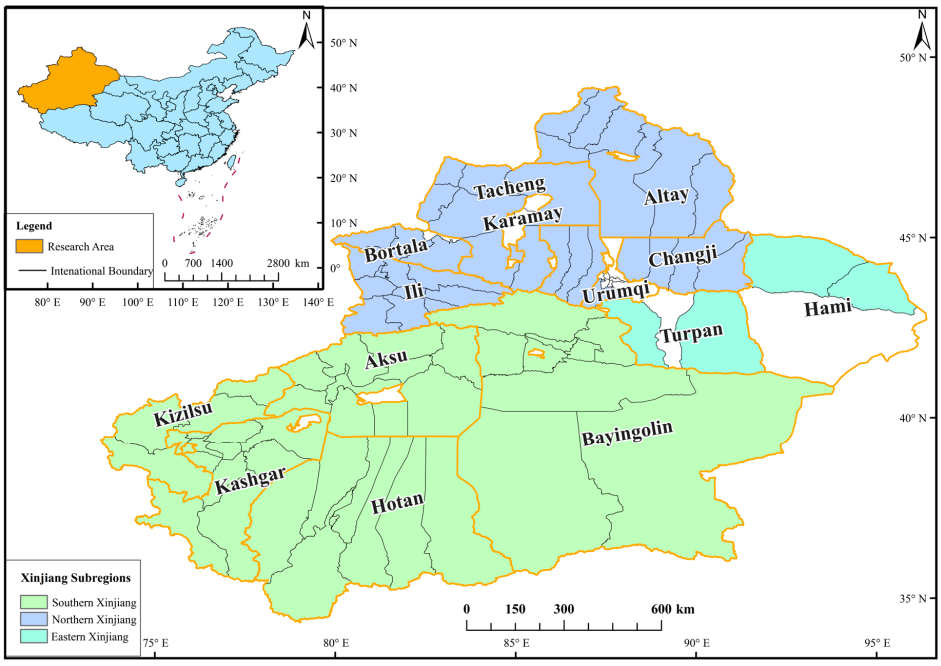


Figure 1. Location and regional division of the study area in Xinjiang.

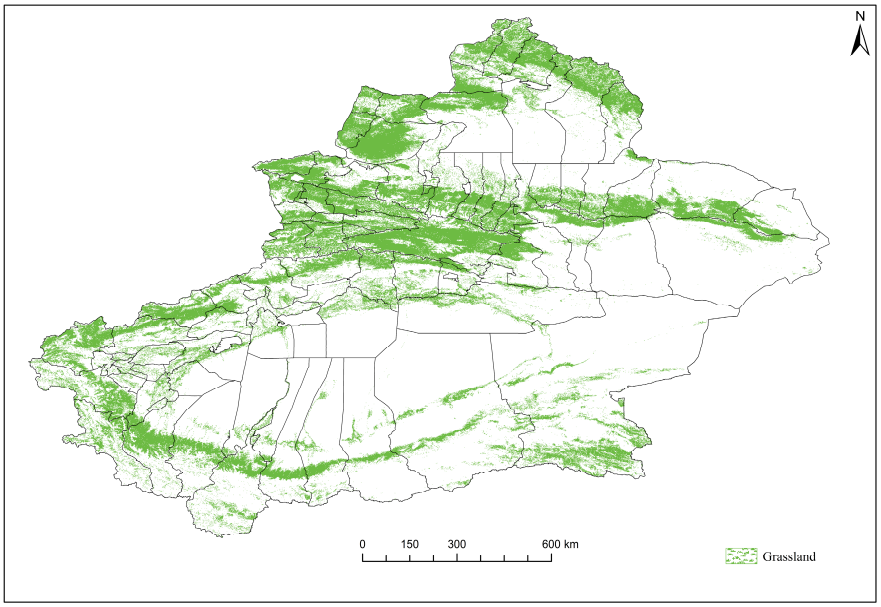


Figure 2. Spatial distribution of grassland area in Xinjiang in 2020.

2.2. Data Sources and Processing

This study used 81 counties in Xinjiang as evaluation units, with the study period spanning 2001–2020. The assessment data included socioeconomic, meteorological, land-use, livestock, and ecological environment data. Socioeconomic data were obtained from the Xinjiang Statistical Yearbook, statistical yearbooks of prefectures and prefecture-level cities, and statistical bulletins on national economic and social development at the county and city levels. These data were used to calculate indicators such as economic density, population density, proportion of animal husbandry output, per capita disposable income of rural residents, basic education support level, total agricultural machinery power, fiscal self-sufficiency rate, and household financial buffering capacity. Meteorological data included mean annual temperature and annual precipitation, which were obtained from the China 1 km resolution monthly mean temperature dataset [21], and the CHM_PRE V2 high-resolution gridded precipitation dataset for mainland China [22], respectively. Land-use data were derived from the China Land Cover Dataset (CLCD) [23], and were used to extract grassland, cropland, and bare land and to calculate the grassland–cropland ratio and bare land proportion. Livestock data were obtained from the annual livestock distribution data of Global Pasture Watch [24] and were used to calculate grazing intensity. Ecological data included the Remote Sensing Ecological Index (RSEI), biodiversity intactness index, landscape ecological risk, and carbon use efficiency. The RSEI was obtained from the continuous 1000 m ecological condition assessment index dataset for China; the biodiversity intactness index was obtained from Nguyen et al. [25]; landscape ecological risk was obtained from Wu [26], and carbon use efficiency was obtained from Running and Zhao [27]. The RSEI values were obtained directly from the continuous 1000 m ecological condition assessment index dataset for China [28] and were not recalculated in this study. According to the dataset documentation, the published RSEI was generated by principal component analysis of MODIS-based Normalized Difference Vegetation Index (NDVI), land surface temperature (LST), wetness (WET), and Normalized Difference Soil Index (NDSI) data. Data from different sources were uniformly converted to the county scale. Raster data were clipped, projected to a unified coordinate system, and processed using zonal statistics to extract annual county-level values, while statistical data were matched to county-level administrative units. To reduce the influence of extreme values on weighting and comprehensive evaluation results, only economic density, per capita disposable income

of rural residents, and household financial buffering capacity were transformed using ln(X + 1). All data processing and statistical analyses were performed using Python 3.10 (Python Software Foundation, Beaverton, OR, USA).

2.3. Indicator Selection and DPSIR Framework

This study constructed a vulnerability assessment indicator system for county-level grassland social–ecological systems in Xinjiang based on the DPSIR framework. The DPSIR framework includes five dimensions: driver, pressure, state, impact, and response. It can reflect the relationships among socioeconomic activities, resource-use pressure, changes in ecological state, ecological and social impacts, and governance responses [15,29]. The relational framework for the vulnerability assessment of grassland social–ecological systems under the DPSIR framework is shown in Figure 3. Indicator selection followed four criteria: conceptual relevance to the DPSIR framework, representativeness of the main climatic, ecological, production, livelihood, and governance processes affecting grassland social–ecological systems in Xinjiang, comparability across counties and years, and continuous data availability for all 81 counties from 2001 to 2020. The indicators were selected with reference to previous studies on grassland social–ecological systems, coupled human–natural systems, grassland ecological condition, grazing pressure, rural livelihoods, and social response capacity [5,12,13,28,30–34]. Within the DPSIR framework, socioeconomic development and dependence on animal husbandry were used to represent drivers; climate conditions, grazing use, and land-surface exposure represented pressures; grassland resources and ecological quality represented state; ecological function and rural livelihoods represented impacts; and public-service, production, fiscal, and household buffering capacities represented responses. The specific literature basis for each indicator is provided in Table 1.

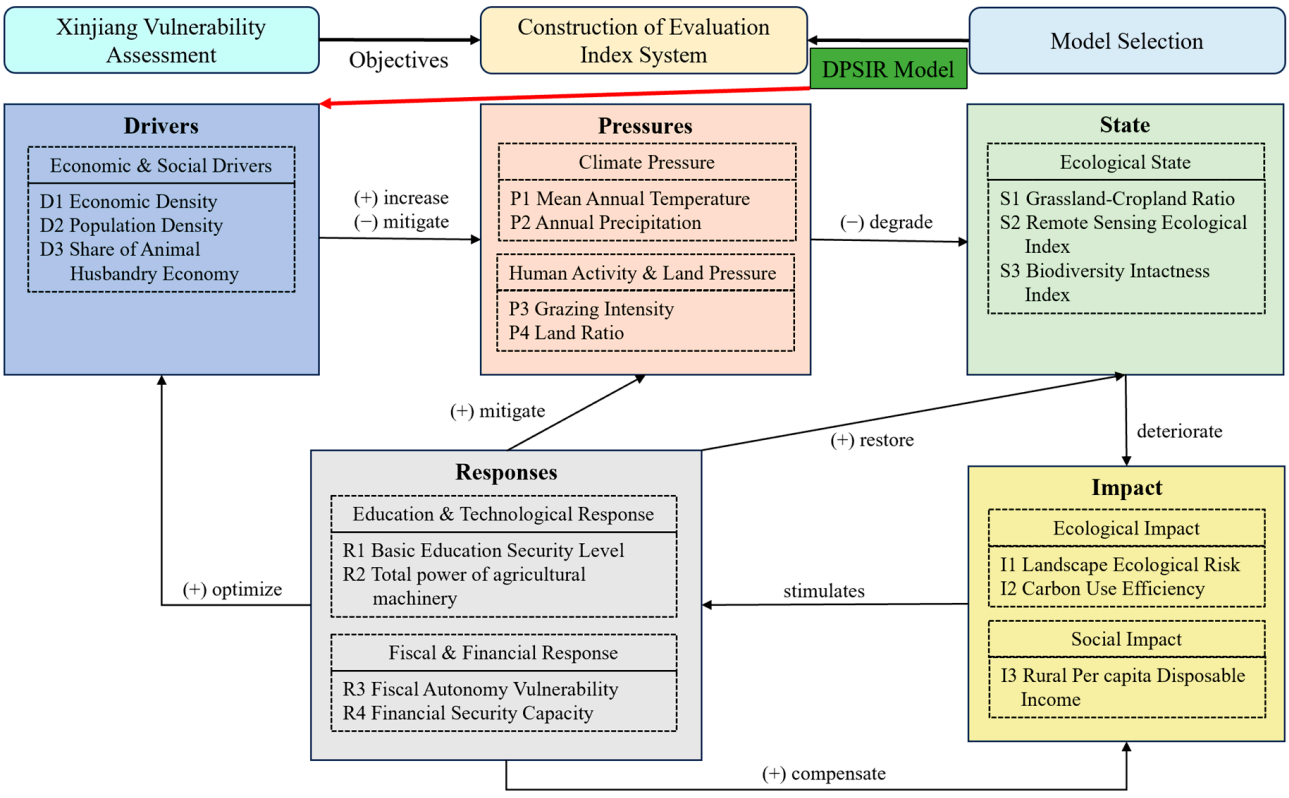


Figure 3. Relational framework for the vulnerability assessment of grassland social–ecological systems under the DPSIR framework.

Table 1. Vulnerability assessment indicator system for grassland social–ecological systems.

Dimension	Indicator Name	Calculation Formula	Unit	Direction	Representation	References
Driver	Economic density	Gross domestic product/administrative area	10^4 yuan km^{-2}	+	County-level economic foundation and resource allocation conditions	[12,13]
Driver	Population density	Year-end resident population/administrative area	persons km^{-2}	–	Degree of population agglomeration and pressure from resource demand	[12,13]
Driver	Proportion of animal husbandry output	Gross output value of animal husbandry/total gross output value of agriculture, forestry, animal husbandry, and fishery × 100%	%	–	Degree of county-level dependence on the grassland animal husbandry economy	[5,30]
Pressure	Mean annual temperature	Mean annual temperature	°C	–	Regional thermal conditions and warming-stress background	[4,9]
Pressure	Annual precipitation	Total annual precipitation	mm	+	Natural water supply conditions for grassland growth	[4,9]
Pressure	Grazing intensity	Number of converted sheep units/grassland area	sheep units km^{-2}	–	Livestock-use pressure borne per unit grassland area	[31,32]
Pressure	Bare land proportion	Bare land area/administrative area × 100%	%	–	Degree of land surface exposure and risk of land degradation	[23,33]
State	Grassland–cropland ratio	Grassland area/cropland area	—	+	Retention status of grassland resources relative to cropland	[23,32]
State	Remote sensing ecological index	Mean county-level remote sensing ecological index	—	+	Comprehensive ecological environmental quality at the county level	[28]
State	Biodiversity intactness index	Mean county-level biodiversity intactness index	—	+	Ecosystem structure and biodiversity maintenance status	[25]
Impact	Landscape ecological risk	Mean annual county-level landscape ecological risk raster value	—	–	Level of ecological risk caused by changes in landscape pattern	[26]
Impact	Carbon use efficiency	CUE = NPP/GPP	—	+	Ecosystem carbon transformation and production function	[27]
Impact	Per capita disposable income of rural residents	Per capita disposable income of rural residents	yuan $person^{-1}$	+	Livelihood level and economic coping capacity of farmers and pastoralists	[6,30]
Response	Basic education support level	Number of students enrolled in basic education/total population × 100%	%	+	County-level provision of basic public services	[5,34]

Table 1. *Cont.*

Dimension	Indicator Name	Calculation Formula	Unit	Direction	Representation	References
Response	Total agricultural machinery power	Total agricultural machinery power	10 4 kW	+	Production input and technical support conditions for agriculture and animal husbandry	[6,32]
Response	Fiscal self-sufficiency rate	General public budget revenue/general public budget expenditure × 100%	%	+	Local fiscal support and public-expenditure support capacity	[5,34]
Response	Household financial buffering capacity	Balance of urban and rural household savings deposits/year-end loan balance of financial institutions	Ratio	+	Risk-buffering capacity of household savings relative to credit scale	[6,30]

Note: Grey areas denote areas not included in the 81 county-level evaluation units of this study. "+" denotes a vulnerability-mitigating indicator, for which a higher original value indicates lower vulnerability, whereas "−" denotes a vulnerability-aggravating indicator, for which a higher original value indicates higher vulnerability. "—" denotes a dimensionless indicator. All indicators were standardized so that higher standardized values indicate higher vulnerab.

The driver dimension was used to characterize the basic effects of county-level socioeconomic development and dependence on animal husbandry on grassland systems, and included economic density, population density, and proportion of animal husbandry output. The pressure dimension was used to characterize external pressures formed by climatic conditions, grazing use, and changes in land surface cover, and included mean annual temperature, annual precipitation, grazing intensity, and bare land proportion. The state dimension was used to characterize grassland resources and ecological environmental conditions, and included the grassland–cropland ratio, remote sensing ecological index, and biodiversity intactness index. The impact dimension was used to characterize the impacts of changes in grassland social–ecological systems on ecological functions and the livelihoods of farmers and pastoralists, and included landscape ecological risk, carbon use efficiency, and per capita disposable income of rural residents. The response dimension was used to characterize the regulatory capacity of county-level social systems in relation to vulnerability, and included basic education support level, total agricultural machinery power, fiscal self-sufficiency rate, and household financial buffering capacity [5,12,13,28,30].

Based on the above DPSIR layering logic, this study finally selected 17 indicators to construct a vulnerability assessment indicator system for county-level grassland social–ecological systems in Xinjiang (Table 1). In Table 1, "+" denotes a vulnerability-mitigating indicator, for which a higher original value indicates lower vulnerability, whereas "−" denotes a vulnerability-aggravating indicator, for which a higher original value indicates higher vulnerability. During standardization, all indicators were transformed so that higher standardized values represented higher vulnerability.

2.4. Vulnerability Assessment and Obstacle Factor Diagnosis Methods

This study evaluated the vulnerability of county-level grassland social–ecological systems in Xinjiang following the steps of "indicator standardization–weight determination–comprehensive evaluation–grade classification–regional difference measurement–trend test–obstacle factor diagnosis". To eliminate dimensional differences and unify indicator

directions, min–max standardization was conducted based on all county samples from 2001 to 2020, so that a larger standardized value indicated higher vulnerability. Here, x_{ij} denotes the original value of indicator j for county-year sample i, z_{ij} denotes the corresponding standardized value, and $\max(x_j)$ and $\min(x_j)$ denote the maximum and minimum values of indicator j across all county-year samples, respectively. For positive indicators, inverse standardization was performed using Equation (1); for negative indicators, namely indicators for which a larger original value indicates higher vulnerability, positive standardization was performed using Equation (2).

$$z_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{1}$$

$$z_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{2}$$

Indicator weights were determined using the CRITIC method under the equal-weight constraint of the five DPSIR dimensions. The weights of the D, P, S, I, and R dimensions were all set to 0.2, and the CRITIC method was used to determine indicator weights within each dimension [17,35,36]. The information content, within-dimension weight, and final weight of the j-th indicator in the h-th dimension were calculated as follows:

$$C_{hj} = \sigma_{hj} \sum_{k=1}^{m_h} \left(1 - r_{hjk}\right) \tag{3}$$

$$\omega_{hj} = \frac{C_{hj}}{\sum_{j=1}^{m_h} C_{hj}} \tag{4}$$

$$W_{hj} = \alpha_h \omega_{hj} \tag{5}$$

$$\alpha_h = 0.2,\ h \in \{D, P, S, I, R\} \tag{6}$$

where C_{hj} is the information content of indicator j in dimension h, σ_{hj} is its standard deviation, r_{hjk} is the correlation coefficient between indicators j and k within dimension h, m_h is the number of indicators in dimension h, w_{hj} is the within-dimension weight, and W_{hj} is the final indicator weight. The CRITIC–TOPSIS approach was selected because it combines objective weighting with comprehensive evaluation. Compared with subjective weighting methods, CRITIC reduces dependence on expert judgment by considering indicator variability and inter-indicator conflict, while TOPSIS evaluates each county-year sample according to its distance from the high- and low-vulnerability ideal solutions. This combination supports consistent comparison across multiple counties and years.

The comprehensive vulnerability index was calculated using the TOPSIS model. First, the weighted standardized matrix was constructed as follows:

$$v_{ij} = W_{hj} z_{ij} \tag{7}$$

Because all standardized indicators represented the vulnerability direction, the positive ideal solution was the high-vulnerability ideal point, and the negative ideal solution was the low-vulnerability ideal point:

$$A^+ = \left(v_1^+, v_2^+, \cdots, v_n^+\right),\ v_j^+ = \max_i \left(v_{ij}\right) \tag{8}$$

$$A^- = \left(v_1^-, v_2^-, \cdots, v_n^-\right),\ v_j^- = \min_i \left(v_{ij}\right) \tag{9}$$

The distances from the i-th sample to the positive and negative ideal solutions were calculated as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} \tag{10}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \tag{11}$$

The vulnerability index was calculated as follows:

$$V_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

where V_i is the vulnerability index of the i-th county-year sample, D_i^+ is the distance from the sample to the high-vulnerability ideal point, and D_i^- is the distance from the sample to the low-vulnerability ideal point. In this study, $D_i^- / \left(D_i^+ + D_i^-\right)$ is used to indicate the degree to which a sample approaches the high-vulnerability ideal point. A larger V_i indicates higher vulnerability of the grassland social–ecological system. For ease of interpretation, the resulting closeness coefficient was multiplied by 100.

Vulnerability grades were classified using the Jenks natural breaks method [37]. Based on the vulnerability indices of all counties from 2001 to 2020, unified classification breakpoints were determined, and vulnerability was divided into five categories: low vulnerability, relatively low vulnerability, moderate vulnerability, relatively high vulnerability, and high vulnerability.

To characterize intra-regional county-level differences, the coefficient of variation (CV) was used to measure the dispersion of vulnerability indices within northern Xinjiang, southern Xinjiang, and eastern Xinjiang:

$$CV_h = \frac{\sigma_h}{\overline{V}_h} \tag{13}$$

When $\beta > 0$, vulnerability shows an increasing trend; when $\beta < 0$, vulnerability shows a decreasing trend; and when $\beta = 0$, vulnerability remains stable.

Trends in county-level vulnerability were identified using Sen's slope estimation and the Mann–Kendall test [38–40], calculated as follows:

$$\beta = \text{Median}\left(\frac{V_j - V_i}{j - i}\right),\ 1 \le i < j \le n \tag{14}$$

When $\beta > 0$, vulnerability shows an increasing trend; when $\beta < 0$, vulnerability shows a decreasing trend; and when $\beta = 0$, vulnerability is basically stable.

The Mann–Kendall test statistic is:

$$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \text{sgn}\left(V_j - V_i\right) \tag{15}$$

The sign function is defined as follows: when $V_j - V_i > 0$, $sgn\left(V_j - V_i\right) = 1$; when $V_j - V_i = 0$, $sgn\left(V_j - V_i\right) = 0$; and when $V_j - V_i < 0$, $sgn\left(V_j - V_i\right) = -1$.

To account for possible tied values, the variance of the Mann–Kendall statistic S is:

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^{g} t_p\left(t_p - 1\right)\left(2t_p + 5\right)}{18} \tag{16}$$

where g is the number of tied groups and t_p is the number of observations in the p-th tied group. When no tied values are present, the correction term is zero.

The standardized statistic is defined as follows: when $S > 0$, $Z = (S-1)/\sqrt{Var(S)}$; when $S = 0$, $Z = 0$; and when $S < 0$, $Z = (S+1)/\sqrt{Var(S)}$.

A trend was considered statistically significant at the 0.05 level when $|\ Z\ | \geq 1.96$; otherwise, it was considered non-significant. Based on β and Z, changes in county-level vulnerability were classified into five categories: significant decrease, non-significant decrease, basic stability, non-significant increase, and significant increase.

To identify the main obstacle factors, the obstacle degree model was used to measure the relative contribution of each indicator to comprehensive vulnerability. Since a larger standardized value indicates higher vulnerability, z_{ij} was directly used to represent the vulnerability contribution of the j-th indicator for the i-th county-year sample. The obstacle degree of the j-th indicator for the i-th sample is calculated as:

$$O_{ij} = \frac{W_j z_{ij}}{\sum_{j=1}^{n} W_j z_{ij}} \tag{17}$$

The obstacle degree of each dimension is the sum of the obstacle degrees of the indicators within that dimension:

$$O_{ih} = \sum\nolimits_{j \in h} O_{ij} \tag{18}$$

where O_{ij} is the obstacle degree of the j-th indicator for the i-th sample, O_{ih} is the obstacle degree of the h-th DPSIR dimension for the i-th sample, W_j is the weight of the j-th indicator, z_{ij} is the standardized indicator value, and n is the number of indicators. A larger obstacle degree indicates a higher relative contribution of the indicator to comprehensive vulnerability.

Based on the final assessment scores, the vulnerability of grassland social–ecological systems was divided into five grades. The classification criteria are shown in Table 2.

Table 2. Classification criteria for the vulnerability index of grassland social–ecological systems.

Grade	Grade Name	Vulnerability Index Range
1	Low vulnerability	$36.50 \leq V < 46.27$
2	Relatively low vulnerability	$46.27 \leq V < 50.72$
3	Moderate vulnerability	$50.72 \leq V < 54.31$
4	Relatively high vulnerability	$54.31 \leq V < 59.09$
5	High vulnerability	$59.09 \leq V \leq 68.42$

3. Results

3.1. System Characteristics and Indicator Weights

3.1.1. Characteristics of the Grassland Social–Ecological System

From 2001 to 2020, county-level grassland social–ecological systems in Xinjiang showed strengthened economic support, while ecological constraints remained. Economic density increased from 35.41×10^4 yuan/km^2 to 226.10×10^4 yuan/km^2, and the per capita disposable income of rural residents increased from 1875 to 14,797 yuan person^{-1}, indicating marked improvements in county-level economic foundations and the livelihood conditions of farmers and pastoralists. Population density increased from 26.74 persons/km^2 to 34.67 persons/km^2, indicating increased resource demand. The proportion of animal husbandry output decreased from 37.03% to 32.25%, indicating a decline in county-level relative dependence on animal husbandry.

Among the pressure-layer indicators, mean annual temperature increased from 6.76 °C to 7.06 °C, while annual precipitation decreased from 262.52 mm to 205.57 mm, reflecting climatic pressure from warming and reduced precipitation on grassland systems. Grazing intensity decreased from 239.60 to 188.12, and the bare land proportion decreased

from 62.34% to 59.79%, indicating reductions in grassland-use pressure and land surface exposure. The state- and impact-layer indicators showed that the grassland–cropland ratio, remote sensing ecological index, and biodiversity intactness index all declined, while landscape ecological risk increased, indicating persistent pressure on grassland resource status and ecological quality. Carbon use efficiency increased slightly, indicating a certain improvement in ecosystem production function.

In the response layer, total agricultural machinery power increased markedly, reflecting enhanced production support capacity for agriculture and animal husbandry. The basic education support level, fiscal self-sufficiency rate, and household financial buffering capacity decreased, indicating that public services, fiscal support, and household risk-buffering capacity remained relatively weak in some counties.

Taken together, strengthened socioeconomic and production support and reduced grazing and bare-land pressures were accompanied by persistent climatic and ecological constraints. These contrasting changes provide the indicator-level basis for interpreting the subsequent vulnerability assessment.

The spatial distributions of the original values of the 17 assessment indicators in 2001, 2005, 2010, 2015, and 2020 are shown in Appendix B, Figures A1–A5.

3.1.2. CRITIC-Based Indicator Weighting Results

This study used the CRITIC method to determine indicator weights under the equal-weight constraint of the five DPSIR dimensions. The weights of the five dimensions were all 20.00%, and the weights within each dimension were jointly determined by indicator standard deviation and correlation conflict. The comprehensive weights of the 17 indicators ranged from 2.33% to 8.29% (Table 3), indicating differences in the discriminative effects of different indicators in the county-level vulnerability assessment.

Table 3. Indicator weights for the vulnerability assessment of grassland social–ecological systems.

Dimension	Indicator Name	Comprehensive Weight
Driver	Economic density	7.53%
Driver	Population density	6.42%
Driver	Proportion of animal husbandry output	6.05%
Pressure	Mean annual temperature	4.86%
Pressure	Annual precipitation	4.60%
Pressure	Grazing intensity	3.75%
Pressure	Bare land proportion	6.78%
State	Grassland–cropland ratio	5.14%
State	Remote sensing ecological index	7.79%
State	Biodiversity intactness index	7.06%
Impact	Landscape ecological risk	4.25%
Impact	Carbon use efficiency	7.46%
Impact	Per capita disposable income of rural residents	8.29%
Response	Basic education support level	2.33%
Response	Total agricultural machinery power	6.70%
Response	Fiscal self-sufficiency rate	8.11%
Response	Household financial buffering capacity	2.86%

The indicators with higher weights were per capita disposable income of rural residents, fiscal self-sufficiency rate, remote sensing ecological index, economic density, and carbon use efficiency, with weights of 8.29%, 8.11%, 7.79%, 7.53%, and 7.46%, respectively. These indicators represent livelihood coping capacity, fiscal support, ecological quality, economic foundation, and ecological function, respectively. Basic education support level, household financial buffering capacity, and grazing intensity had lower weights, at 2.33%,

2.86%, and 3.75%, respectively. In the CRITIC framework, higher weights indicate greater statistical information content and discriminatory ability within the dataset.

3.2. Spatiotemporal Evolution Characteristics of Grassland Social–Ecological System Vulnerability

3.2.1. Temporal Evolution Characteristics

Based on the TOPSIS results, the mean vulnerability index decreased from 55.82 in 2001 to 50.27 in 2020, representing a decline of 5.54 points (9.93%). The stage averages were 54.71 in 2001–2005, 53.50 in 2006–2010, 51.34 in 2011–2015, and 50.12 in 2016–2020. The lowest annual mean occurred in 2018 (49.88), followed by slight increases to 50.16 in 2019 and 50.27 in 2020. The annual standard deviation remained between 3.80 and 4.31, indicating persistent differences among counties (Figure 4).

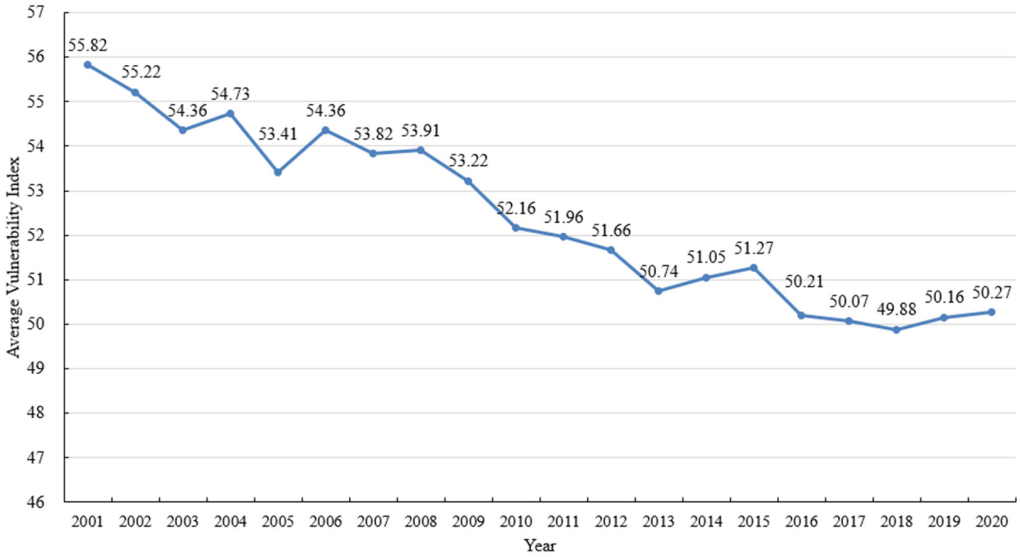


Figure 4. Changes in the vulnerability index of county-level grassland social–ecological systems in Xinjiang from 2001 to 2020.

The number of counties with low and relatively low vulnerability increased from 6 in 2001 to 44 in 2020, while the number with relatively high and high vulnerability decreased from 57 to 11. High-vulnerability counties decreased from 14 to 2. These changes indicate a general shift toward lower vulnerability levels, although differences among counties remained (Figure 5).

3.2.2. Spatial Differentiation Characteristics

From 2001 to 2020, the vulnerability of county-level grassland social–ecological systems in Xinjiang showed clear spatial differences. Among the three major regions, southern Xinjiang had the highest multi-year mean vulnerability index, at 53.71, followed by eastern Xinjiang at 51.44 and northern Xinjiang at 50.98. In 2001, the mean values for southern Xinjiang, eastern Xinjiang, and northern Xinjiang were 57.00, 54.64, and 54.54, respectively; by 2020, they had decreased to 51.62, 48.66, and 48.84, respectively (Table 4). These results indicate that vulnerability declined in all three regions, while southern Xinjiang remained at a relatively high level. The evolution of the spatial pattern of grassland social–ecological system vulnerability across counties in Xinjiang is shown in Figure 6.

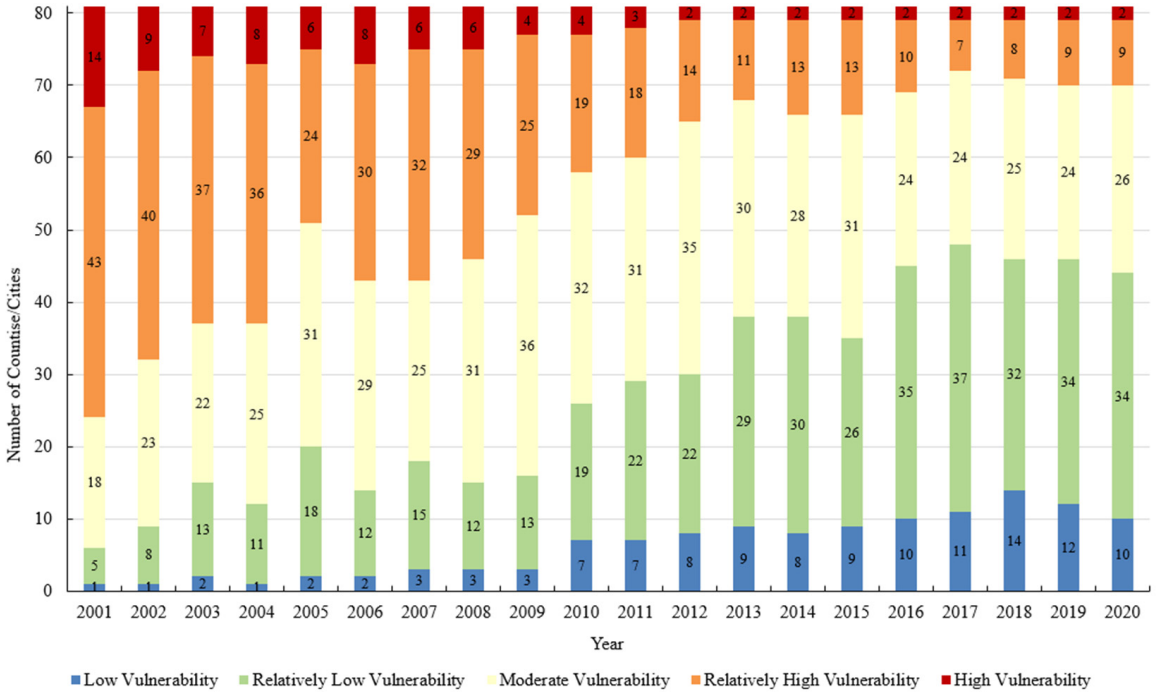


Figure 5. Changes in the vulnerability grade structure of county-level grassland social–ecological systems in Xinjiang from 2001 to 2020.

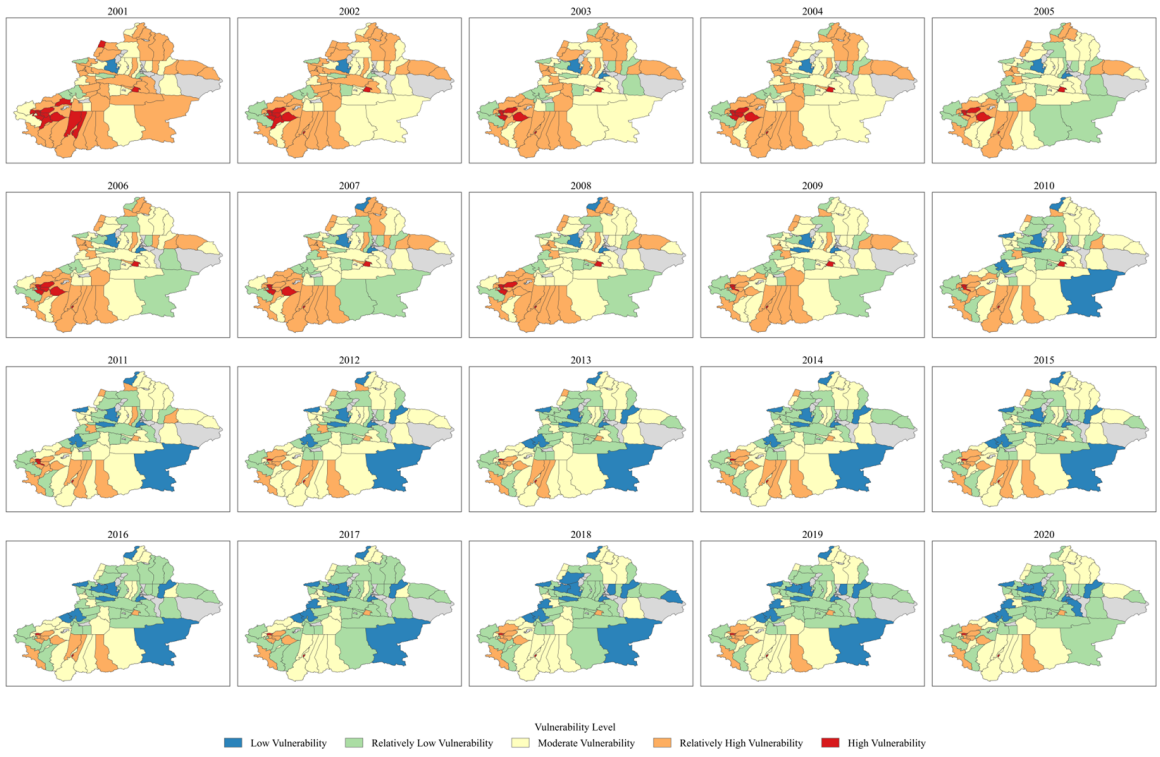


Figure 6. Evolution of the spatial pattern of county-level grassland social–ecological system vulnerability in Xinjiang from 2001 to 2020.Grey areas denote areas not included in the 81 county-level evaluation units of this study.

Based on multi-year county-level mean values, high-vulnerability counties were mainly concentrated in southern Xinjiang. Hotan City, Kashgar City, Shule County, and Bohu County had relatively high multi-year mean vulnerability indices, at 65.68, 62.27, 59.90, and 59.25, respectively. Jiashi County, Yingjisha County, Maigaiti County, Yuepuhu

County, Moyu County, and Luopu County were also at relatively high levels. Low-vulnerability counties mainly included Wusu City, Urumqi County, Wenquan County, and Xinyuan County, with multi-year mean values of 40.05, 43.39, 45.78, and 45.80, respectively, which were generally lower than those of most counties in Xinjiang.

In terms of grade structure, in 2001, southern Xinjiang had 34 counties with relatively high and high vulnerability, northern Xinjiang had 20, and eastern Xinjiang had 3. By 2020, northern Xinjiang and eastern Xinjiang no longer had counties with relatively high or high vulnerability, while southern Xinjiang still had 9 relatively high-vulnerability counties and 2 high-vulnerability counties. This indicates that southern Xinjiang remained the main concentration area of grassland social–ecological system vulnerability in Xinjiang.

The coefficient of variation (CV) results show that southern Xinjiang had the largest intra-regional differences, with a mean CV of 0.0762; northern Xinjiang followed, with a mean CV of 0.0708; and eastern Xinjiang had the lowest mean CV, at 0.0300. The low CV in eastern Xinjiang should be interpreted mainly as a description of intra-regional dispersion because it included only four counties. Combining regional means and grade structures, county-level vulnerability in Xinjiang generally showed a spatial pattern characterized by relatively high vulnerability in southern Xinjiang, relatively low vulnerability in northern Xinjiang, and smaller county-level differences in eastern Xinjiang.

Table 4. Statistics of vulnerability indices and coefficients of variation in the three major regions.

Region	Number of Counties	Mean Value in 2001	Mean Value in 2020	Mean Value in 2001–2020	Mean CV	Minimum CV	Maximum CV
Northern Xinjiang	35	54.54	48.84	50.98	0.0708	0.0637	0.0775
Southern Xinjiang	42	57.00	51.62	53.71	0.0762	0.0667	0.0842
Eastern Xinjiang	4	54.64	48.66	51.44	0.0300	0.0130	0.0436

3.3. Trends in County-Level Vulnerability and Significance Tests

Based on county-level vulnerability indices from 2001 to 2020, Sen's slope and the Mann–Kendall test were used to identify change trends. The results showed that the Sen's slopes of all 81 counties were negative, ranging from −0.61 to −0.03, with a mean of −0.32, indicating an overall declining trend in the vulnerability of county-level grassland social–ecological systems in Xinjiang during the study period. The Mann–Kendall test results showed that 80 counties passed the 0.05 significance test, accounting for 98.77% of all counties; only Shanshan County showed a non-significant decrease. No counties showed an increasing trend in vulnerability during the study period.

By region, the mean Sen's slopes for northern Xinjiang, southern Xinjiang, and eastern Xinjiang were −0.34, −0.30, and −0.35, respectively, all indicating decreasing trends. All counties in northern Xinjiang and southern Xinjiang showed significant decreases. In eastern Xinjiang, except for Shanshan County, Yiwu County, Toksun County, and Barkol Kazakh Autonomous County all showed significant decreases.

At the county level, Shache County, Tuoli County, Qitai County, Yiwu County, and Shule County had faster rates of decline, with larger absolute values of Sen's slope. The Sen's slope of Shanshan County was −0.03 and did not pass the 0.05 significance test, indicating a relatively small decrease in vulnerability. The trend results indicate that improvement in county-level vulnerability in Xinjiang was widespread, but the rate of decline differed among counties. Although some counties in southern Xinjiang showed significant decreases, their absolute vulnerability levels remained relatively high.

3.4. Obstacle Factor Diagnosis

After calculating obstacle degrees based on standardized values z, the response layer, state layer, and pressure layer were identified as the main limiting dimensions. Among them, the response layer had the highest mean obstacle degree, at 0.3097; the state layer and pressure layer had mean obstacle degrees of 0.2244 and 0.1987, respectively; and the driver layer and impact layer had relatively low values, at 0.1352 and 0.1320, respectively.

At the indicator level, fiscal self-sufficiency rate, total agricultural machinery power, grassland–cropland ratio, economic density, and remote sensing ecological index had relatively high obstacle degrees, at 0.1210, 0.1034, 0.0887, 0.0882, and 0.0850, respectively (Table 5). These indicators correspond to local fiscal support, production support for agriculture and animal husbandry, grassland resource status, county-level economic foundation, and ecological quality, respectively, and represent the main obstacle factors affecting county-level vulnerability.

Table 5. Statistics of indicator obstacle contributions.

Dimension	Indicator Name	Mean Obstacle Degree
Response	Fiscal self-sufficiency rate	0.1210
Response	Total agricultural machinery power	0.1034
State	Grassland–cropland ratio	0.0887
Driver	Economic density	0.0882
State	Remote sensing ecological index	0.0850
Pressure	Bare land proportion	0.0659
Impact	Carbon use efficiency	0.0632
Pressure	Annual precipitation	0.0619
Impact	Per capita disposable income of rural residents	0.0601
Pressure	Mean annual temperature	0.0559
State	Biodiversity intactness index	0.0507
Response	Household financial buffering capacity	0.0462
Driver	Proportion of animal husbandry output	0.0407
Response	Basic education support level	0.0391
Pressure	Grazing intensity	0.0150
Impact	Landscape ecological risk	0.0087
Driver	Population density	0.0063

In terms of temporal changes, the response-layer obstacle degree increased from 0.2918 in 2001 to 0.3128 in 2020, the state-layer obstacle degree increased from 0.2090 to 0.2463, and the pressure-layer obstacle degree increased from 0.1903 to 0.2118. The driver-layer and impact-layer obstacle degrees decreased from 0.1469 and 0.1621 to 0.1214 and 0.1076, respectively. This indicates that limiting factors in the later period were more concentrated in fiscal support, production support, grassland resource status, and ecological quality.

4. Discussion

4.1. Mechanisms of Change in Grassland Social–Ecological System Vulnerability

County-level grassland social–ecological system vulnerability in Xinjiang declined overall from 2001 to 2020, although changes across the indicator dimensions were not uniform. Lower vulnerability was associated with higher economic density, rural disposable income, and total agricultural machinery power, together with lower grazing intensity and bare land proportion. These concurrent changes indicate stronger socioeconomic coping capacity and lower grassland-use pressure, while ecological and climatic constraints remained. Similar combinations of climatic and human influences, together with marked regional variation, have also been reported for Xinjiang grasslands [4,20].

Within the pressure dimension, the declines in grazing intensity and bare land proportion indicate lower direct pressure from livestock use and land-surface exposure. This

pattern is consistent with studies of forage–livestock balance and grassland management that reported reduced grazing pressure in some grassland areas [31,32]. In contrast, increasing temperature and declining precipitation indicate that thermal and water stress remained persistent climatic constraints [4,9]. The coexistence of lower use pressure and continued climatic stress provides important context for the uneven changes observed across the vulnerability dimensions.

The state and impact dimensions showed a different pattern from the overall vulnerability index. The grassland–cropland ratio, remote sensing ecological index, and biodiversity intactness index decreased, while landscape ecological risk increased, indicating continued pressure on grassland resource structure and ecological quality. These changes occurred alongside increasing temperature, declining precipitation, and continuing land-use pressures reported in Xinjiang grasslands [4,9,20]. Because the comprehensive vulnerability index integrates ecological, socioeconomic, and response dimensions, improvements in some socioeconomic and pressure indicators coexisted with deterioration in several ecological-state indicators.

From a socioeconomic perspective, increases in economic density, per capita disposable income of rural residents, and total agricultural machinery power were consistent with stronger county-level economic and production-support capacity [6,30]. Previous studies have associated forage–livestock balance, grazing prohibition, seasonal grazing rest, and grassland ecological compensation with changes in livestock management and grazing pressure, although outcomes vary with household operating scale, livestock structure, compensation standards, and local resource conditions [41,42]. Overall vulnerability declined alongside lower grazing pressure and stronger socioeconomic conditions, while ecological conditions remained under pressure.

4.2. Regional Differences in Obstacle Factors

The response, state, and pressure dimensions had the highest mean obstacle degrees and accounted for the largest shares of the calculated constraints within the assessment framework. At the indicator level, fiscal self-sufficiency rate, total agricultural machinery power, the grassland–cropland ratio, economic density, and the remote sensing ecological index had relatively high obstacle degrees. These indicators accounted for the largest relative contributions within the composite assessment. Related studies have also shown that grassland changes in Xinjiang are shaped by the combined effects of climate change, land use, and human activities, and that water availability, grazing use, and ecological engineering all affect grassland productivity and ecological state [4,9,20].

Southern Xinjiang exhibited the strongest overlap of multiple constraints. Its multi-year mean vulnerability index was 53.71, higher than those of northern and eastern Xinjiang, and relatively high- and high-vulnerability counties remained in 2020. Hotan City, Kashgar City, Shule County, Jiashi County, and Yingjisha County had relatively high vulnerability levels. Factors such as fiscal self-sufficiency rate, bare land proportion, remote sensing ecological index, and grassland–cropland ratio are more likely to form compound constraints in southern Xinjiang, making it the main concentration area of high vulnerability and compound obstacles.

Northern Xinjiang had a relatively low level of vulnerability, but structural weaknesses remained. Counties such as Wusu City, Urumqi County, Wenquan County, and Xinyuan County had relatively low multi-year mean vulnerability indices, indicating certain advantages in ecological foundation, economic conditions, or social response capacity. Thus, vulnerability constraints in northern Xinjiang were less associated with overall high vulnerability and more associated with localized ecological-state pressure and uneven response capacity.

The obstacle factors in eastern Xinjiang exhibited typical characteristics of arid regions. Shanshan County, Toksun County, Barkol Kazakh Autonomous County, and Yiwu County all showed an overall decline in vulnerability during the study period, and all shifted to low or relatively low vulnerability grades by 2020. However, eastern Xinjiang has low precipitation and strong evaporation, and its grassland ecosystems are sensitive to water variability and land-use disturbance. The main obstacle factors involved fiscal self-sufficiency rate, total agricultural machinery power, grassland–cropland ratio, remote sensing ecological index, and annual precipitation. The declining trend in Shanshan County did not pass the significance test, indicating that although some counties showed improvement, the magnitude of improvement was limited.

Regional differences were characterized by higher composite vulnerability and overlapping constraints in southern Xinjiang, localized ecological-state and response constraints in northern Xinjiang, and persistent water-related pressure in eastern Xinjiang. These differences support region-specific governance priorities based on the diagnosed obstacle factors.

4.3. Grassland Protection and Region-Specific Governance

County-level grassland protection in Xinjiang should implement differentiated governance based on the main obstacle factors and regional differences. The results of this study show that fiscal self-sufficiency rate, total agricultural machinery power, grassland–cropland ratio, economic density, and remote sensing ecological index were the main obstacle factors affecting county-level vulnerability, indicating that the vulnerability of grassland social–ecological systems was jointly influenced by fiscal support, production conditions, grassland resources, and ecological quality. Future governance should coordinate grassland protection, pastoral household livelihoods, and county-level development, and improve the synergy among grassland ecological compensation, forage–livestock balance, grazing prohibition and seasonal grazing rest, and grassland restoration policies [43,44].

Southern Xinjiang should be treated as a priority governance area. Counties such as Hotan City, Kashgar City, Shule County, and Bohu County had relatively high vulnerability levels, mainly affected by insufficient fiscal support, weak grassland resources, bare land pressure, and declining ecological quality. Such counties should strengthen bare land management along oasis margins, enclosure and restoration of degraded grasslands, construction of artificial forage land, and forage–livestock balance management, while improving the matching between compensation policies and the opportunity costs of pastoral households [45]. Northern Xinjiang had generally lower vulnerability, and governance should focus on maintaining ecological state and preventing risks, strictly controlling the conversion of grassland to cropland and construction land, and improving dynamic grassland monitoring and livestock carrying capacity regulation. Eastern Xinjiang was clearly constrained by aridity and water availability, and should strengthen enclosure-based restoration, wind prevention and sand fixation, and degraded grassland restoration. Counties with limited improvement, such as Shanshan County, require continuous monitoring.

County-level governance can establish a closed-loop mechanism of "obstacle factor identification–governance measure matching–annual monitoring and evaluation". Counties with insufficient fiscal support should improve the efficiency of grassland protection funding. Counties with weak ecological state should prioritize grassland restoration and ecological quality monitoring. Counties under strong pressure should strengthen forage–livestock balance, grazing prohibition and seasonal grazing rest, and bare land management. Differences in the operating scale of pastoral households, non-pastoral employment levels, and income structure can also affect policy implementation outcomes. Future governance should shift from uniform compensation toward region-specific classification and differentiated support [46,47].

The DPSIR–CRITIC–TOPSIS framework can also be applied to other grassland regions where comparable ecological and socioeconomic data are available, because it provides a consistent structure for integrating environmental pressures, ecological conditions, livelihood impacts, and response capacity. However, the indicator system should be adjusted according to local grassland types, dominant disturbances, production systems, and data availability. The limiting factors identified in Xinjiang may provide a reference for other arid and semi-arid pastoral regions, but their relative importance should be reassessed under local conditions.

4.4. Limitations and Future Improvements

This study has several limitations. First, socioeconomic and animal husbandry data were mainly obtained from statistical yearbooks, statistical bulletins, and gridded products. Differences in statistical calibers across years, regions, and departments may affect the comparability of county-level indicators. Second, indicators such as land use, the remote sensing ecological index, biodiversity intactness index, landscape ecological risk, and carbon use efficiency were derived from remote sensing or model products. They are affected by spatial resolution, mixed pixels, classification accuracy, and algorithmic assumptions, and may contain errors in mountain grasslands, desert grasslands, and oasis ecotones. Third, this study used counties as evaluation units, and county-level mean values may smooth internal differences in topography, hydrothermal conditions, grassland types, and utilization patterns. Fourth, the directions of some indicators involve judgment. Economic density, total agricultural machinery power, and fiscal self-sufficiency rate were defined in this study as factors that reduce vulnerability, but in areas with high resource development intensity, their ecological effects may be more complex. Fifth, the CRITIC–TOPSIS model is suitable for multi-indicator relative evaluation and county-level ranking, but the results do not constitute causal identification among climate change, policy implementation, grazing pressure, and vulnerability decline.

Future research can be improved in three aspects. First, pastoral household surveys, grassland plot monitoring, and local management data can be combined to verify the reliability of socioeconomic and remote sensing indicators. Second, township, watershed, grassland-type, or grazing-unit scales can be introduced on the basis of the county scale to reduce bias caused by spatial aggregation. Third, spatial econometric models, scenario simulation, or causal inference methods can be combined to further identify the relative effects of climate, grazing, land use, and policy responses on the vulnerability of grassland social–ecological systems.

5. Conclusions

This study used 81 counties in Xinjiang as evaluation units and analyzed the spatiotemporal changes in the vulnerability of grassland social–ecological systems in Xinjiang from 2001 to 2020 using the DPSIR framework, the CRITIC–TOPSIS model, Sen's slope estimator, the Mann–Kendall test, and the obstacle degree model. The main conclusions are as follows.

(1) From 2001 to 2020, the vulnerability of county-level grassland social–ecological systems in Xinjiang generally declined, with the mean vulnerability index decreasing from 55.82 to 50.27. The vulnerability grade structure improved markedly. The number of counties with low and relatively low vulnerability increased from 6 to 44, while the number of counties with relatively high and high vulnerability decreased from 57 to 11, indicating a reduction in the comprehensive risk of county-level grassland systems.

(2) Vulnerability showed clear spatial differentiation, with southern Xinjiang having higher vulnerability than northern and eastern Xinjiang. The multi-year mean vulnera-

bility index of southern Xinjiang was 53.71, higher than that of eastern Xinjiang (51.44) and northern Xinjiang (50.98). High-vulnerability counties were mainly concentrated in southern Xinjiang, where intra-regional differences were also larger, indicating that arid environmental conditions, the grassland resource base, and county-level socioeconomic conditions jointly shaped the vulnerability pattern.

(3) County-level vulnerability was dominated by declining trends. The Sen's slopes of all 81 counties were negative, ranging from −0.61 to −0.03, with a mean value of −0.32. Among them, 80 counties passed the 0.05 significance test, and only Shanshan County showed a non-significant decrease. All three major regions showed declining trends, although the magnitude of improvement differed among regions.

(4) The response, state, and pressure dimensions had the highest mean obstacle degrees. At the indicator level, fiscal self-sufficiency rate, total agricultural machinery power, the grassland–cropland ratio, economic density, and the remote sensing ecological index made the largest statistical contributions to the composite vulnerability index. During the study period, declining vulnerability coincided with lower grazing intensity and bare land proportion and with increases in economic density, rural disposable income, and total agricultural machinery power. Meanwhile, decreases in the grassland–cropland ratio, remote sensing ecological index, and biodiversity intactness index, together with an increase in landscape ecological risk, indicated continued pressure on grassland ecological conditions.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/agronomy16161613/s1. Supplementary Data S1: Assessment results for the vulnerability of county-level grassland social–ecological systems in Xinjiang from 2001 to 2020, including indicator weights, classification thresholds, annual and regional statistics, county-level averages, trend-test results, obstacle degrees, and county-year vulnerability indices; Supplementary Data S2: Original data for the 17 assessment indicators of 81 counties in Xinjiang from 2001 to 2020; Supplementary File S3: Python code used for data transformation, CRITIC weighting, TOPSIS assessment, Jenks natural-break classification, Sen's slope estimation, Mann–Kendall testing, coefficient of variation calculation, and obstacle degree analysis.

Author Contributions: Conceptualization, C.B. and D.J.; methodology, C.B., J.W. and D.J.; software, C.B.; validation, J.W., L.X., M.Z., H.Z. and D.J.; formal analysis, C.B.; investigation, C.B., L.X., M.Z. and H.Z.; resources, J.W. and D.J.; data curation, C.B.; writing—original draft preparation, C.B.; writing—review and editing, J.W., L.X., M.Z., H.Z. and D.J.; visualization, C.B.; supervision, J.W. and D.J.; project administration, J.W.; funding acquisition, J.W. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data supporting the findings of this study are provided in the Supplementary Materials. Supplementary Data S1 contains the vulnerability assessment results, including indicator weights, classification thresholds, annual and regional statistics, county-level averages, trend-test results, obstacle degrees, and county-year vulnerability indices. Supplementary Data S2 contains the processed data for the 17 assessment indicators across 81 counties in Xinjiang from 2001 to 2020. Supplementary File S3 contains the Python code used for data processing and statistical analysis. The original third-party datasets are publicly available from the sources cited in the Section 2.

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

Abbreviations

The following abbreviations are used in this manuscript:

DPSIR	Driver–Pressure–State–Impact–Response
PSR	Pressure–State–Response
CRITIC	Criteria Importance Through Intercriteria Correlation
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Productivity
GPP	Gross Primary Productivity
GDP	Gross Domestic Product
CUE	Carbon Use Efficiency
CLCD	China Land Cover Dataset
MODIS	Moderate Resolution Imaging Spectroradiometer
LST	Land Surface Temperature
WET	Wetness
NDSI	Normalized Difference Soil Index
RSEI	Remote Sensing Ecological Index
CV	Coefficient of Variation

Appendix A. County-Level Evaluation Units

Table A1. List of the 81 county-level evaluation units included in the assessment by regional classification.

Regional Classification	County-Level Evaluation Units
Northern Xinjiang	Altay City; Bole City; Burqin County; Qapqal Xibe Autonomous County; Changji City; Emin County; Fuhai County; Fukang City; Fuyun County; Gongliu County; Habahe County; Hoboksar Mongol Autonomous County; Hutubi County; Huocheng County; Jeminay County; Jimsar County; Jinghe County; Kuitun City; Manas County; Mulei Kazakh Autonomous County; Nilka County; Qitai County; Qinghe County; Shawan County; Tacheng City; Tekes County; Tuoli County; Wenquan County; Urumqi County; Wusu City; Xinyuan County; Yining City; Yining County; Yumin County; Zhaosu County
Southern Xinjiang	Akqi County; Aksu City; Akto County; Artux City; Awat County; Bachu County; Baicheng County; Bohu County; Cele County; Jiashi County; Hejing County; Heshuo County; Hotan City; Hotan County; Kashgar City; Keping County; Kuqa County; Korla City; Luntai County; Luopu County; Maigaiti County; Minfeng County; Moyu County; Pishan County; Qiemo County; Ruoqiang County; Shaya County; Shache County; Shufu County; Shule County; Tashkurgan Tajik Autonomous County; Yuli County; Wensu County; Wuqia County; Wushi County; Xinhe County; Yanqi Hui Autonomous County; Yecheng County; Yingjisha County; Yutian County; Yuepuhu County; Zepu County
Eastern Xinjiang	Barkol Kazakh Autonomous County; Shanshan County; Toksun County; Yiwu County

Appendix B. Spatial Distributions of Assessment Indicators in Selected Years

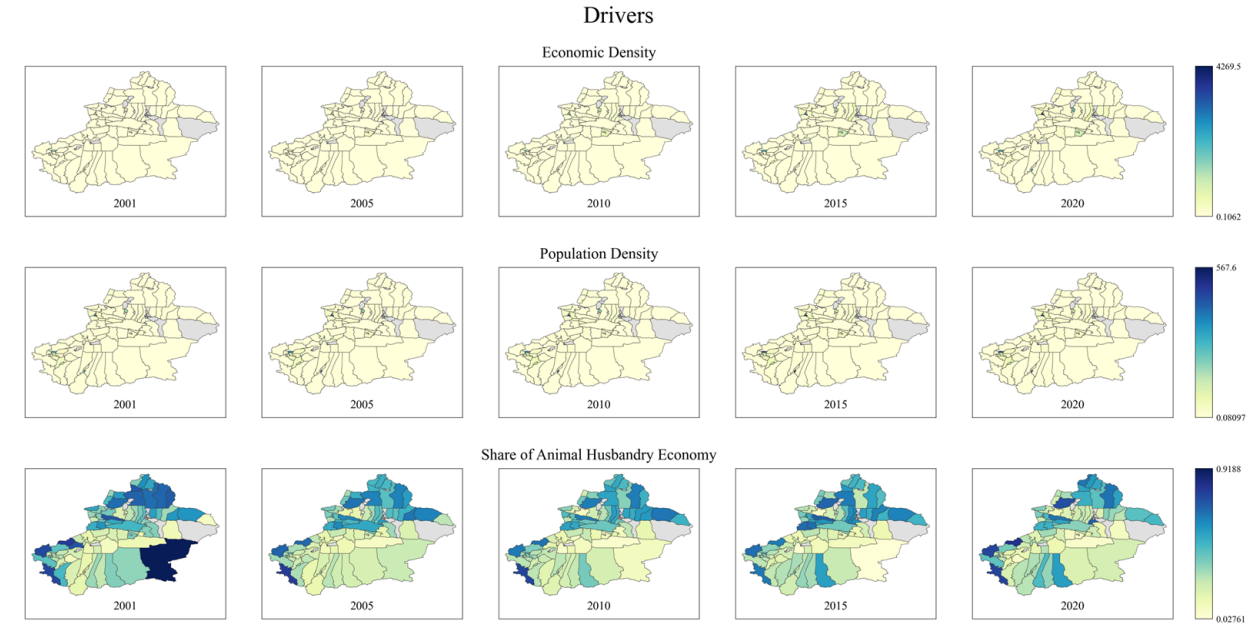


Figure A1. Spatial distributions of the original values of driver-layer indicators in 2001, 2005, 2010, 2015, and 2020.

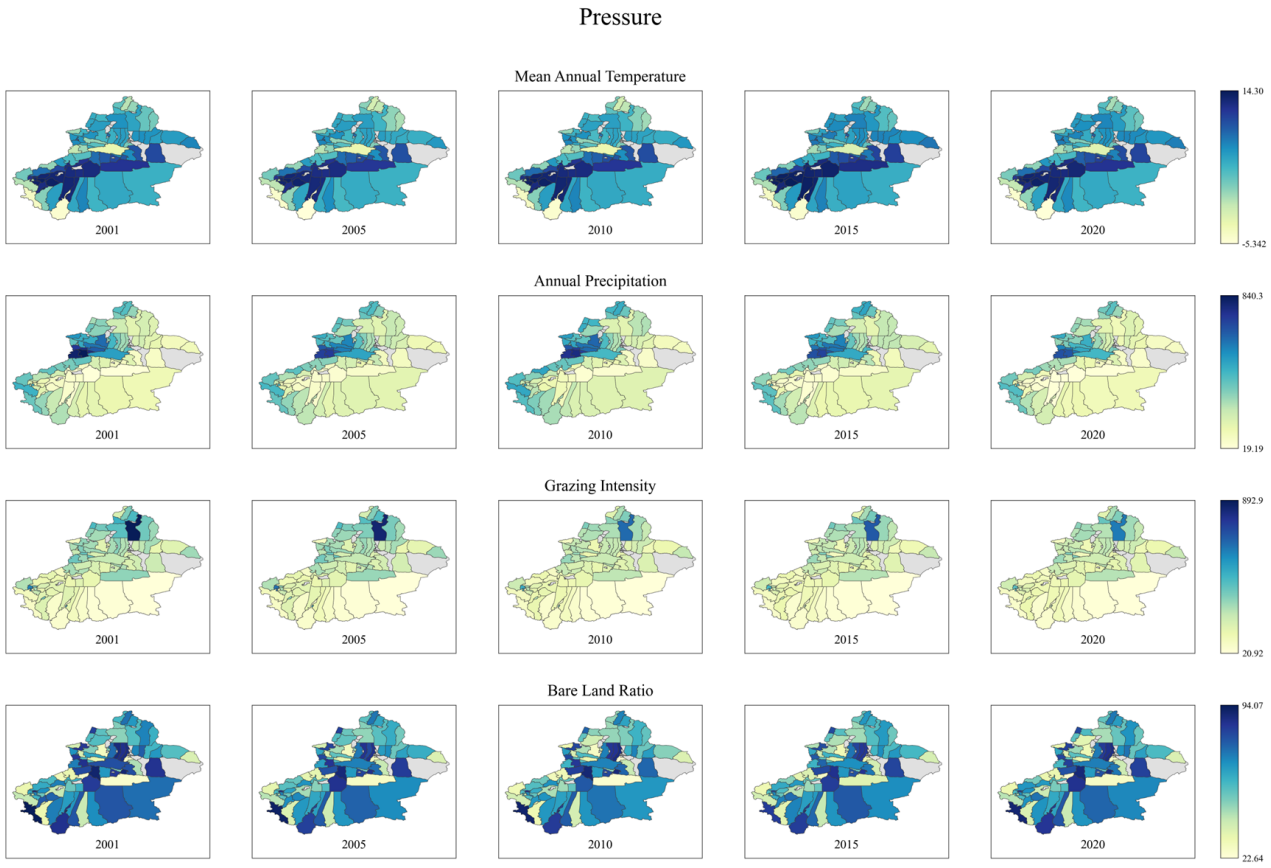


Figure A2. Spatial distributions of the original values of pressure-layer indicators in 2001, 2005, 2010, 2015, and 2020.

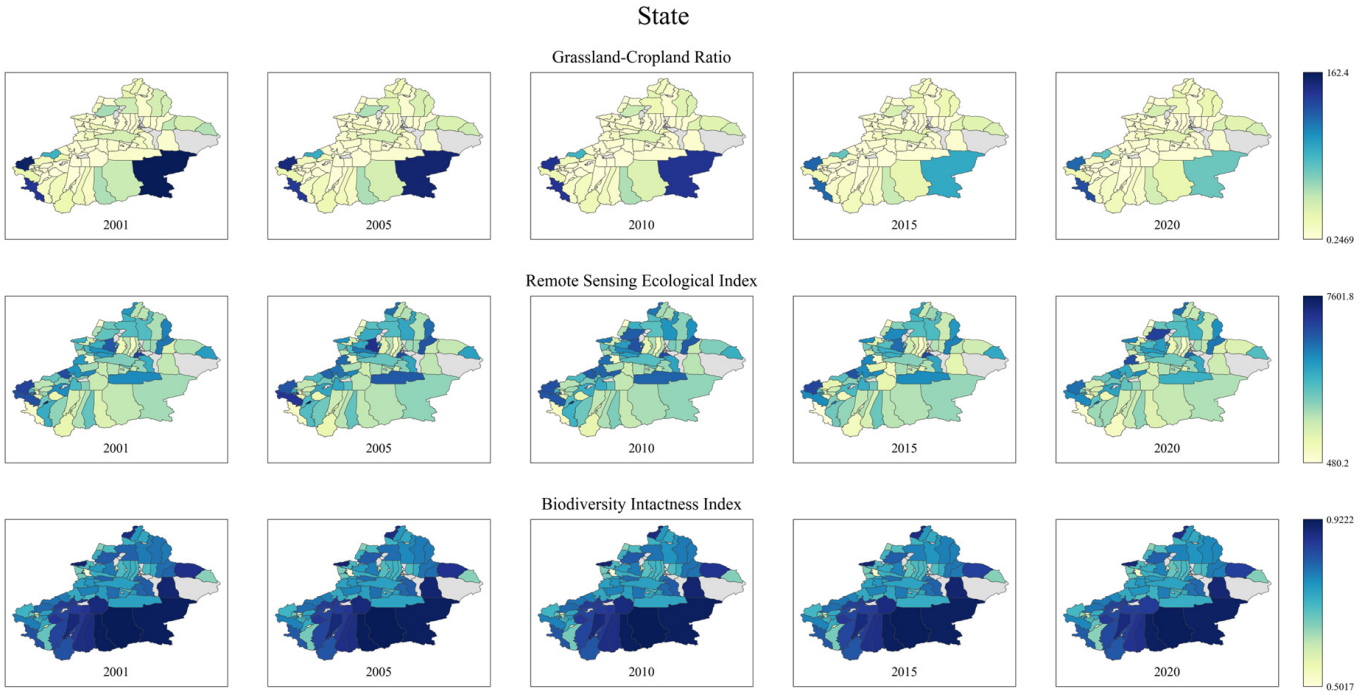


Figure A3. Spatial distributions of the original values of state-layer indicators in 2001, 2005, 2010, 2015, and 2020.

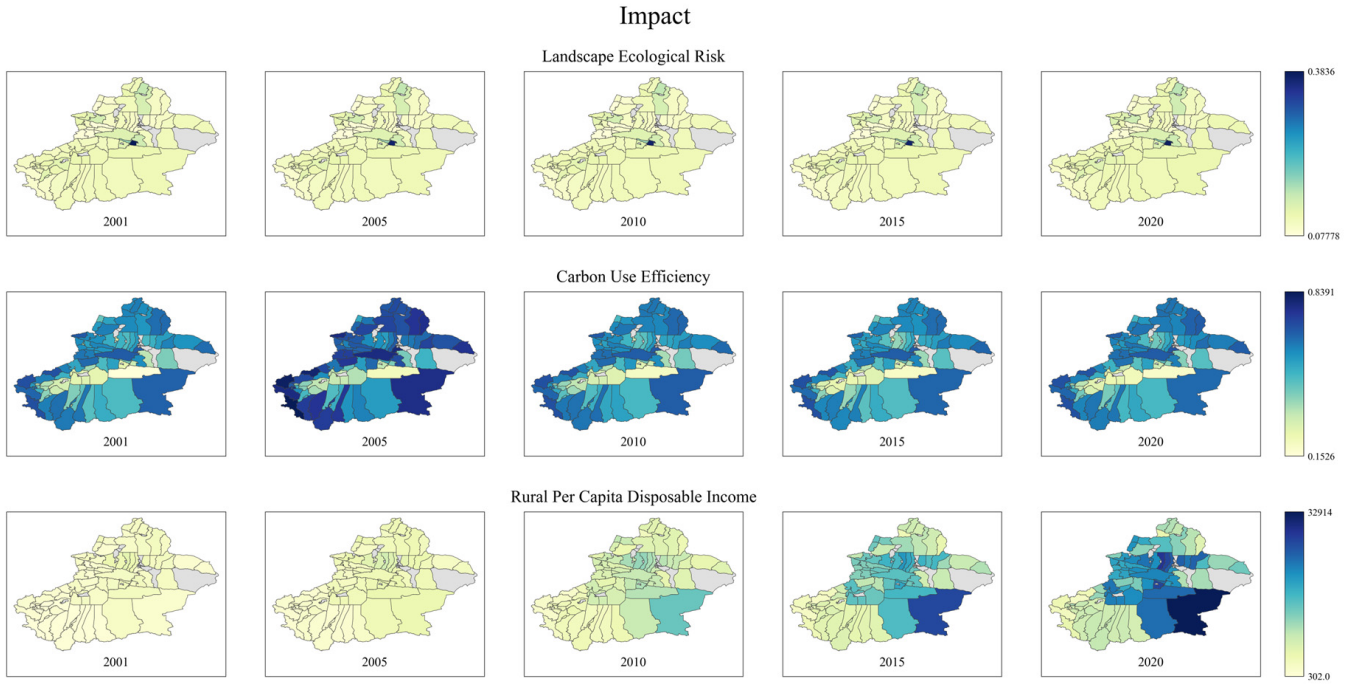


Figure A4. Spatial distributions of the original values of impact-layer indicators in 2001, 2005, 2010, 2015, and 2020.

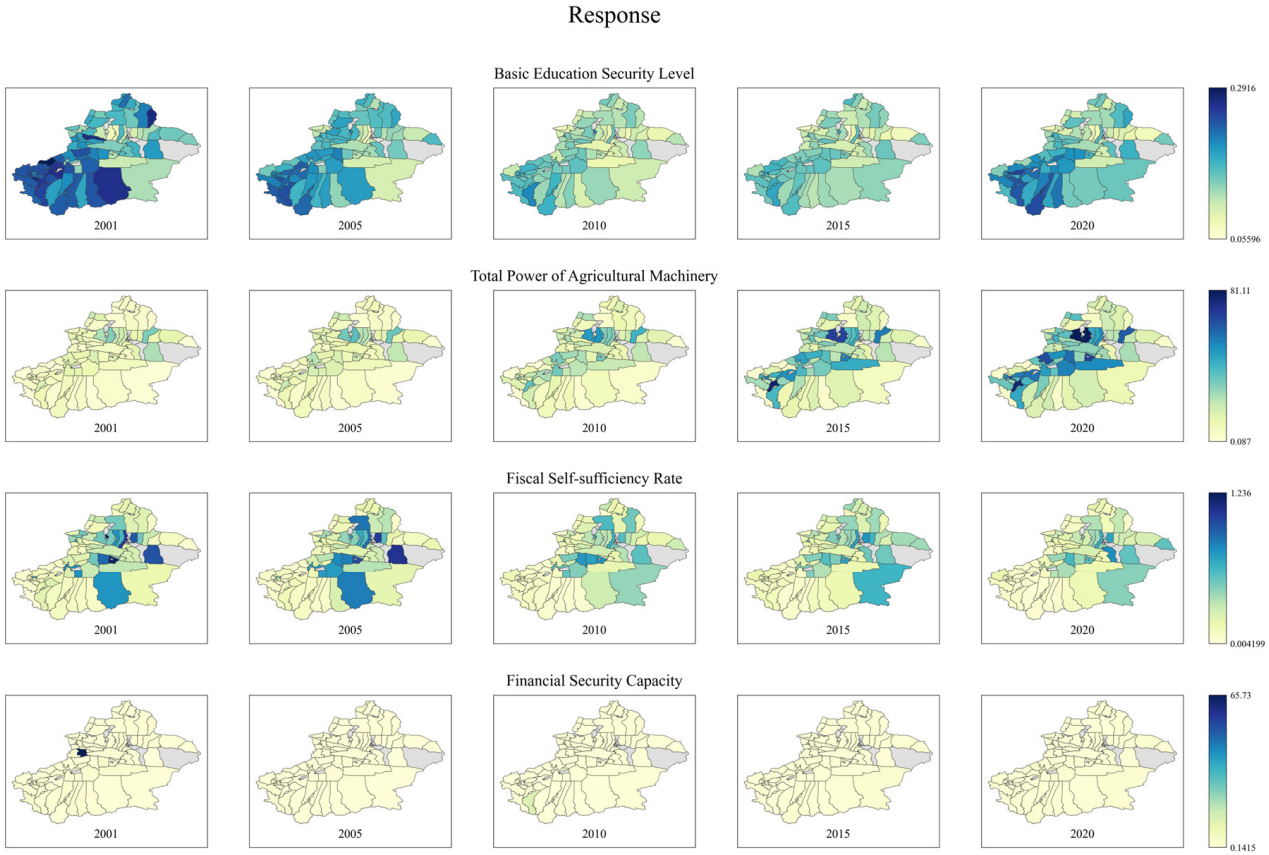


Figure A5. Spatial distributions of the original values of response-layer indicators in 2001, 2005, 2010, 2015, and 2020.

References

1. Bardgett, R.D.; Bullock, J.M.; Lavorel, S.; Manning, P.; Schaffner, U.; Ostle, N.; Chomel, M.; Durigan, G.; Fry, E.L.; Johnson, D.; et al. Combatting global grassland degradation. *Nat. Rev. Earth Environ.* **2021**, *2*, 720–735. [CrossRef]
2. Zhang, R.; Guo, J.; Yin, G. Response of net primary productivity to grassland phenological changes in Xinjiang, China. *PeerJ* **2021**, *9*, e10650. [CrossRef] [PubMed]
3. Liu, J.; Mooney, H.; Hull, V.; Davis, S.J.; Gaskell, J.; Hertel, T.; Lubchenco, J.; Seto, K.C.; Gleick, P.; Kremen, C.; et al. Systems integration for global sustainability. *Science* **2015**, *347*, 1258832. [CrossRef] [PubMed]
4. Rui, H.; Luo, B.; Wang, Y.; Zhu, L.; Zhu, Q. Quantitative impacts of climate change and human activities on grassland growth in Xinjiang, China. *Front. Plant Sci.* **2025**, *15*, 1497248. [CrossRef] [PubMed]
5. Liu, Y.; Zhao, W.; Ding, J. Research progress and prospects on grassland social-ecological systems. *Resour. Sci.* **2024**, *46*, 1523–1539. [CrossRef]
6. Xu, T.; Zhao, X.; Geng, Y.; Wang, X.; Mao, S.; Xu, S. Key technologies and optimization model for ecological protection and grass-based livestock husbandry in the source region of the Yellow River. *Resour. Sci.* **2020**, *42*, 508–516. [CrossRef]
7. Li, Y.-Y.; Dong, S.-K.; Wen, L.; Wang, X.-X.; Wu, Y. Three-dimensional framework of vigor, organization, and resilience (VOR) for assessing rangeland health: A case study from the alpine meadow of the Qinghai-Tibetan Plateau, China. *EcoHealth* **2013**, *10*, 423–433. [CrossRef] [PubMed]
8. Liu, Y.; Zhang, Z.; Tong, L.; Khalifa, M.; Wang, Q.; Gang, C.; Wang, Z.; Li, J.; Sun, Z. Assessing the effects of climate variation and human activities on grassland degradation and restoration across the globe. *Ecol. Indic.* **2019**, *106*, 105504. [CrossRef]
9. Liu, Y.; Zheng, J.; Guan, J.; Han, W.; Liu, L. Concurrent and lagged effects of drought on grassland net primary productivity: A case study in Xinjiang, China. *Front. Ecol. Evol.* **2023**, *11*, 1131175. [CrossRef]
10. Wu, J.; Sun, Z.; Yao, Y.; Liu, Y. Trends of grassland resilience under climate change and human activities on the Mongolian Plateau. *Remote Sens.* **2023**, *15*, 2984. [CrossRef]
11. Binder, C.R.; Hinkel, J.; Bots, P.W.G.; Pahl-Wostl, C. Comparison of frameworks for analyzing social-ecological systems. *Ecol. Soc.* **2013**, *18*, 26. [CrossRef]
12. Liu, J.; Dietz, T.; Carpenter, S.R.; Alberti, M.; Folke, C.; Moran, E.; Pell, A.N.; Deadman, P.; Kratz, T.; Lubchenco, J.; et al. Complexity of coupled human and natural systems. *Science* **2007**, *317*, 1513–1516. [CrossRef] [PubMed]

13. Ostrom, E. A general framework for analyzing sustainability of social-ecological systems. *Science* **2009**, *325*, 419–422. [CrossRef] [PubMed]
14. Smeets, E.; Weterings, R. *Environmental Indicators: Typology and Overview*; Technical Report No. 25; European Environment Agency: Copenhagen, Denmark, 1999. Available online: https://www.eea.europa.eu/en/analysis/publications/tec25 (accessed on 2 June 2026).
15. Carr, E.R.; Wingard, P.M.; Yorty, S.C.; Thompson, M.C.; Jensen, N.K.; Roberson, J. Applying DPSIR to sustainable development. *Int. J. Sustain. Dev. World Ecol.* **2007**, *14*, 543–555. [CrossRef]
16. Gedefaw, A.; Atzberger, C.; Bauer, T.; Agegnehu, S.; Mansberger, R. Analysis of land cover change detection in Gozamin District, Ethiopia: From remote sensing and DPSIR perspectives. *Sustainability* **2020**, *12*, 4534. [CrossRef]
17. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining objective weights in multiple criteria problems: The CRITIC method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
18. Hwang, C.L.; Yoon, K. *Multiple Attribute Decision Making: Methods and Applications*; Springer: Berlin/Heidelberg, Germany, 1981. [CrossRef]
19. Xinjiang Uygur Autonomous Region People's Government. Geographical Location. Available online: https://en.wikipedia.org/wiki/People's_Government_of_the_Xinjiang_Uygur_Autonomous_Region (accessed on 2 June 2026).
20. Zhang, R.; Liang, T.; Guo, J.; Xie, H.; Feng, Q.; Aimaiti, Y. Grassland dynamics in response to climate change and human activities in Xinjiang from 2000 to 2014. *Sci. Rep.* **2018**, *8*, 2888. [CrossRef] [PubMed]
21. Peng, S. *1-km Monthly Mean Temperature Dataset for China (1901–2024)*; National Tibetan Plateau/Third Pole Environment Data Center: Beijing, China, 2019.
22. Hu, J.; Miao, C.; Su, J.; Zhang, Q.; Gou, J.; Sun, Q. An upgraded high-precision gridded precipitation dataset for the Chinese mainland considering spatial autocorrelation and covariates. *Earth Syst. Sci. Data* **2025**, *17*, 3987–4004. [CrossRef]
23. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
24. Parente, L.; Ehrmann, S.; Hengl, T.; Fritz, S.; Bonannella, C.; Malek, Ž.; Gonzalez Fischer, C.; Pérez-Guzmán, K.; Stanimirova, R.; Meyer, C.; et al. *Global Pasture Watch—Annual Livestock Headcount Layers for Cattle, Goats, Sheep, Horses, and Buffaloes at 1-km 2000–2022 (FAOSTAT-Adjusted), Version v1*; Zenodo: Geneva, Switzerland, 2025. [CrossRef]
25. Nguyen, C.T.; Vačkářová, D.; Weinzettel, J. Consistent global dataset on biodiversity intactness footprint of agricultural production from 2000 to 2020. *Sci. Data* **2025**, *12*, 1613. [CrossRef] [PubMed]
26. Wu, B. *Land Use Intensity and Landscape Ecological Risk Datasets for China (1992–2022), Version v1.0*; Zenodo: Geneva, Switzerland, 2026. [CrossRef]
27. Running, S.; Zhao, M. *MODIS/Terra Net Primary Production Gap-Filled Yearly L4 Global 500m SIN Grid V061*; NASA Land Processes Distributed Active Archive Center: Sioux Falls, SD, USA, 2021. [CrossRef]
28. He, Y.; You, N.; Cui, Y.; Xiao, T.; Hao, Y.; Dong, J. Spatio-temporal changes in remote sensing-based ecological index in China since 2000. *J. Nat. Resour.* **2021**, *36*, 1176–1185. [CrossRef]
29. Atampugre, G.; Tilahun, S.A.; Oke, A.; Mabhaudhi, T.; Cofie, O.; Igbadun, H.E.; Olaleye, A.O. Social-ecological landscape sustainability in West Africa: Applying the driver pressure state impact response framework in Ghana and Nigeria. *Discov. Sustain.* **2024**, *5*, 413. [CrossRef]
30. Waldron, S.; Brown, C.; Longworth, J. Grassland degradation and livelihoods in China's western pastoral region: A framework for understanding and refining China's recent policy responses. *China Agric. Econ. Rev.* **2010**, *2*, 298–320. [CrossRef]
31. Dong, S.; Yang, M.; Ren, J.; Shang, Z.; Zhao, X.; Dong, Q.; Liu, W.; Renqing, D.; Dou, S.; Zhou, X.; et al. Sustainable management of grassland based on grazing system unit: Concepts and models. *Pratacult. Sci.* **2020**, *37*, 403–412.
32. Li, S.; Jiao, J.; Degen, A.A.; Wang, W.; Qi, T.; Huang, M.; Xu, S.; Shang, Z. Cooperative management can mitigate trade-offs between livestock production and ecological functions to promote grassland sustainability. *Agric. Ecosyst. Environ.* **2024**, *370*, 109057. [CrossRef]
33. Zhang, M.; Sun, J.; Wang, Y.; Li, Y.; Duo, J. State-of-the-art and challenges in global grassland degradation studies. *Geogr. Sustain.* **2025**, *6*, 100229. [CrossRef]
34. Song, Y.; Zhang, X.; Ma, B.; Xue, D. Assessment of social-ecological system resilience in energy-rich areas oriented toward SDGs. *Resour. Sci.* **2024**, *46*, 1807–1821. [CrossRef]
35. Nardo, M.; Saisana, M.; Saltelli, A.; Tarantola, S.; Hoffman, A.; Giovannini, E. *Handbook on Constructing Composite Indicators: Methodology and User Guide*; OECD Publishing: Paris, France, 2008. [CrossRef]
36. Greco, S.; Ishizaka, A.; Tasiou, M.; Torrisi, G. On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Soc. Indic. Res.* **2019**, *141*, 61–94. [CrossRef]
37. Jenks, G.F. The data model concept in statistical mapping. *Int. Yearb. Cartogr.* **1967**, *7*, 186–190.
38. Mann, H.B. Nonparametric tests against trend. *Econometrica* **1945**, *13*, 245–259. [CrossRef]

39. Kendall, M.G. *Rank Correlation Methods*, 4th ed.; Charles Griffin: London, UK, 1975. Available online: https://search.worldcat.org/title/Rank-correlation-methods/oclc/3827024 (accessed on 2 June 2026).
40. Sen, P.K. Estimates of the regression coefficient based on Kendall's tau. *J. Am. Stat. Assoc.* **1968**, *63*, 1379–1389. [CrossRef]
41. Hu, Y.; Huang, J.; Hou, L. Impacts of the grassland ecological compensation policy on household livestock production in China: An empirical study in Inner Mongolia. *Ecol. Econ.* **2019**, *161*, 248–256. [CrossRef]
42. Hou, L.; Xia, F.; Chen, Q.; Huang, J.; He, Y.; Rose, N.; Rozelle, S. Grassland ecological compensation policy in China improves grassland quality and increases herders' income. *Nat. Commun.* **2021**, *12*, 4683. [CrossRef]
43. Zhang, Y.; Wuriliga; Ding, Y.; Li, F.; Zhang, Y.; Su, M.; Li, S.; Liu, L. Effectiveness of grassland protection and pastoral area development under the grassland ecological conservation subsidy and reward policy. *Agriculture* **2022**, *12*, 1177. [CrossRef]
44. Li, Z.; Su, B.; Liu, M. Research progress on the theory and practice of grassland eco-compensation in China. *Agriculture* **2022**, *12*, 721. [CrossRef]
45. Liu, H.; Hou, L.; Nan, Z.; Huang, J.; Su, L. Herders' willingness to accept compensation for grassland grazing ban in Northwest China. *J. Integr. Agric.* **2025**, *24*, 366–379. [CrossRef]
46. Ouyang, W.; Ju, F.; Han, J.; Gai, Z.; Zhang, B. The impact of grassland ecological compensation policy on overgrazing behavior of herdsmen with non-pastoral employment: Evidence from Inner Mongolia, China. *Front. Sustain. Food Syst.* **2025**, *9*, 1605850. [CrossRef]
47. Han, F.; Zhang, X.; Zhou, R. A review and prospect of grassland ecological compensation and its impact on herders' behavior. *Resour. Sci.* **2024**, *46*, 1447–1459. [CrossRef]

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