EVALUATION AND ANALYSIS OF TEMPORAL AND SPATIAL EVOLUTION OF ECO-ENVIRONMENTAL VULNERABILITY IN GANSU PROVINCE OF CHINA

LI, H. F.

Graduate University of Mongolia, Ulaanbaatar City 16052, Mongolia
(e-mail: zhaoq2000@@tsnu.edu.cn)

(Received 13th Jun 2024; accepted 16th Oct 2024)

Abstract. In this study, the ecological pressure intensity–ecological sensitivity–ecological resilience (PSR) model was used to build a comprehensive index of ecological and environmental vulnerability to analyze the characteristics of ecological and environmental vulnerability in Gansu Province of China, and the influence degree of spatial and temporal distribution difference of ecological, environmental vulnerability in Gansu Province of China during 1992-2022 was analyzed. The results showed that (1) the eco-environmental vulnerability index of Gansu Province of China varied from 1.4857 to 4.0896, presenting the grades of mild vulnerability. Regarding spatial distribution, Longnan city and Tianshui city in Gansu Province of China have higher vulnerability levels, while Jiuquan city, Jiayuguan city, Zhangye city and Jinchang city have lower vulnerability levels. (2) Among the land use types in Gansu Province of China, cultivated land was mainly distributed in the mildly vulnerable and moderately vulnerable areas, forest land was mainly distributed in the mildly vulnerable, grassland was mainly distributed in the mildly vulnerable areas, water and construction land were distributed in the potentially vulnerable areas. (3) Average annual temperature, average annual precipitation, biological richness index were the main factors affecting the spatial distribution of eco-environmental vulnerability in Gansu Province of China.
Keywords: *PSR model, ecological environment fragility, Gansu Province of China, time and space, geographical detector*

Introduction

In recent years, with global warming and the increase of human activities, ecological and environmental problems have emerged in large numbers (Huang et al., 2024). The destruction of ecosystems has become increasingly severe, which has a significant impact on the survival and development of human beings (Okembo et al., 2024). The problem of ecological vulnerability has become increasingly prominent. Studies on the ecological environment can be traced back to Clements (1905) (Zhang et al., 2024), an American scholar in the early 20th century who first introduced ecological ecotone into ecology (Park et al., 2024; Zhang et al., 2024). So far, foreign scholars have conducted in-depth studies on the construction, connotation, causes and characteristics of ecological environment vulnerability assessment models (Gao et al., 2024; Takahashi and Ihara, 2023a).

Moreover, many evaluation methods on regional ecological environment vulnerability have been improved. Ecological environment vulnerability refers to the state of the ecological environment when the degradation of the ecological environment exceeds the degree that can be restored by the current level of social economy and technology, which is jointly determined by regional natural environment characteristics and human economic activities (Tang et al., 2024; Wang et al., 2024). Ecological environment vulnerability refers to the ability of the ecosystem to resist natural or social development that is not conducive to its survival or development after external interference or pressure (Singh et al., 2024). The vulnerability of the ecological

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

environment is the resistance of the natural ecological environment to the development of human society and economy under the influence of various natural environmental factors and human activities (Li et al., 2022). It not only includes the degree of influence of natural factors on the social and economic development of human beings but also includes the ability of human beings to resist the process of social and economic development, which is the ecological environment vulnerability (Hu et al., 2024). The vulnerability assessment of the ecological environment is an integral part of vulnerability research, which mainly analyzes the changes and causes of vulnerability characteristics of the ecological environment in a specific region and puts forward suggestions for ecological protection and restoration (Okembo et al., 2024). From the perspective of research content, the ecological environment vulnerability assessment is mainly based on regional characteristics, related evaluation methods, indicators and systems. In terms of research methods, PSR, SRP and other models combined in entropy, fuzzy evaluation (Li et al., 2022), principal component analysis, and other comprehensive evaluation methods are used for in-depth research (Cao and Li, 2023; He et al., 2022). From the perspective of research areas, it is mainly reflected in the coastal and developed areas, while there are few related studies on the arid northwest inland area (Huang et al., 2023; Lechner and Kirisits, 2022). With the development of computer network technology, the study of ecological environmental vulnerability assessment began to use remote sensing (RS) and geographic information systems (GIS) to acquire and analyze data, and the research results expressed a good visualization effect (Yu et al., 2023).

Located in the upper reaches of the Yangtze River and the Yellow River, Gansu Province of China is at the intersection of the Qinghai-Tibet Plateau, the Loess Plateau and the Inner Mongolia Plateau (Zhong et al., 2023). It is also at the intersection of three natural regions: the arid region in Northwest China, the Qinghai-Tibet Plateau and the eastern monsoon region (Nie et al., 2023). At the same time, due to the constraints of terrain, most cities and populations are concentrated in the valley area, with narrow space and limited natural environment capacity (Gong et al., 2023). Therefore, protecting and building the ecological environment in Gansu Province of China is difficult. Its ecological environment is affected by natural stress and a robust social economy (Getachew and Manjunatha, 2022), showing prominent vulnerability characteristics (Han et al., 2023). A good ecological environment is the basic premise of economic development and social progress. Protecting, developing and utilizing the ecological environment is the inevitable choice to promote economic development and social progress (Xu et al., 2022). As a relatively fragile ecological environment, Gansu Province of China has always taken the protection of the ecological environment as an essential prerequisite for its own development and has achieved specific results (Koko et al., 2023). However, land desertification and other ecological problems are still severe (Takahashi and Ihara, 2023b). Gansu Province of China is in an essential stage of rapid economic development, and the ecological environment is an essential factor affecting economic development. Therefore, the ecological environment of Gansu Province of China should be evaluated (Liu et al., 2023).

Based on the dynamic evolution trend of the ecological environment and the spatial and temporal distribution characteristics of its vulnerability, this paper took Gansu Province of China as the research object, applied the ecological pressure - ecological sensitivity - ecological resilience (PSR) model, natural breakpoint method (Freire et al., 2024), entropy value method, and combined with the comprehensive index of ecological

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

environmental vulnerability to analyze the spatial distribution characteristics and temporal changes of ecological environmental vulnerability (Fedorov et al., 2021; Liang et al., 2021). The degree of influence of index factors on temporal and spatial differentiation of ecological and environmental vulnerability was investigated using a geographical detector model. This research provides scientific basis for ecological environment protection and sustainable development.

Materials and methods

Study area

In the inner land of Northwest China, Gansu has plateau terrain inclined from South-west to North-east between 32°11 '–42°57' N, 92°13 '–108°46' E, and located west of the Yellow River, connecting with the Inner Mongolia Plateau in the north, relying on the Tibetan Plateau in the south, and connecting to the Loess Plateau in the east. The province covers an area of 454,400 km2 and has 14 prefecture-level cities under its jurisdiction. The terrain is distributed in a narrow east-west shape, with complex and diverse landforms, including mountains, plateaus, plains, valleys, deserts, and Gobi, with staggered distribution, and the terrain slopes from southwest to northeast. The climate belongs to the temperate monsoon climate, with apparent characteristics of continental climate transition. The primary climate type is temperate continental climate. The province is dry and short of rain, with a significant temperature difference. The four seasons climate is characterized by less rain and snow in winter and prolonged cold times. The temperature rises quickly in spring, and the cold and warm changes considerably. In summer, the temperature is high, and the precipitation is concentrated. The temperature drops quickly in autumn, and the first frost comes early. The average annual temperature is about -0.3℃–14.8℃. The ecological environment of Gansu Province of China is complex, diverse and fragile (Li et al., 2023). The regional differences are apparent: Hexi region has a dry climate, less precipitation, and is mainly composed of patches of Gobi and desert, with severe soil erosion; Longdong and Longzhong are dotted with gullies, loess is widely distributed, vegetation is scarce, and soil erosion is severe. Longnan mountain gully is deep; the terrain is complex, and the annual precipitation is more, especially heavy precipitation, prone to debris flow and other geological disasters (Xu et al., 2023). The ecological environment of Gansu Province of China is complex and fragile, and the overall economic development level is also low, and the economic development is seriously backward (*Fig. 1*).

Research methods

Evaluation model

(1) PSR model

In the late 1980s, the Organization for Economic Cooperation and Development (OECD) and the United Nations Environment Program (UNEP) jointly proposed the PSR conceptual model to comprehensively evaluate the ecological environmental vulnerability of a specific region, including three factors: ecological pressure intensity, sensitivity and resilience. The ecological stress index reflects the impact of human activities on the ecosystem. Select the index factors of population density and economic density (Penny et al., 2023). Ecological sensitivity refers to the sensitivity

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

of an area to interference by internal or external factors in a certain period. The index factors of elevation, slope, slope direction, vegetation cover index, average annual temperature and average annual precipitation were selected. Ecological resilience refers to the ability of the regional system to adjust and recover under internal and external disturbances. Biological richness, general budget revenue of local finance, and number of students in ordinary middle schools were selected (Ma et al., 2023; Rodrigues et al., 2016).

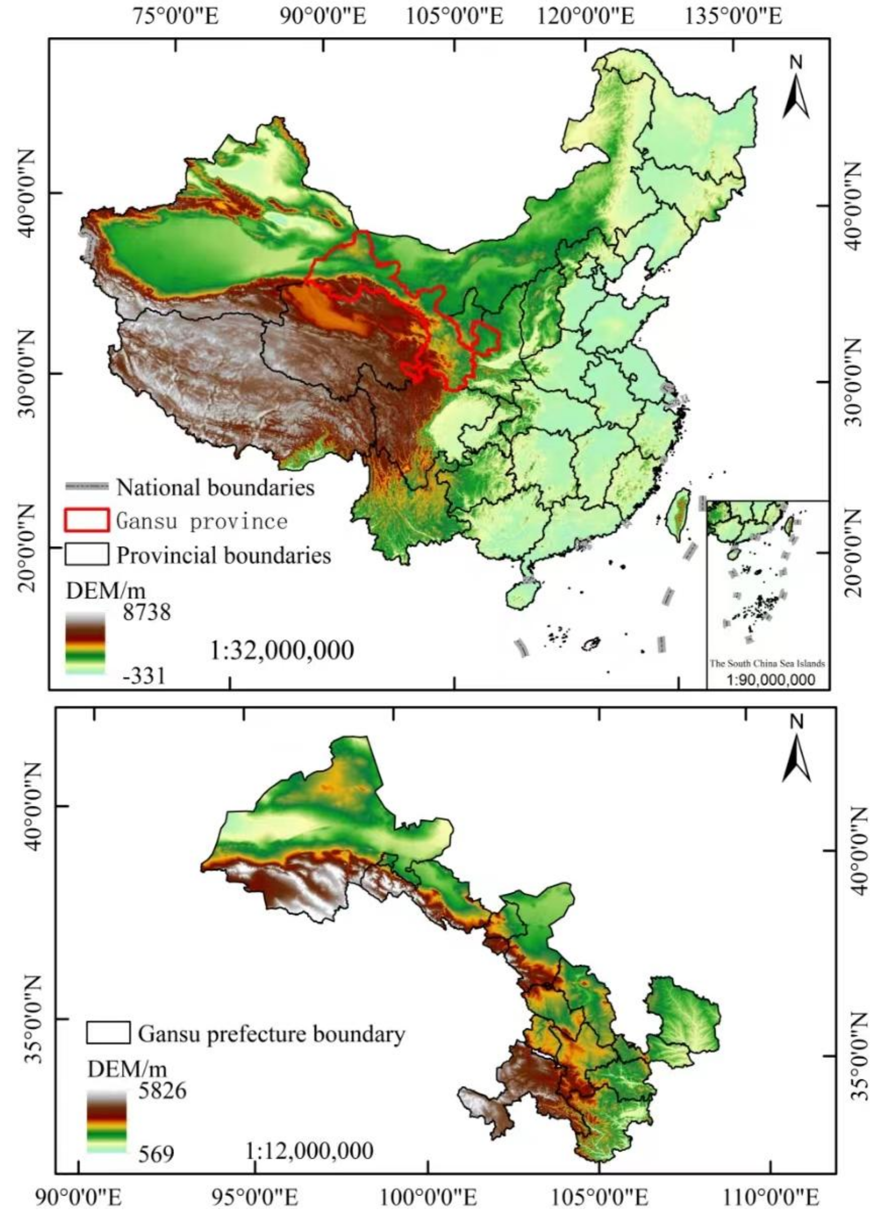

Figure 1. *Study area location map*

(2) Natural breakpoint method

The natural breakpoints method is a commonly used data analysis method in statistics, which can help us identify natural breakpoints in the data better to understand the distribution and trend of the data. The basic principle is to divide the data into

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

several subsets so that the data within each subset is more similar and the data between different subsets is less similar. The goal is to find natural breakpoints, turning points or inflexion points in the data distribution. It can be applied to various types of data, including time series, spatial, and multidimensional data. This method is entirely based on the distribution law of data and avoids the interference of human factors (Han et al., 2023). According to the characteristics of land topography combined with the landform of Gansu Province of China, the elevation is divided into five categories: <800, 800–1000, 1000–2000, 2000 –3000, ≥ 3000 by natural break method. According to the natural terrain characteristics of Gansu Province of China, the slope is divided into ≤2°, 2°–6°, 6°–15°, 15°–25°, and >25° (Gao et al., 2023).

Construction of evaluation index system

Establishing an ecological environment vulnerability assessment index system must present regional vulnerability characteristics. Combined with the environmental characteristics of the study area, the PSR model is used to select 11 evaluation indicators to construct the ecological environment vulnerability assessment index system of Gansu Province of China. The entropy method is used to calculate the weight of each index. The concept of entropy in the entropy method comes from thermodynamics and is a measure of the state uncertainty of the system. Information theory measures the degree of order in a system where the absolute values are equal, but the signs are opposite. According to this property, the weight of each indicator is calculated (*Table 1*). The calculation steps are as follows:

(1) Find references and determine the index types of each indicator

(2) Standardize each indicator

Positive indicators:

$$X_{ij} = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}} \tag{Eq.1}$$

Negative indicators:

$$X_{ij} = \frac{maxX_{ij} - X_{ij}}{\max X_{ij} - minX_{ij}} \tag{Eq.2}$$

(3) Calculate the proportion of the index value

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \tag{Eq.3}$$

(4) Calculate index information entropy

$$E_{ij} = -K \times \sum_{i=1}^{n} P_{ij} \times lnP_{ij} \tag{Eq.4}$$

(5) Calculate the difference coefficient of indicators

$$D_j = 1 - E_j \tag{Eq.5}$$

(6) Calculate index weights

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

$$W_j = \frac{D_j}{\sum_{i=1}^{n} D_j} \quad \text{(Eq.6)}$$

Ecological environment vulnerability assessment model

The PSR model and entropy method were used to obtain the weight coefficient of the index, and the calculation formula of the ecological environmental vulnerability index value (EEVI) was as follows (Hong et al., 2022):

$$EEVI = \sum_{i=1}^{n} X_i Y_i \quad \text{(Eq.7)}$$

where: EEVI represents the ecological environment vulnerability index; Xi represents the grading value of the i index; Yi represents the weight of the i th indicator. The index of EEVI ranges from 0 to 5, and the higher the value, the more fragile the ecological environment.

Geographical detector model

The causes of the spatial evolution of eco-environmental vulnerability in Gansu Province of China were detected using a geographical detector, and the degree of influence of each index factor was detected by combining it with the actual situation of the eco-environment in Gansu Province of China (Xu et al., 2022b). The calculation formula is:

$$q = 1 - \frac{1}{N} \sum_{m=1}^{Z} N_i S_i^2 \quad \text{(Eq.8)}$$

where q is the spatial differentiation of an index, $q \in [0,1]$; N is the total number of samples in the study area; S^2 is the variance of this index; m indicates the partition, $m = (1,2, \ldots, Z)$. The magnitude of q reflects the degree of spatial differentiation. The larger the q value is, the stronger the difference in spatial stratification is. On the contrary, the randomness of the spatial distribution is more vital.

Table 1. *Index weights of the eco-environmental vulnerability rating index system of Gansu Province of China*

Target layer	Index level	Index type	Index weight
Pressure (P)	Population density	+	0.1045
	Economic density	+	0.0434
Sensitivity (S)	elevation	+	0.0820
	Slope	+	0.0728
	Aspect of slope	+	0.1315
	NDVI	-	0.1002
	Average annual temperature	+	0.1009
	Average annual precipitation	+	0.1238
Resilience (R)	Biological richness index	+	0.1206
	General budget revenue of local governments	+	0.0147
	Number of students enrolled in ordinary middle schools	+	0.1054

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

Data source and preprocessing

Indicators of ecological pressure

The population density of 1992, 2002, 2012, and 2022 was obtained from WorldPop, and the economic density data were obtained from the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences. Then, raster processing was carried out in ArcGIS.

Ecological sensitivity index

The digital elevation model (DEM) is derived from the geospatial data cloud. ArcGIS software is used to process the DEM data, such as clipping and data conversion, and extract the slope, slope direction and elevation of the study area. The vegetation cover index (NDVI) was derived from the Institute of Geographic Sciences and Natural Resources Research of the Chinese Academy of Sciences, and the annual precipitation and average annual temperature were derived from the National Tibetan Plateau Scientific Data Center (published by Peng Shouzhang). After processing, such as cropping and projection by ArcGIS software, the resolution and file number were unified.

Ecological resilience index

Bioabundance index, local budget revenue and the number of students in middle school were selected to characterize the self-recovery ability of the regional ecosystem. The Biorichness index is based on 1992, 2002, 2012 and 2022 land use data from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences. The biological richness index of Gansu Province of China in different periods was calculated. Biological richness index = (0.35× forest area + 0.21× grassland area + 0.28× water area + 0.11× cultivated land area + 0.04× construction land + 0.01× unused land)/regional area. The index factors of the general budget revenue of local finance and the number of students in ordinary middle schools are derived from the China County Statistical Yearbook.

Results and analysis

Overall distribution of ecological and environmental vulnerability

With reference to the calculation results in *Table 1*, using ArcGIS, the ecological environment vulnerability index of Gansu Province of China was calculated and graded. According to the data characteristics, Ecological environmental vulnerability is divided into five categories: potential vulnerability (1.4–1.9), slight vulnerability (1.9–2.6), mild vulnerability (2.6–3.3), moderate Vulnerability (3.3–4.0), and severe vulnerability (4.0–4.7), as shown in *Figure 1.* As can be seen from *Figure 2* and *Table 2,* the ecological environment vulnerability index in 1992 ranged from 1.5712 to 3.9580, with an average value of 2.5621. The areas of slight vulnerability are large, accounting for 48.52% and 40.92%, respectively (*Table 2*), indicating that the ecological environment vulnerability of Gansu Province of China in this period presents a slight vulnerability. The potentially vulnerable areas are concentrated in Jiuquan City. The micro-vulnerable areas are mainly concentrated in Jiuquan, Jiayuguan, Zhangye, Jinchang, Wuwei and other cities. The mildly vulnerable areas are mainly distributed in Lanzhou City, Baiyin City, Linxia Hui Autonomous Prefecture, Dingxi City, Pingliang City, Qingyang City, Gannan

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

Tibetan Autonomous Prefecture, Tianshui City and Longnan City, and a few of them are distributed in Jiuquan City, Zhangye City and Wuwei City. Moderately vulnerable areas are mainly distributed in the cities of Tianshui and Longnan. There are no severely vulnerable areas in Gansu Province of China. In 2002, the eco-environmental vulnerability index ranged from 1.4857 to 4.0896, with an average value of 2.5995. The mild and mild vulnerability areas were significant, accounting for 47.84% and 47.66%, respectively. The areas of potential and moderate vulnerability were 6.02% and 5.19%, respectively, and there was no severe vulnerability. The results showed that the ecological environment in most regions of Gansu Province of China was slightly vulnerable during this period. Compared with 1992, the area of slightly vulnerable areas decreased, and the area of mildly vulnerable areas increased in 2002, indicating that the ecological and environmental vulnerability of Gansu Province of China had decreased. In this period, the main distribution areas of potentially vulnerable, slightly vulnerable, mild, and severely vulnerable areas were the same as in 1992. The moderately vulnerable areas are mainly distributed in Longnan City, Tianshui City, Pingliang City and Qingyang City. In 2012, the ecological and environmental vulnerability index ranged from 1.500 to 4.007, with an average of 2.5634. The slight and mild vulnerability areas are relatively large, at 53.55% and 42.09%, respectively. The area ratio of potential Vulnerability (1.23%) and moderate vulnerability (3.13%) decreased compared to 2002. The Ecological and Environmental vulnerability Index 2022 is between 1.500 and 3.897, with an average of 2.5154. The statistical results showed that the areas of slight, mild, and moderate vulnerability were 58.18%, 37.54% and 2.23%, respectively. The area of potential vulnerability was the smallest, accounting for 2.04%, and there was no severe vulnerability area. During this period, the area of the slightly vulnerable area increased significantly, while the area of the mildly vulnerable decreased, and the area changed significantly compared with 2012 (*Fig. 2*).

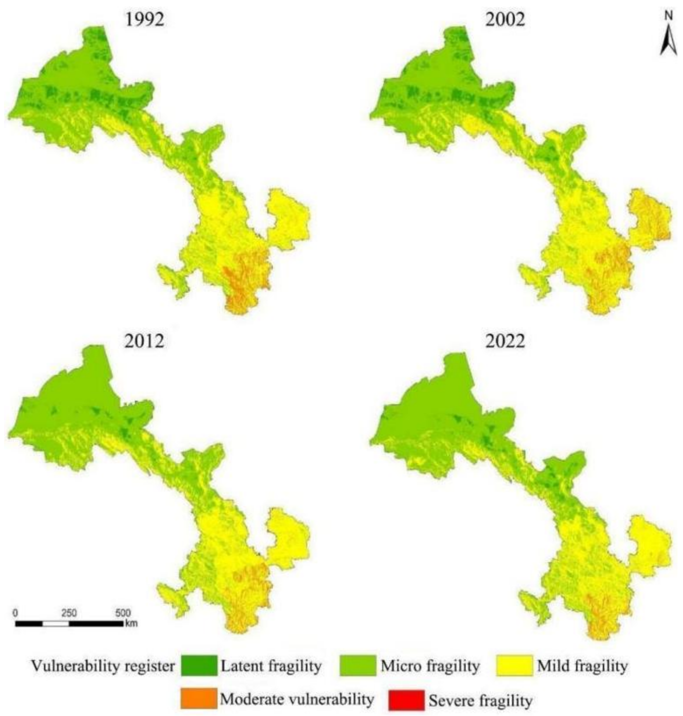

Figure 2. *Distribution of ecological and environmental vulnerability levels in Gansu Province of China from 1992 to 2022*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

Table 2. *Area and proportion of eco-environmental vulnerability in the four periods from 1992 to 2022 in Gansu Province of China*

Vulnerability grade	The year of 1992		The year of 2002		The year of 2012		The year of 2022	
	Area/km²	Scale/%	Area/km²	Scale/%	Area/km²	Scale/%	Area/km²	Scale/%
Latent vulnerability	26074	6.13%	25626	6.02%	5227	1.23%	8682	2.04%
Microfragility	206418	48.52%	189043	44.44%	227802	53.55%	247515	58.18%
Mild fragility	174088	40.92%	188662	44.35%	179057	42.09%	159715	37.54%
Moderate vulnerability	18835	4.43%	22082	5.19%	13327	3.13%	9503	2.23%
Severe fragility	0	0.00%	2	0.00%	2	0.00%	0	0.00%

Changes in ecological environment vulnerability with elevation

According to the terrain characteristics of Gansu Province of China, the elevation of the study area was divided into <800, [800, 1000), [1000, 2000), [2000, 3000), and ≥3000. The elevation classification map and the ecological environment vulnerability classification map were superimposed to draw the ecological environment vulnerability classification map (*Fig. 2*). In 1992, the area proportion of no potential vulnerability, slight vulnerability and severe vulnerability with elevation less than 800 m was 0.01%. In the elevation range of 1000–2000 m, there is no severe vulnerability, the proportion of moderate vulnerability is the largest (0.58%), and the proportion of potential vulnerability (0.12%), mild vulnerability (0.17%) and moderate vulnerability (0.05%) are tiny. In 2002, there was no vulnerability grade for the elevation less than 800 m. In the height range of 800–1000 m, the area proportion of slight vulnerability is 0.58%, and that of slight vulnerability is 0.21%. In the height range of 1000–2000 m, the area of the slightly vulnerable area is the largest (27.73%), the area of the next to the mildly vulnerable area is 19.70%, the area of the potentially vulnerable area is 5.97%, and the area of the medium vulnerable area is the most minor (2.90%). In the height range of 2000–3000, the area proportion of the mildly vulnerable area is the largest (10.76%), the area proportion of the mildly vulnerable area is 9.81%, and the area proportion of the moderately vulnerable area is 1.33%. In the range of altitudes greater than or equal to 3000 m, the area proportion of mainly slight vulnerability and mild vulnerability is 10.39% and 10.25%, respectively; in 2012, there was no vulnerability grade in the range of altitudes less than 800 m; in the range of 800–1000 m, mainly slight vulnerability has no significant change. In the height range of 1000–2000 m, the proportion of slightly vulnerable areas increased to 31.95%, the proportion of mildly vulnerable areas increased to 21.06%, and the proportion of potentially vulnerable and moderately vulnerable areas decreased to 1.07% and 2.21%. In the height range of 2000–3000 m, the area proportion of mild and moderate vulnerability increases to 10.20%, and the area proportion of mild and moderate vulnerability decreases to 10.90% and 0.81%, respectively. In the height range greater than 3000 m, the area proportion of mainly mild and mild Vulnerability is 10.81% and 10.88%, respectively. In 2022, there is no vulnerability grade for elevations less than 800 m, and only 0.59% of the area is slightly vulnerable for elevations between 800 and 1000 m. In the height range of 1000–2000 m, 34.22% and 18.25% of the areas were mainly slightly vulnerable and slightly vulnerable, and a small part were potentially vulnerable (1.79%) and moderately vulnerable (1.43%). In the height range of 2000–3000 m, the area ratio of the slightly vulnerable area is mainly 11.19%, the area ratio of the mildly vulnerable area is 9.91%, and the area

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

ratio of the moderately vulnerable area is a small part (0.71%). In the height range greater than 3000 m, the area ratio of the mildly vulnerable area is 12.17%, and the area ratio of the mildly vulnerable area is 8.57%. Therefore, with the increase of elevation, the area proportion of ecological and environmental vulnerability decreases; ecological and environmental vulnerability is mainly micro-vulnerability and mild vulnerability, and the ecological environment is gradually improved (*Fig. 3*).

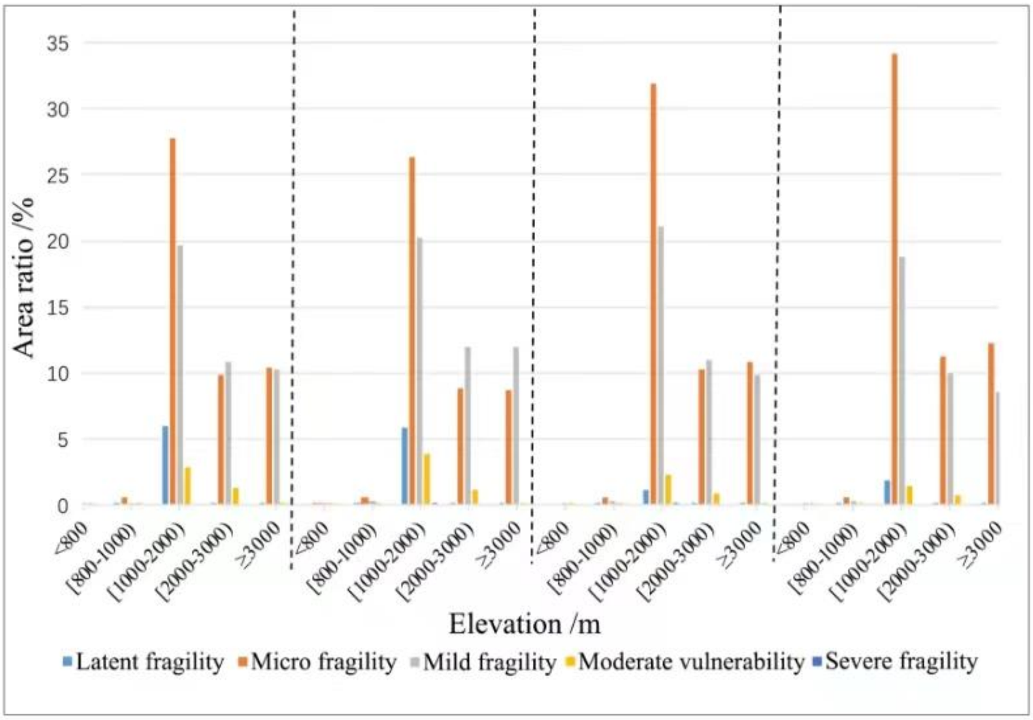

Figure 3. *Area and proportion of eco-environmental vulnerability with elevation in the four periods from 1992 to 2022 in Gansu Province of China*

Change of ecological environment vulnerability with land use

According to the ecological environment vulnerability distribution map and land use type distribution map of Gansu Province of China, the proportion of ecological environment vulnerability levels in different land use types in different periods was statistically analyzed, and the results are shown in *Table 3*. As seen from *Table 3,* the statistical analysis of ecological environmental vulnerability changes of different land use types in 1992, 2002, 2012 and 2022 shows that the primary land use types of potentially vulnerable and slightly vulnerable areas in different periods are unused land. The area proportion of unused land ranges from 0.39% to 4.89% in the potentially vulnerable area and from 29.01% to 35.62% in the slightly vulnerable area. Compared with 2002, the proportion of arable land, forest land, grassland, water area and construction land in the potentially vulnerable areas has mostly stayed the same. It decreased in 2012; In 2022, the proportion of area increased, and the overall proportion was small. In the slightly vulnerable area, except for unused land and grassland, which accounted for more than 25% and 10%, the other land types accounted for a small proportion of the area, and the range of change was small. In 1992, the top three land types were grassland (19.27%), cultivated land (9.71%) and forest land (5.87%). In

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

2002, 2012, and 2022, the area of the three types of land increased or decreased, but the overall ranking did not change. The proportion of arable land and grassland in the moderately vulnerable area is more significant. The proportion of unused land in the moderately vulnerable area is reduced. In 1992, 2002, 2012 and 2022, the severely vulnerable areas did not account for the proportion of the area. Cultivated land is mainly distributed in the areas of slight vulnerability, slight vulnerability and moderate vulnerability. The forest land is mainly distributed in the slightly vulnerable and slightly vulnerable areas. The grassland is mainly distributed in the slightly vulnerable and slightly vulnerable areas. The water area and construction land are distributed in potential vulnerability, slight vulnerability, mild vulnerability and moderate vulnerability, but the proportion of the area is small. The unused land is mainly distributed in the areas of potential vulnerability, slight vulnerability and slight vulnerability.

Table 3. *Distribution of eco-environmental Vulnerability under different land use types in Gansu Province of China from 1992 to 2022*

Years	Land use type	Latent vulnerability		Microfragility		Mild fragility		Moderate vulnerability		Severe fragility	
		Area/km²	Scale/%	Area/km²	Scale/%	Area/km²	Scale/%	Area/km²	Scale/%	Area/km²	Scale/%
1992	Cultivated land	2409	0.57	15871	3.74	41222	9.71	5812	1.37	0	0.00
	Forest land	226	0.05	8615	2.03	24902	5.87	4137	0.97	0	0.00
	Grassland	2250	0.53	49949	11.77	81754	19.27	8297	1.96	0	0.00
	Water area	181	0.04	1579	0.37	1375	0.32	111	0.03	0	0.00
	Construction land	192	0.05	1115	0.26	2079	0.49	317	0.07	0	0.00
	Unused land	20750	4.89	127871	30.14	21815	5.14	103	0.02	0	0.00
2002	Cultivated land	2982	0.70	14147	3.33	40501	9.55	7483	1.76	0	0.00
	Forest land	269	0.06	6093	1.44	28200	6.65	3825	0.90	0	0.00
	Grassland	2222	0.52	43053	10.15	87805	20.69	9754	2.30	0	0.00
	Water area	161	0.04	1351	0.32	1789	0.42	155	0.04	0	0.00
	Construction land	180	0.04	1210	0.29	2322	0.55	508	0.12	2	0.00
	Unused land	19812	4.67	123076	29.01	27761	6.54	342	0.08	0	0.00
2012	Cultivated land	2531	0.60	15534	3.66	42759	10.08	4270	1.01	1	0.00
	Forest land	98	0.02	10513	2.48	24491	5.77	2829	0.67	0	0.00
	Grassland	633	0.15	51643	12.17	84312	19.87	5633	1.33	0	0.00
	Water area	132	0.03	1707	0.40	1420	0.33	103	0.02	0	0.00
	Construction land	191	0.05	1405	0.33	2605	0.61	373	0.09	1	0.00
	Unused land	1639	0.39	145507	34.29	22513	5.31	90	0.02	0	0.00
2022	Cultivated land	4553	1.07	18361	4.33	38674	9.11	2534	0.60	0	0.00
	Forest land	139	0.03	11336	2.67	24461	5.76	2414	0.57	0	0.00
	Grassland	997	0.23	62524	14.74	75836	17.87	4209	0.99	0	0.00
	Water area	163	0.04	1973	0.46	1565	0.37	57	0.01	0	0.00
	Construction land	269	0.06	1988	0.47	2948	0.69	233	0.05	0	0.00
	Unused land	2561	0.60	151143	35.62	15991	3.77	50	0.01	0	0.00

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

Discussion on the causes of ecological environment vulnerability

The effects of various indicators on spatial differentiation of eco-environmental vulnerability in Gansu Province of China in 1992, 2002, 2012 and 2022 were investigated using a geographical detector model. In 1992, the top five factors were average annual precipitation (59.97%), average annual temperature (58.18%), biological richness index (57.19%), number of students in ordinary middle schools (54.39%) and vegetation cover index (35.63%). The influence of other factors was all below 30%. Population density and economic density factors did not pass the significance test. In 2002, the explanatory contributions of each index factor to the spatial distribution of ecological environmental vulnerability changed significantly. The explanatory power of the biological richness index (56.91%), number of students in ordinary middle schools (52.55%), average annual precipitation (50.12%), average annual temperature (43.41%) and vegetation coverage (35%) ranked in the top five. The contribution rate of the slope factor increased to 22.35%, the contribution rate of local financial general budget revenue decreased to 12.58%, and the influence degree of other factors was all lower than 10%. Population density, economic density, elevation, slope direction and local financial general budget revenue factors failed the significance test. In 2012, the top six factors that could explain the spatial distribution of ecological environmental vulnerability were average annual precipitation (60.92%), biological richness index (58.85%), number of students in ordinary middle schools (54.01%), vegetation cover index (46.10%) and average annual temperature (43.27%), and the influence degree of other factors was lower than 40%. Population density and economic density factors did not pass the significance test. In 2022, the explanatory ability of the spatial distribution vulnerability of ecological environment was as follows: biological richness index (56.46%), average annual precipitation (52.53%), number of students in ordinary middle schools (51.28%), average annual temperature (48.91%), and vegetation cover index (34.80%). The degree of influence of other factors is less than 20%, and the population density and economic density factors need to pass the significance test. Overall, the biological richness index, the average annual precipitation, the average annual temperature, the number of middle school students, the vegetation cover index and the slope were the main factors affecting the distribution of ecological and environmental vulnerability in Gansu Province of China. The impacts of annual precipitation, average annual temperature, biological richness index, the number of students in middle schools, and other factors on the spatial distribution of ecological and environmental vulnerability decreased from 2002 to 2012 and 2022. The population density, economic density, elevation and slope direction do not affect the spatial distribution of the vulnerable eco-environment in Gansu Province of China (*Table 4*).

Discussion

In this paper, the PSR model was used to evaluate the ecological environmental vulnerability assessment of 11 indicators in the four periods of 1992, 2002, 2012 and 2022 in Gansu Province of China, and the geographical detector model was used to analyze the impact of indicator factors on the spatial distribution difference of ecological, environmental vulnerability in Gansu Province of China. The characteristics, changes and influence degree of ecological environment vulnerability were discussed theoretically. The results show that from 1992 to 2022, the vulnerability index of Gansu

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

Province of China ranges from 1.4857 to 4.0896, and the average values of the ecological environment vulnerability index in the four periods are 2.5621, 2.5995, 2.5634 and 2.5154, respectively, showing a slight vulnerability and a slight vulnerability. Overall, the ecological environment vulnerability changed significantly from 1992 to 2022, characterized by a decrease in the proportion of potentially vulnerable areas, indicating that the ecological environment vulnerability has improved. The slightly vulnerable areas decreased from 2002 to 2012 and increased in 2022. The mild and moderate vulnerability areas increased from 2002 to 2012 and 2022. In terms of spatial distribution, the ecological and environmental vulnerability of Gansu Province of China shows that the ecological and environmental vulnerability of Longzhong and Longnan is relatively poor and has improved. The ecological environment of Longzhong and Hexi is still at the level of potential vulnerability and slight vulnerability. The ecological environmental vulnerability of the Gannan region, as a region with special ecological environmental conditions in Gansu Province of China, is slightly vulnerable and slightly vulnerable.

Table 4. *Detection results of driving factors of the spatial distribution of eco-environmental Vulnerability in Gansu Province of China*

Driving factor	1992 year		2002 year		2012 year		2022 year	
	Q value	P value	Q value	P value	Q value	P value	Q value	P value
Population density	0.0313	1.0000	0.0005	1.0000	0.0148	1.0000	0.0027	1.0000
Economic density	0.0313	1.0000	0.0294	1.0000	0.0057	1.0000	0.0042	1.0000
Elevation	0.0853	0.0000	0.0410	0.3007	0.0799	0.0077	0.0683	0.0464
Slope	0.2148	0.0000	0.2235	0.0000	0.1953	0.0000	0.1893	0.0000
Aspect of slope	0.0241	0.0030	0.0243	0.1702	0.0229	0.0041	0.0217	0.0044
Vegetation cover index	0.3563	0.0000	0.3500	0.0000	0.4610	0.0000	0.3480	0.0000
Average annual temperature	0.5818	0.0000	0.4341	0.0000	0.4327	0.0000	0.4891	0.0000
Average annual precipitation	0.5997	0.0000	0.5012	0.0000	0.6092	0.0000	0.5253	0.0000
Biological richness index	0.5719	0.0000	0.5691	0.0000	0.5885	0.0000	0.5646	0.0000
General budget revenue of local governments	0.2745	0.0000	0.1258	0.0437	0.3800	0.0000	0.1488	0.0000
Number of students enrolled in ordinary middle schools	0.5439	0.0000	0.5255	0.0000	0.5401	0.0000	0.5128	0.0000

With the increase in elevation, the vulnerability level of the ecological environment decreases. The most prominent is that the area of potentially vulnerable and slightly vulnerable areas in the elevation range of 1000–2000 m increases from 1992 to 2022 because the ecological environment in the area with more significant elevation is relatively better. In the elevation range of 2000 to 3000 m and greater than or equal to 3000 m, there is no significant change in the area proportion of mild and moderate vulnerability, and it is the same. According to the geographical detector model analysis results, the main factors affecting the ecological environment vulnerability in Gansu Province of China are average annual temperature, annual precipitation, biological richness index (Waidler et al., 2022). The vegetation cover index, general budget revenue of local finance, and slope also greatly influence Gansu Province of China’s eco-environmental vulnerability. The influence of elevation and slope direction on eco-environmental vulnerability in Gansu Province of China is not significant. Population

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

density and economic density did not significant affect ecological environment vulnerability in Gansu Province of China.

The ecological vulnerability of Gansu Province is higher than the average ecological vulnerability of the whole country (Liu et al., 2022). In addition, the study also found that the ecological environmental vulnerability of the study area is not the result of a single factor, but the comprehensive effect of multiple factors interacting with each other and reinforcing each other. It should be noted that all factors with strong explanatory power for ecological environmental vulnerability are mostly related to human activities. The core problem of ecological environmental protection lies in raising the public awareness of environmental protection and strengthening the publicity of ecological environmental protection policies, so as to promote the concept of ecological environmental protection. In addition, it is also necessary to strengthen ecological protection measures and strengthen the construction of ecological environment restoration projects.

Conclusion

(1) The eco-environmental vulnerability index of Gansu Province of China in the four periods from 1992 to 2022 ranged from 1.4857 to 4.0896, with average values of 2.5621, 2.5995, 2.5634 and 2.5154, respectively, showing a slight vulnerability and a slight vulnerability.

(2) As the elevation increased, the area proportion of ecological environmental vulnerability decreased, mainly manifested as slight and mild vulnerability. There is no vulnerability level for those with an elevation less than 800 m, and vulnerable areas are mainly distributed in the elevation range of 1000–2000 m.

(3) Cultivated land was mainly distributed in the areas of slight, slight, and moderate vulnerability. The forest land is mainly distributed in the slightly vulnerable and slightly vulnerable areas. The grassland is mainly distributed in the slightly vulnerable and slightly vulnerable areas. The water area and construction land are distributed in potential vulnerability, slight vulnerability, mild vulnerability and moderate vulnerability, but the proportion of the area is small. The unused land is mainly distributed in the areas of potential vulnerability, slight vulnerability and slight vulnerability. There were no severely vulnerable areas.

(4) The main factors affecting the eco-environmental Vulnerability in Gansu Province of China were average annual temperature, annual precipitation, biological richness index, and the number of students in ordinary middle schools. The vegetation cover index, local financial revenue, and slope also greatly influence the ecological environment vulnerability in Gansu Province of China. The influence of elevation and slope direction on eco-environmental vulnerability in Gansu Province of China is not significant. Population density and economic density did not affect ecological environment vulnerability in Gansu Province of China.

Acknowledgments. Many thanks to Chun Hong for their technical assistance in the laboratory work.

Funding. This research was supported by the Youth Innovative Talent Team Project of Gansu Province, China (No.2022LQTD50).

Conflict of interests. The authors declare no conflicts of interests.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

REFERENCES

[1] Cao, J., Li, T. (2023): Analysis of spatiotemporal changes in cultural heritage protected cities and their influencing factors: evidence from China. – Ecological Indicators 151: 110327.

[2] Fedorov, A. V., Dubinin, Y. V., Yeletsky, P. M., Fedorov, I. A., Shelest, S. N., Yakovlev, V. A. (2021): Combustion of sewage sludge in a fluidized bed of catalyst: Aspen Plus model. – J Hazard Mater 405: 124196.

[3] Gao, F., Xin, X., Song, J., Li, X., Zhang, L., Zhang, Y., Liu, J. (2023): Simulation of LUCC dynamics and estimation of carbon stock under different SSP-RCP scenarios in Heilongjiang Province. – Land 12(9): 1665.

[4] Gao, J., Gong, J., Li, Y., Yang, J., Liang, X. (2024): Ecological network assessment in dynamic landscapes: multi-scenario simulation and conservation priority analysis. – Land Use Policy 139: 107059.

[5] Getachew, B., Manjunatha, B. R. (2022): Impacts of land-use change on the hydrology of lake tana basin, upper Blue Nile River basin, Ethiopia. – Global Challenges 6(8).

[6] Gong, J., Du, H., Sun, Y., Zhan, Y. (2023): Simulation and prediction of land use in urban agglomerations based on the PLUS model: a case study of the Pearl River delta, China. – Frontiers in Environmental Science 11.

[7] Han, P., Xiang, J., Zhao, Q. (2023): Spatial differentiation and scenario simulation of cultivated land in mountainous areas of western Hubei, China: a PLUS model. – Environ Sci Pollut Res Int 30(18): 52804-52817.

[8] He, Y., Mu, X., Jiang, X., Song, J. (2022): Runoff variation and influencing factors in the Kuye River basin of the middle yellow river. – Frontiers in Environmental Science 10.

[9] Hong, C., Zhao, H., Qin, Y., Burney, J. A., Pongratz, J., Hartung, K., Liu, Y., Moore, F. C., Jackson, R. B., Zhang, Q., Davis, S. J. (2022): Land-use emissions embodied in international trade. – Science 376(6593): 597-603.

[10] Hu, Z., Song, G., Hu, Z., Fang, J. (2024): An improved dynamic game analysis of farmers, enterprises and rural collective economic organizations based on idle land reuse policy. – Land Use Policy 140: 107098.

[11] Huang, C., Zhou, Y., Wu, T., Zhang, M., Qiu, Y. (2024): A cellular automata model coupled with partitioning CNN-LSTM and PLUS models for urban land change simulation. – Journal of Environmental Management 351: 119828.

[12] Huang, T., Wang, Z., Wu, Z., Xiao, P., Liu, Y. (2023): Attribution analysis of runoff evolution in Kuye River basin based on the time-varying Budyko framework. – Frontiers in Earth Science 10.

[13] Koko, A. F., Han, Z., Wu, Y., Zhang, S., Ding, N., Luo, J. (2023): Spatiotemporal analysis and prediction of urban land use/land cover changes using a cellular automata and novel patch-generating land use simulation model: a study of Zhejiang Province, China. – Land 12(8): 1525.

[14] Lechner, C., Kirisits, C. (2022): The effect of land-use categories on traffic noise annoyance. – Int J Environ Res Public Health 19(23).

[15] Li, R., Zhao, X., Tian, Y., Shi, Y., Gu, X., Wang, S., Zhang, R., An, J., Su, L., Wang, X. (2023): Different responses of Japanese encephalitis to weather variables among eight climate subtypes in Gansu, China, 2005-2019. – BMC Infect Dis 23(1): 114.

[16] Li, X., Liu, Z., Li, S., Li, Y. (2022): Multi-scenario simulation analysis of land use impacts on habitat quality in Tianjin based on the PLUS model coupled with the invest model. – Sustainability 14(11): 6923.

[17] Li, Y., Li, J., Chu, J. (2022): Research on land-use evolution and ecosystem services value response in mountainous counties based on the SD-PLUS model. – Ecol Evol 12(10): e9431.

[18] Liang, X., Guan, Q., Clarke, K. C., Liu, S., Wang, B., Yao, Y. (2021): Understanding the drivers of sustainable land expansion using a patch-generating land use simulation

(PLUS) model: a case study in Wuhan, China. – Computers, Environment and Urban Systems 85: 101569.
[19] Liu, Q., Yu, F., Mu, X. (2022): Evaluation of the ecological environment quality of the Kuye River source basin using the remote sensing ecological index. – International Journal of Environmental Research and Public Health 19(19): 12500.
[20] Liu, Y., Jing, Y., Han, S. (2023): Multi-scenario simulation of land use/land cover change and water yield evaluation coupled with the GMOP-PLUS-InVEST model: a case study of the Nansi Lake basin in China. – Ecological Indicators 155: 110926.
[21] Nie, W., Xu, B., Yang, F., Shi, Y., Liu, B., Wu, R., Lin, W., Pei, H., Bao, Z. (2023): Simulating future land use by coupling ecological security patterns and multiple scenarios. – Science of the Total Environment 859: 160262.
[22] Okembo, C., Morales, J., Lemmen, C., Zevenbergen, J., Kuria, D. (2024): A land administration data exchange and interoperability framework for Kenya and its significance to the sustainable development goals. – Land 13(4): 435.
[23] Park, S. S., Lee, Y. K., Choi, Y. W., Lim, S. B., Park, S. H., Kim, H. K., Shin, J. S., Kim, Y. H., Lee, D. H., Kim, J. H., Park, T. J. (2024): Cellular senescence is associated with the spatial evolution toward a higher metastatic phenotype in colorectal cancer. – Cell Rep 43(3): 113912.
[24] Penny, J., Ordens, C. M., Barnett, S., Djordjević, S., Chen, A. S. (2023): Small-scale land use change modelling using transient groundwater levels and salinities as driving factors– an example from a sub-catchment of Australia's Murray-Darling Basin. – Agricultural Water Management 278: 108174.
[25] Singh, P., Fu, N., Dale, S., Orzol, S., Laird, J., Markovitz, A., Shin, E., O'Malley, A. S., McCall, N., Day, T. J. (2024): The comprehensive primary care PLUS model and health care spending, service use, and quality. – JAMA 331(2): 132-146.
[26] Takahashi, T., Ihara, Y. (2023a): Spatial evolution of human cultures inferred through Bayesian phylogenetic analysis. – J R Soc Interface 20(198): 20220543.
[27] Takahashi, T., Ihara, Y. (2023b): Corrigendum to: 'spatial evolution of human cultures inferred through Bayesian phylogenetic analysis' (2023) by Takahashi and Ihara. – J R Soc Interface 20(202): 20230249.
[28] Tang, H., Halike, A., Yao, K., Wei, Q., Yao, L., Tuheti, B., Luo, J., Duan, Y. (2024): Ecosystem service valuation and multi-scenario simulation in the Ebinur Lake basin using a coupled GMOP-PLUS model. – Sci Rep 14(1): 5071.
[29] Waidler, J., Gilbert, U., Mulokozi, A., Palermo, T. (2022): A "PLUS" model for safe transitions to adulthood: impacts of an integrated intervention layered onto a national social protection program on sexual behavior and health seeking among Tanzania's youth. – Stud Fam Plann 53(2): 233-258.
[30] Wang, S., Zhai, C., Zhang, Y. (2024): Evaluating the impact of urban digital infrastructure on land use efficiency based on 279 cities in China. – Land 13(4): 404.
[31] Xu, L., Liu, X., Tong, D., Liu, Z., Yin, L., Zheng, W. (2022): Forecasting urban land use change based on cellular automata and the PLUS model. – Land 11(5): 652.
[32] Xu, X., Wang, C., Wang, P., Chu, Y., Guo, J., Bo, X., Lin, A. (2023): Bioaerosol dispersion and environmental risk simulation: method and a case study for a biopharmaceutical plant of Gansu Province, China. – Sci Total Environ 860: 160506.
[33] Yu, Z., Zhao, M., Gao, Y., Wang, T., Zhao, Z., Wang, S. (2023): Multiscenario simulation and prediction of land use in Huaibei City based on CLUE-S and PLUS models. – Applied Sciences 13(12): 7142.
[34] Zhang, J., Wang, J., Zhao, N., Shi, J., Wang, Y. (2024a): Analysis of changes in runoff and sediment load and their attribution in the Kuye River basin of the middle yellow river based on the slope change ratio of cumulative quantity method. – Water (Basel) 16(7): 944.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585

[35] Zhang, Z., Li, X., Liu, X., Zhao, K. (2024b): Dynamic simulation and projection of land use change using system dynamics model in the Chinese Tianshan mountainous region, Central Asia. – Ecological Modelling 487: 110564.
[36] Zhong, Y., Zhang, X., Yang, Y., Xue, M. (2023): Optimization and simulation of mountain city land use based on MOP-PLUS model: a case study of Caijia cluster, Chongqing. – ISPRS International Journal of Geo-Information 12(11): 451.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2301_569585