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An Analysis of Eco–Environmental Changes in Rural Areas in China Based on Sustainability Indicators between 2000 and 2015

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Abstract: Ecological zoning and green–development assessment at the village–town scale in China are significant tasks for sustainable planning in China. In this study, we build an index system to calculate the eco–environmental vulnerability score and divide the results into extreme, heavy, moderate, light, and slight levels based on evidence from 43,046 villages and towns in China from 2000 to 2015; then, we build a sustainable–development score calculation criterion to perform sustainability assessments. The results show that nine indexes (digital elevation model (DEM), slope, net primary productivity (NPP), total rainfall per year, per capita cultivated land, farmland proportion, grassland proportion, forestland proportion, and construction–land proportion) are the main factors in the variation in eco–environmental vulnerability under the conditions of urbanization. The eco–environment is found to have worsened from 2000 to 2015, and the deterioration areas are mainly concentrated in Tibet, the eastern area of Xinjiang and the Xing'an Mountains region. Economic growth and ecological protection can achieve common development when eco–environmental vulnerability is at light and slight levels, while when eco–environmental vulnerability is fragile, the inhibitory effect of economic growth is obvious in rural areas. The results can provide useful information for village–town planning.

Keywords: eco–environmental vulnerability zoning; entropy weight method (EWM); sustainable–development assessment; village–town scale; economic growth

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1. Introduction

In the years since the reform and opening up, China has gone through rapid urban and economic development. From 1978 to 2016, the urbanization rate of China increased from less than 20% to 57.35% [1]. With the rapid development of human society in China, the constraints on resources and the environment have become increasingly tightened, and threats to ecological security are becoming gradually prominent [2,3].

The eco–environmental problem caused by urbanization is mainly due to the increase in urban land use and the excessive concentration of the population [4,5]. Since damage to ecological zones could lead to much natural and societal loss, the identification and protection of ecological zones are significant tasks for guiding human activities in the creation of equivalent economic value with lower environmental costs [6], which requires more approaches and cases to fit various purposes and situations. With the development of GIS and RS technology, multitemporal datasets [7,8] are applied in eco–environmental–problem/–hazard studies [9–14]. Liu et al. explored ecological zoning in Bohai Rim by applying an integrated GIS approach involving multiple factors and provided a basis for preventing high–quality ecological areas from undergoing rapid human development in Bohai Rim [15]. Del Carmen Sabatini et al. [16] developed a quantitative method for zoning within protected areas by offering many zonation scheme alternatives with minimum cost, time and effort, which effectively worked in achieving zoning designs more compatible with biological–diversity protection. Ecological zoning, the identification of highly important ecological areas, and their protection from anthropogenic interference are effective measures for regional environmental protection and sustainable development.

Policy implementation has strong influence on future landscape services [17]. China's environmental regulation is closely related to its administrative systems, mechanisms, policies, and other factors, such as economic growth target management, which is an effective motivational tool for local governments and officials that played a critical role in China's rapid economic growth for more than four decades. Its presence can be found throughout China's entire political system, at all governmental levels, and within all administrative departments and Party committees [18–22]. In rural areas, villages have become established social units because of the connection between people and the land, historical factors, and sociopolitical relationships (e.g., cultural identity) [23,24]. The overall planning of urban and rural areas is the focus of municipal administrative area (MAA) [25,26] planning in the process of economic globalization, and village–town system planning is the key to the overall planning of urban and rural areas [27]. There is a very close relationship between urbanization, economic growth, and environmental pollution [28]. Liang et al. [20] explored the interaction between urbanization, economic growth, and environmental pollution based on 2006–2015 panel data covering 30 provinces and cities in China and found that environmental pollution had a significant inhibitory effect on urbanization. Xie et al. (2018) thought that with the improvement in the urbanization rate, environmental quality was improved [29]. China's economic development not only depends on the institutional division of the market economy but also benefits from the economic stimulus policy enforced by the government. The coupling effect of effective market and promising government is the core of the socialist market economy with Chinese characteristics [30]. Therefore, the government holds great practical significance for green development from the perspective of economic growth targets [31]. Conducting green–development assessments in MMAs or village–town areas in China holds great significance. In recent years, especially since 1978, two questions have yet to be successfully answered: (1) How have rural settlements changed over the last several decades? (2) What are the key factors influencing the changes in the spatial pattern of rural settlements [32]? Currently, most previous studies have focused on a certain city or county, and little attention has been paid to these two issues, especially at the village scale, in rural areas in China.

The sustainability of China's development is reflected in the sustainability of its resources and environmental carrying capacities (RECCs), as well as government organization [33,34]. The RECC concept is considered to be a total description of the maximum affordability threshold of regional systems in response to external environmental changes [35]. RECC assessments have been applied at macro–, meso–, and microscale levels, such as countries, urban agglomerations, regions, provinces, prefecture–level cities, municipal districts, county–level cities, and even disaster areas [36], with factor analysis methods, equation decision methods, state space methods, the analytic hierarchy process and entropy methods [37]. Martire et al. [38] evaluated the forest resource carrying capacity and eco–environment carrying capacity in alpine mountain areas and discussed them in order to contribute to face the challenge of energy planning at local scale, which is helpful for highlighting some challenges in resource planning and use at local scale. Zhou et al. [39] analyzed types of areas and their development paths in rural China and built a comprehensive index system and measurement model to measure the level of rural development from the perspectives of resource endowments, the geographical environment, humanistic elements and the economic level, which can provide a theoretical basis and decision–making guidance to smoothly promote the rural revitalization strategy.

Learning from the RECC concept and its evaluation method, in this study, we explore the sustainability of China's development at the village scale based on evidence from 43,046 villages and towns from 2000 to 2015. Two main aspects are included: (1)

eco–environmental vulnerability (ecosystem stability) zoning, i.e., how environmental vulnerability has changed from 2000 to 2015 and the triggering factors; and (2) sustainable–development assessment, i.e., under the conditions of environmental constraints, how China's economy and society can achieve sustainable development.

2. Materials and Methods

2.1. Study Area

In this study, we focus on the question at the rural–area scale. The study area includes 43,046 villages and towns in China (2020), while data on Taiwan are not included (Figure 1). Land use variation has a close relationship with the eco–environmental variation in and the urbanization process of rural areas [4,5]. Land uses in China are divided into 7 different types: farmland, forest, grassland, water, building area, unused land, and ocean (Figure 2). From 2000 to 2015, the land use of the 43,046 villages and towns considerably changed (Table 1), and the main land cover types were farmland, forest, grassland, and unused land. From 2000 to 2015, the percentages of farmland and grassland decreased by 0.16% and 3.67%, from 18.96% to 18.8% and from 31.84% to 28.17%, respectively. In contrast, the percentages of forest, water, building area, and unused land increased by 0.48%, 0.12%, 0.79%, and 2.43, from 23.45% to 23.93%, from 2.77% to 2.89%, from 1.81% to 2.6%, and from 21.18 to 23.61, respectively. Most grassland degraded to unused land, such as in northern Tibet.

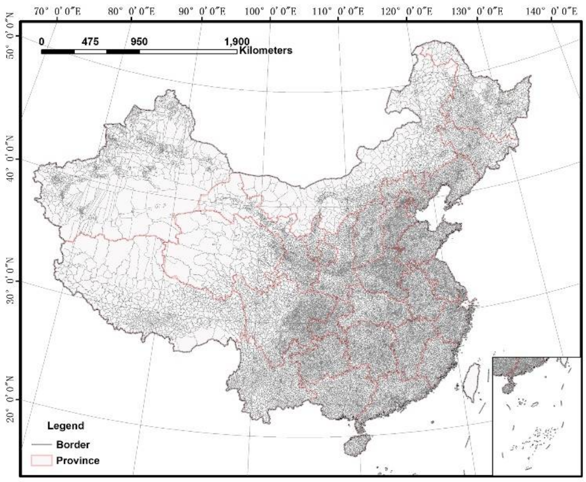

Figure 1. Study area.

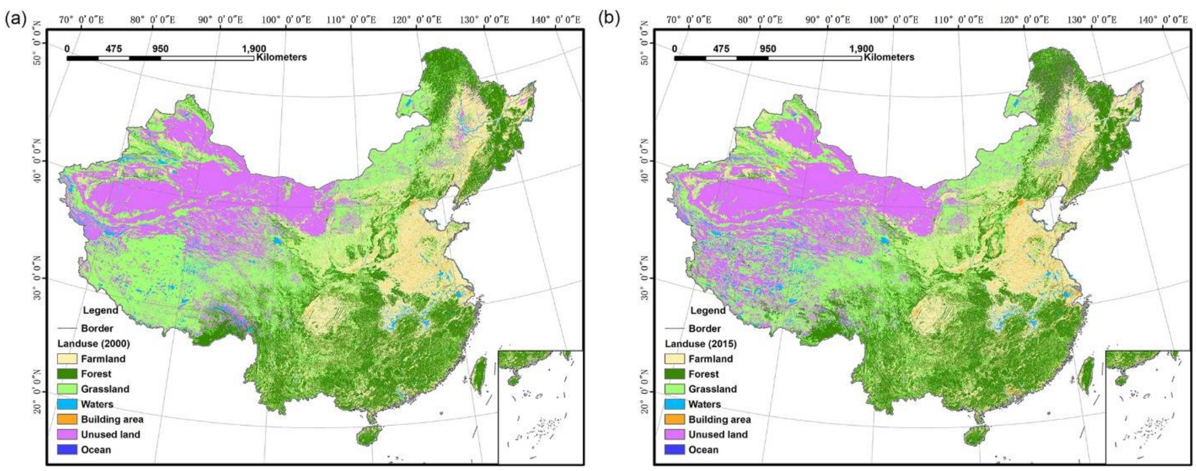

Figure 2. Land use in China in (**a**) 2000 and (**b**) 2015 at a 30 m spatial resolution.

Table 1. Land use in 2000 and 2015.

Land Use Type	Area Ratio (×100%)		Variation (×100%)
	2000	2015	
farmland	18.96	18.80	−0.16
forest	23.45	23.93	0.48
grassland	31.84	28.17	−3.67
waters	2.77	2.89	0.12
building area	1.81	2.60	0.79
unused land	21.18	23.61	2.43
ocean	0.00	0.00	0

2.2. Methods

In this study, we aim to perform ecological–zoning and green–development assessment at the village–town scale in China, the framework of the study is shown in Figure 3. For ecological zoning at the rural–area scale, we first need to build an index system from the perspective of the geographical environment, humanistic elements, resource endowments, and the economic level, and second, to calculate the comprehensive score and then perform eco–environmental vulnerability zoning based on the information weight model. Lastly, eco–environmental vulnerability and sustainable–development assessment are conducted at the rural–area scale in China.

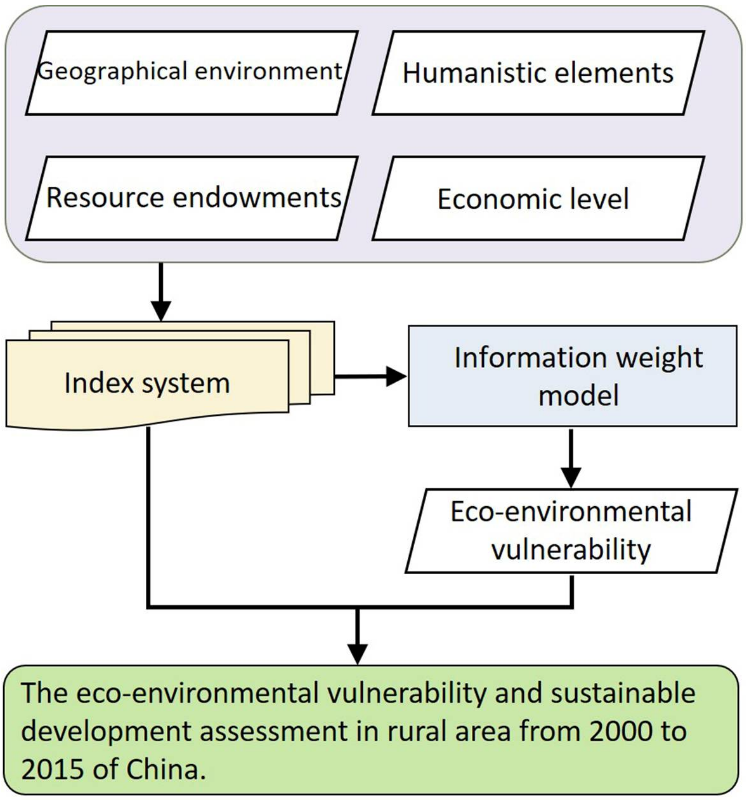

Figure 3. Framework of the study.

2.2.1. Materials and Preprocessing

For generalized ecological elements, all factors that may have any impact on the environment are classified as ecological elements, such as meteorological conditions, water resources, vegetation types, topography, soil types, population density, economic density, industrial structure and layout, land use status, building density, and environmental pollution conditions. However, most of the factors in rural areas are not available, and the variability in most factors, such as meteorological conditions, water resources, and soil types, is small at the village–town scale. The dataset used in this study are shown in Table 2. Moreover, there are 13 parameters built for ecological zoning based on the dataset in Table 2 from the perspective of resource endowments, geographical environment, humanistic elements, and economic level, as shown in Table 3.

Table 2. Datasets used in the construction of the index system.

Dataset	Spatial Resolution	Temporal Resolution	Time	Data Source
Digital elevation model (DEM)	30 m	–	2003	SRTM DEM
Net primary productivity (NPP)	500 m	Annual	2000, 2015	GLASS poduct (http://www.glass.umd.edu/Download.html (accessed on 10 August 2022))
Landuse	30 m	Annual	2000, 2015	Resource and Environment Science and Data Center (https://www.resdc.cn/Default.aspx (accessed on 10 August 2022))
Rain	1 km	Annual	2000, 2015	
Population density	1 km	Annual	2000, 2015	
Aging population	City	Annual	2020	https://www.sohu.com/a/476746607_121106832 (accessed on 10 August 2022)
Road	–	–	2014	–
GDP	1 km	Annual	2000, 2015	Resource and Environment Science and Data Center (https://www.resdc.cn/Default.aspx (accessed on 10 August 2022))

Table 3. Index system built during dataset preprocessing.

Criteria	Indicators	Definition	Positive (1)/ Negative (2)
Geographical environment	DEM	Mean elevation of each rural area	2
	Slope	Proportion of the area with a slope greater than 15°	2
	Broken index of the surface	Standard deviation of elevation in each rural area	2
	Net primary productivity (NPP)	Mean value of each rural area	1
Resource endowments	Per capita cultivated land	Ratio between farmland area and whole population (calculated with population density and rural area)	1
	Total rainfall per year	Mean annual rainfall over the years (1980–2015)	1
	Farmland proportion	Proportion of farmland area	1
	Grassland proportion	Proportion of grassland area	1
	Forestland proportion	Proportion of forestland area	1
	Construction–land proportion	Proportion of construction–land area	2 [20] *
Humanistic elements	Road traffic density	Total length of roads per unit area of each rural area	2
Economic level	Per capita GDP	Ratio between GDP and population at the 1 km scale	1
	Agricultural development advantage degree	The ratio between variation in farmland area and variation in GDP from 2000 to 2015	1

* The development of infrastructure construction, especially the construction industry, will cause more serious pollution problems, leading to a negative influence on green development [20].

2.2.2. Entropy Weight Method (EWM)

The entropy weight method (EWM) is an information weight model that has been widely used in decision–making [40,41], such as in assessments of lake water quality [42], the stress factors and efficiency of water management measures [43], and to study water characteristics, such as eutrophication, health, and spatial distribution [44]. Compared with other various subjective weighting models, the EWM improves the objectivity of the comprehensive evaluation results because it prevents human factors from interfering with the weight of indexes [45].

In the EWM, we assume that there are m indexes and n samples in the evaluation, and the measured value of the ith index in the jth sample is recorded as x_{ij}.

When analyzing eco–environmental vulnerability, since different indexes have different units, the extreme–value method is used to standardize the original data of each index with Equation (1):

$$X_{ij} = \begin{cases} \frac{(a-b)*\left(x_{ij}-\min(x_i)\right)}{\max(x_i)-\min(x_i)} + b\ for\ positive\ indicators \\ \frac{(a-b)*\left(\max(x_i)-x_{ij}\right)}{\max(x_i)-\min(x_i)} + b\ for\ negative\ indicators \end{cases} \quad (1)$$

where X_{ij} refers to the standardized value of the ith index in the jth sample, and a = 0.002 and b = 0.996 are the standardized thresholds. The positive and negative information for each parameter is listed in Table 3.

Then, each specific weight (P_{ij}) of the jth sample in the ith index is calculated:

$$P_{ij} = \frac{X_{ij}}{\sum_{j=1}^{n} X_{ij}} \quad (2)$$

Then, entropy value E_i of the ith index is calculated with Equation (3) [46]:

$$E_i = \frac{\sum_{j=1}^{n} P_{ij} \times \ln P_{ij}}{\ln n} \quad (3)$$

The range of entropy value E_i is [0, 1]. The larger the value of E_i is, the greater the differentiation degree of index i is, and the greater the amount of information that can be derived is. Then, in the EWM, the method of calculating weight ω_i [47,48] is defined with Equation (4):

$$\omega_i = \frac{1 - E_i}{\sum_{i=1}^{m} 1 - E_i} \quad (4)$$

Then, the comprehensive score is calculated with Equation (5):

$$S = 100 \times \omega_i \times X_i{}' \quad (5)$$

Lastly, we normalize the scoring result from 0 to 1.

Because all the indexes are normalized in the positive or negative directions, the comprehensive score calculated with the EWM can reflect the ecosystem stability, which means that, the higher the value is, the better the ecological environment is. We use eco–environmental vulnerability to represent ecosystem stability. In this study, we divide the comprehensive scoring result into five levels based on the natural breaks method [49] to evaluate the eco–environmental vulnerability of each village/town.

3. Results and Discussion

3.1. Index–System Construction

From a previous study, the EWM evaluates the index by measuring the degree of differentiation; the higher the degree of dispersion of the index is, the higher the weight given to the index is [50]. In this study, the original datasets were normalized with the extreme–value method to minimize the inconsistency caused by the dimensions of each index. We calculated the standard deviation (SD) value of each index (standardized results) of 43,046 villages and towns shown in Table 3 and found that these nine indexes (geographical environment (DEM, slope, NPP) and resource endowments (total rainfall per year, per capita cultivated land, farmland proportion, grassland proportion, forestland proportion, construction–land proportion)) with high SDs are the main factors influencing the vulnerability of the eco–environment (Figure 4) with high weights (Table 4), which indicates that the EWM is effective in measuring the degree of these nine indexes. The results show that eco–environmental vulnerability at the rural–area scale is mainly determined by the geographical environment and resource endowments, with little relationship with humanistic elements and the economic level. The forestland proportion is the main index affecting eco–environmental vulnerability, followed by the grassland proportion index. From 2000 to 2015, we also find that the influence of the grassland proportion index and the forestland proportion index decrease, while the influence of the farmland proportion index and the per capita cultivated–land index increase. Compared with the work by Zhou et al. [39], we find that most of the indexes that influence the regional types at the county scale are not significant at the rural–area scale. Performing ecological zoning at the village scale holds great significance.

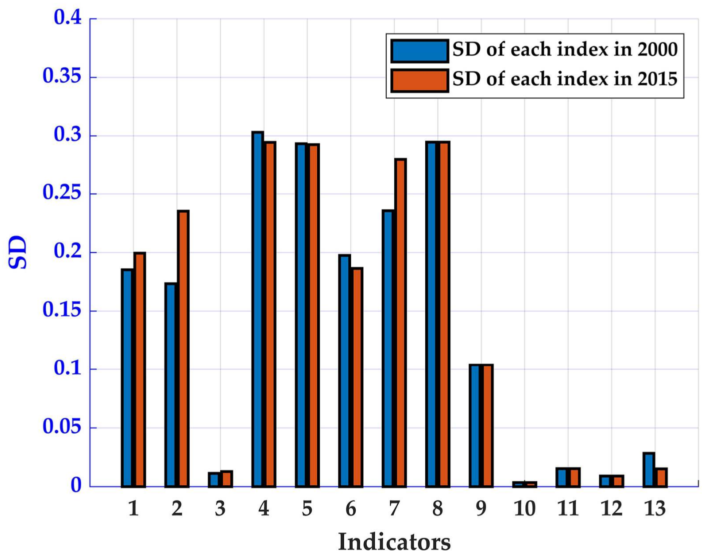

Figure 4. The SD results of each index of 43,046 villages and towns in China.

Table 4. Weigh of each index calculated with EWM in 2000 and 2015.

No. in Figure 4	Name in Table 3	Weight	
		2000	2015
1	NPP	0.0525	0.0514
2	Total rainfall per year	0.0665	0.0723
3	Per capita cultivated land	0.1395	0.1508
4	Farmland proportion	0.1158	0.1207
5	Grassland proportion	0.2381	0.2235
6	Forestland proportion	0.3276	0.315
7	Construction–land proportion	0.0198	0.0289
8	Slope	0.0321	0.03
9	DEM	0.008	0.0074
10	Agricultural development advantage degree	–	–
11	Broken index of the surface	–	–
12	Road traffic density	–	–
13	Per capita GDP	–	–

3.2. Eco–Environmental Vulnerability at the Rural–Area Scale

With the weight information of each indicator shown in Table 4, we calculate the comprehensive score of each town/village with Equation (5) and then normalize the scoring result; we divide the comprehensive scoring result into five levels and then the classification criteria of the eco–environmental vulnerability at the rural–area scale are built and are shown in Table 5. The eco–environmental vulnerability at the rural–area scale in 2000 and 2015 is shown in Figure 5. It is obvious that the eco–environmental vulnerability in 2000 and 2015 is greatly different, especially in Tibet, Northeast China and the pan–Pearl River Delta area.

Table 5. Classification criteria of eco–environmental vulnerability.

Grading Level	Classification Criteria	Eco–Environmental Vulnerability
1	[0, 0.26]	Extreme
2	(0.26, 0.43]	Heavy
3	(0.43, 0.56]	Moderate
4	(0.56, 0.69]	Light
5	(0.69, 1]	Slight

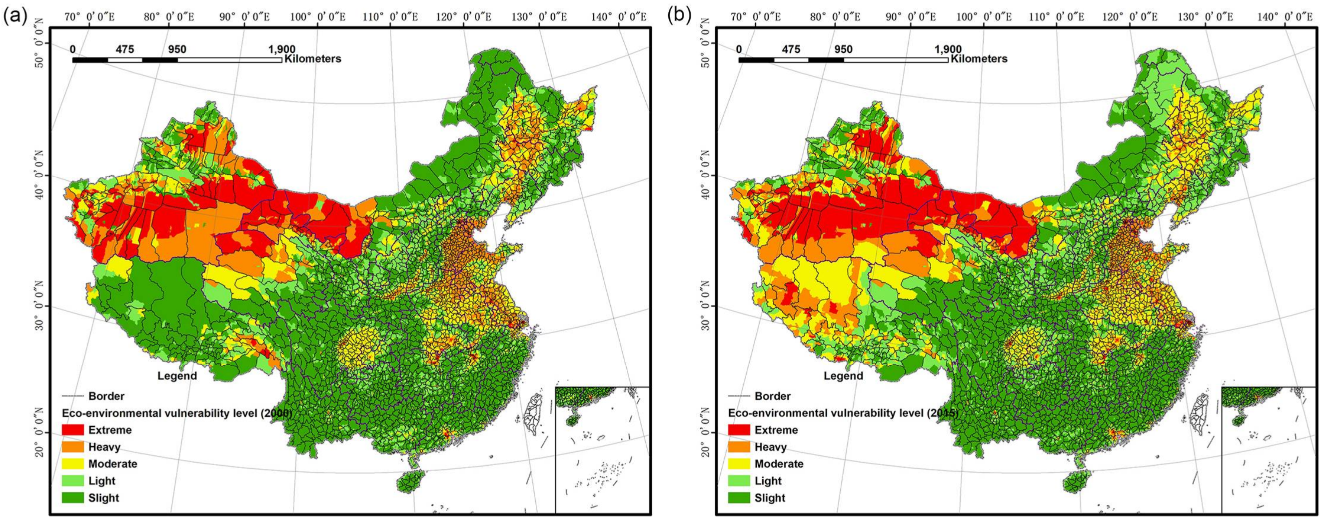

Figure 5. Eco–environmental vulnerability at the rural–area level in (**a**) 2000 and (**b**) 2015 shown at the county level representing the administrative units.

Among the 43,046 villages and towns in China (2020), there are 29,703 in 2000 and 30,384 in 2015 with moderate, light, and slight eco–environmental vulnerability, and the share in area of these rural areas is higher than 74% for both years, which indicates that the eco–ecological environment of China is of high quality (Table 6). However, for the whole country, the ecological environment is found to have worsened from 2000 to 2015; more villages and towns become extreme eco–environmental vulnerability zones, and the villages and towns in slight eco–environmental vulnerability zones decrease. The percentage change in the area at each grading level is much higher than the percentage change in quantity. For example, for rural areas at grading level 5, from 2000 to 2015, the percentage change in number decreases by 0.55%, but the percentage change in area decreases by 4.62%, which demonstrates that the variation in area is a better indicator than the variation in quantity when analyzing the eco–environmental variation based on administrative divisions at the village level (Table 6).

Table 6. Detailed information on the villages and towns at each grading level.

Grading Level	2000				2015			
	Number	Proportion	Area ($\times 10^{12}$ m^2)	Area Ratio	Number	Proportion	Area ($\times 10^{12}$ m^2)	Area Ratio
1	5355	0.1244	1.09	0.1107	6566	0.1525	1.23	0.1247
2	7988	0.1856	1.45	0.1467	6096	0.1416	1.33	0.1342
3	8360	0.1942	1.29	0.1307	9174	0.2131	1.84	0.1869
4	7295	0.1695	1.54	0.1558	7401	0.1719	1.85	0.1873
5	14,048	0.3263	4.5	0.4561	13,809	0.3208	3.62	0.3670

The policy–making of each administrative division (i.e., taking the province level, city level, and county level as the units of analysis) plays an important role in analyses of ecological development [18–22]. Theoretically, the boundaries of administrative divisions have a deep relationship with the division of the ecological environment. When analyzing the ecological environment based on datasets at a 30 m spatial resolution, it is clear that the boundary effect is not obvious at the county–level scale, and the results of ecological environment development are discontinuous at the county–level scale. For each county, the ecological zoning of different villages and towns is inconsistent (Figure 5). Additionally, most of the national plan for developing functional zones [24,25,28] is at the village–level scale. Thus, it is necessary and meaningful to perform an analysis at the level of a smaller (village–level scale) administrative unit.

3.3. Variation in Eco–Environmental Vulnerability from 2000 to 2015 at the Rural–Area Scale

When analyzing the variation in eco–environmental vulnerability from 2000 to 2015, the grading–level variation includes nine types (Figure 6 and Table 7). In terms of number and area, over 77% and 69.78% of villages and towns, respectively, have no changes in ecological sensitivity, and the percentage change in number is 22.83% (9828 out of 43,406). The deterioration areas are mainly concentrated in Tibet, the eastern area of Xinjiang, and the Xing'an Mountains region. Most of the central region of China shows sustainable development. Over 20% of the area changes at a one–unit scale.

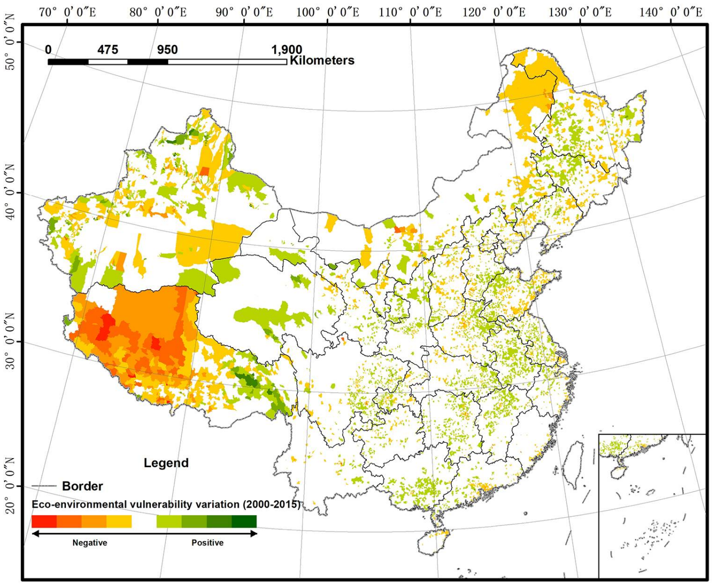

Figure 6. Variation in eco–environmental vulnerability from 2000 to 2015 at the rural–area scale.

Table 7. Detailed information on the variation in eco–environmental vulnerability from 2000 to 2015.

Nine Types of Grading Level Variation	Number	Proportion (×100%)	Area (m^2)	Area Ratio (×100%)
−4	29	0.0007	2.96×10^{10}	0.0030
−3	104	0.0024	2.24×10^{11}	0.0226
−2	499	0.0116	4.24×10^{11}	0.0429
−1	4424	0.1028	1.19×10^{12}	0.1206
0	33,218	0.7717	6.89×10^{12}	0.6978
1	4629	0.1075	1.02×10^{12}	0.1034
2	114	0.0026	7.89×10^{10}	0.0080
3	25	0.0006	1.57×10^{10}	0.0016
4	4	0.0001	2.68×10^{8}	0.0000

For the nine grading–level variation types, the deterioration areas show a higher percentage change in area equal to 7.82% with more than two grading–level variations, while the percentage change in number is 1.8%. The ecological environment of some larger villages and towns is found to have greatly changed. When evaluating variation, it is important to take administrative divisions as the standard for changes in both the number and area of villages and towns.

3.4. Sustainable–Development Evaluation at the Rural–Area Scale

3.4.1. Relationship with Economic Development

From Section 3.1, the economic level and humanistic elements are not included in the index system built to calculate the eco–environmental vulnerability of the study area. From a previous study, economic growth can influence eco–environmental vulnerability [28]. Shen et al. found that economic growth targets have significant inhibitory effects on green technology innovation [31]. For the study of the relationship between the economy and the environment, the Cruz Nez curve theory is widely accepted [51,52]. Kuznets pointed out that the relationship between per capita income and income inequality is an inverted U–shaped curve [53], and there is an inflection point between economic growth and environmental pollution. The level of environmental pollution rises with economic growth. However, when the per capita income exceeds a certain level (i.e., inflection point), the environment improves with economic growth. Nevertheless, for some countries or regions, the relationship between environmental pollution and economic growth is not fully consistent with the theoretical hypothesis of an inverted U–shaped relationship, which hypothesizes a fully consistent inverted U–shaped curve [54–56].

To explore the inhibitory effect of economic growth on eco–environmental vulnerability at the rural–area scale in China, we detect the relationship between the annual growth rate of per capita GDP and the variation in eco–environmental vulnerability from 2000 to 2015 (Figure 7). The variation in eco–environmental vulnerability has a close relationship with the annual growth rate of per capita GDP. The SD of the annual growth rate of per capita GDP has a high value when the eco–environmental vulnerability shows negative grading–level variation, while it sharply decreases with positive grading–level variation from 0 to 4. This finding indicates that the variation in the annual growth rate of per capita GDP of villages and towns in the negative direction is greater, and the economic development pattern in these areas is seriously inconsistent with the goals of sustainable development. The decreasing SD values also demonstrate the credibility of the positively changing GDP inhibitory effect.

We also found that the economy is growing at an extremely high rate, which may strongly damage the ecological system. The grading–level variation and the mean annual growth rate of per capita GDP show a negative correlation (the red dashed line in Figure 7). When the annual growth rate of per capita GDP is higher than 0.47, the GDP mainly shows a negative influence on the environment of most villages and areas, especially when the mean annual growth rate of per capita GDP is higher than 0.65. When the mean annual growth rate of per capita GDP is lower than 0.47, the GDP mainly shows a positive influence on the environment, which is more consistent with the requirements of sustainable development. At the data level of representation adopted, economic development shows a close relationship with the geological environment, and the study results can provide some reference for the sustainable development of rural areas in China.

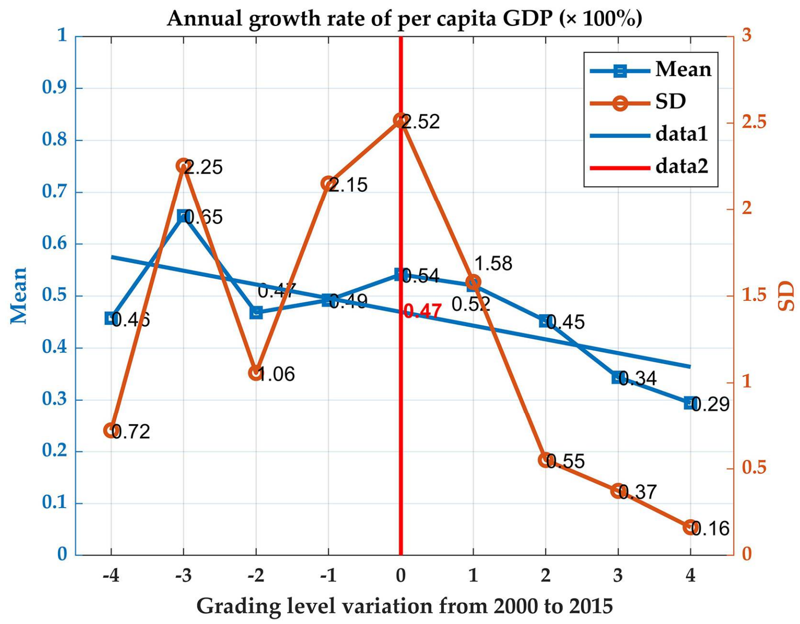

Figure 7. Relationship between the annual growth rate of per capita GDP (×100%) and the variation in eco–environmental vulnerability from 2000 to 2015.

3.4.2. Sustainable–Development Evaluation Score

Based on the results shown in Sections 3.2 and 3.3, there are five different grading levels (Table 5) and nine grading variation levels (Table 7) of eco–environmental vulnerability. The total grading–level variations from 2000 to 2015, including 25 change types, are shown in Table 8. To perform a sustainable assessment based on the eco–environmental vulnerability results, we define the sustainable development evaluation score of each village and evaluate the sustainable–development of rural areas in China from 2000 to 2015. Four rules are set to calculate the sustainable–development evaluation score:

1. The sustainable–development evaluation score ranges from 1 to 25.
2. Based on the grading results in 2015, the higher the eco–environmental vulnerability in 2015 is, the higher the sustainable–development evaluation score is.
3. For positive variation, the higher the grading–level variation from 2000 to 2015 is, the higher the sustainable–development evaluation score is. In contrast, for negative variation, the higher the grading–level variation is, the lower the sustainable–development evaluation score is.
4. For villages with the same grading level, the sustainability development evaluation score of positive change is higher than that of negative change with respect to this level from 2000.

The sustainability score of the 25 change types is calculated, as shown in Table 8, and serves as the criterion for the potential of social development. We draw the sustainable–development evaluation score map shown in Figure 8. The higher the sustainable–development evaluation score is, the higher the potential for social development of the village is. The results can provide useful information for MMA planning.

Table 8. Detailed information on the 25 types of variation and the sustainable–development evaluation score.

Change Type	Time		Grading–Level Variation	Sustainable–Development Evaluation Score	Number	Area (m^2)
	2000	2015				
1	5	1	−4	1	29	2.96×10^{10}
2	4	1	−3	2	33	5.47×10^{9}
3	3	1	−2	3	170	1.73×10^{10}
4	2	1	−1	4	1226	2.87×10^{11}
5	1	1	0	5	5108	8.91×10^{11}
6	5	2	−3	6	71	2.18×10^{11}
7	4	2	−2	7	137	4.07×10^{10}
8	3	2	−1	8	1117	1.2×10^{11}
9	2	2	0	9	4568	7.74×10^{11}
10	1	2	1	10	203	1.72×10^{11}
11	5	3	−2	11	192	3.66×10^{11}
12	4	3	−1	12	783	1.76×10^{11}
13	3	3	0	13	6029	9.31×10^{11}
14	2	3	1	14	2139	3.47×10^{11}
15	1	3	2	15	31	2.45×10^{10}
16	5	4	−1	16	1298	6.07×10^{11}
17	4	4	0	17	5055	1.01×10^{12}
18	3	4	1	18	1000	1.96×10^{11}
19	2	4	2	19	39	2.92×10^{10}
20	1	4	3	20	9	4.88×10^{9}
21	5	5	0	21	12,458	3.28×10^{12}
22	4	5	1	22	1287	3.05×10^{11}
23	3	5	2	23	44	2.53×10^{10}
24	2	5	3	24	16	1.09×10^{10}
25	1	5	4	25	4	2.68×10^{8}

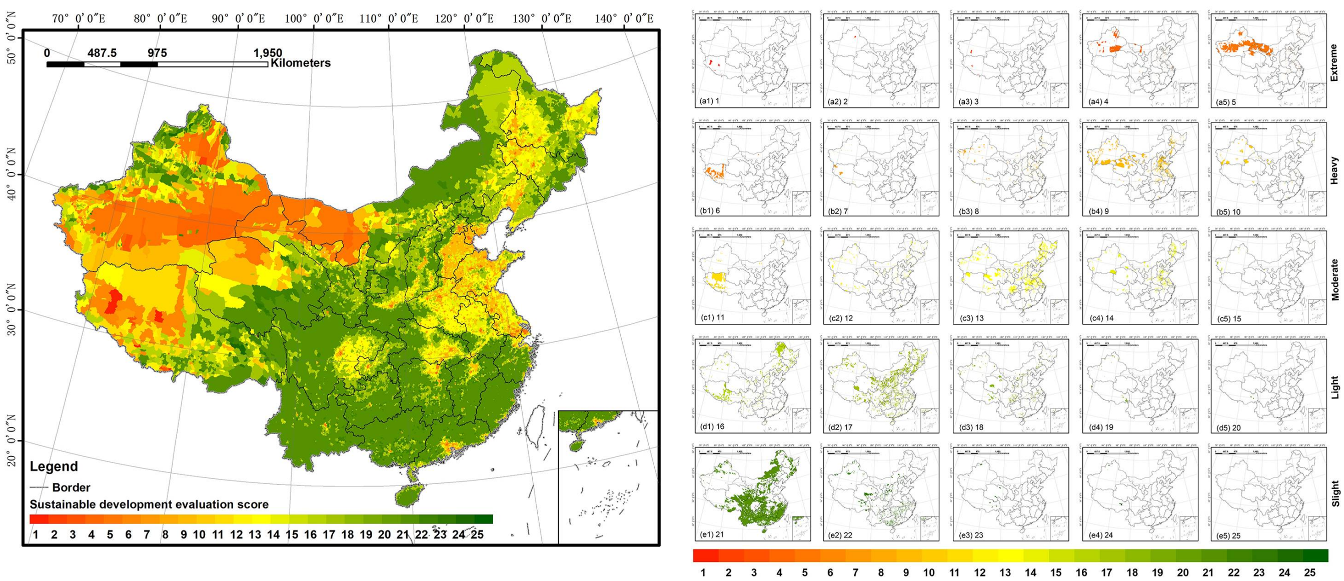

Figure 8. Sustainable–development evaluation score from 2000 to 2015 at the rural–area scale.

We also analyze the relationship between economic growth rate and the sustainable–development score (Figure 9). The SD value of the annual growth rate of per capita GDP shows violent oscillations with high values and decreases along with the increase in the sustainable–development evaluation score; it tends to be stable after reaching a score of 16, while the mean value of the annual growth rate of per capita GDP slightly decreases and remains nearly stable after reaching a score of 16. The results indicate that when eco–environmental vulnerability is at light and slight levels, economic growth and ecological protection can achieve common development. However, when eco–environmental vulnerability is more fragile, the inhibitory effect of economic growth is obvious in rural areas.

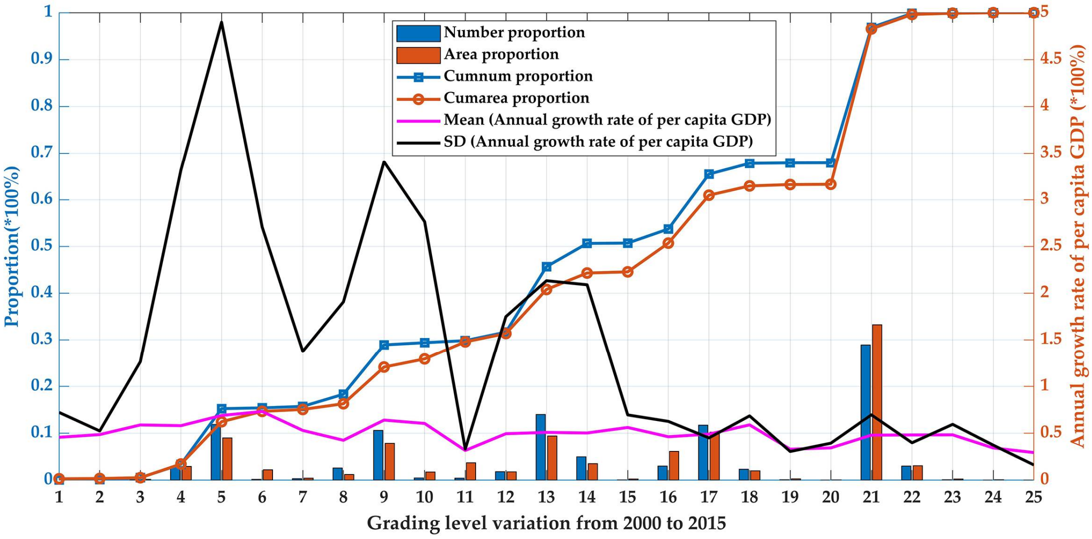

Figure 9. Relationship between the annual growth rate of per capita GDP and the sustainable–development evaluation score.

4. Conclusions

Ecological zoning considering the village–town administrative unit holds great significance for the sustainable development of village–town system planning. In this study, we first build an index system with the EWM method to evaluate eco–environmental vulnerability and then build a sustainable–development score calculation criterion to explore the sustainability of China's development at the village scale based on evidence from 43,046 villages and towns from 2000 to 2015. The following conclusions are drawn from the results of this study:

- Eco–environmental vulnerability is mainly determined by the geographical environment and resource endowments at the village–town scale. Nine indicators, including DEM, slope, NPP, total rainfall per year, per capita cultivated land, farmland proportion, grassland proportion, forestland proportion, and construction–land proportion, are the main indicators influencing eco–environmental vulnerability;
- The eco–environmental vulnerability results are divided into extreme, heavy, moderate, light, and slight levels. Among the 43,046 villages and towns in China (2020), there are 29,703 in 2000 and 30,384 in 2015 with moderate, light, and slight eco–environmental vulnerability. The ecological environment is found to have worsened from 2000 to 2015, and the variation in area is a better indicator than the variation in quantity when analyzing eco–environmental variation based on administrative divisions at the village level;
- The variation in eco–environmental vulnerability has a close relationship with the annual growth rate of per capita GDP. The economic growth rate shows an inhibitory effect on the environment at the rural–area scale from 2000 to 2015. The critical threshold for negative environmental impact of the annual growth rate of per capita GDP is 0.47; the higher the value is, the more serious the negative effects on the environment are. Economic growth and ecological protection can achieve common development when eco–environmental vulnerability is at light and slight levels. However, when eco–environmental vulnerability is more fragile, the inhibitory effect of economic growth is obvious in rural areas.

This study provides new insights into eco–environmental vulnerability zoning at the village–town scale and sustainable–development assessment under the conditions of rapid urban and economic development. The results obtained in this study can provide useful information on how to enhance the positive interaction between urbanization and economic growth and how to promote the construction of new sustainable urban development in China.

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