

Village-level multidimensional poverty measurement in China: Where and how

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Abstract: Village is an important implementation unit of national poverty alleviation and development strategies of rural China, and identifying the poverty degree, poverty type and poverty contributing factors of each poverty-stricken village is the precondition and guarantee of taking targeted measures in poverty alleviation strategies of China. To respond it, we construct a village-level multidimensional poverty measuring model, and use indicator contribution degree indices and linear regression method to explore poverty factors, while adopting Least Square Error (LSE) model and spatial econometric analysis model to identify the villages' poverty types and poverty difference. The case study shows that: (1) Spatially, there is obvious territoriality in the distribution of poverty-stricken villages, and the poverty-stricken villages are concentrated in contiguous poverty-stricken areas. The areas with the highest VPI, in a descending order, are Gansu, Yunnan, Guizhou, Guangxi, Hunan, Qinghai, Sichuan, and Xinjiang. (2) The main factors contributing to the poverty of poverty-stricken villages in rural China include road construction, terrain type, frequency of natural disasters, per capita net income, labor force ratio, and cultural quality of labor force. The main causes of poverty include underdeveloped road construction conditions, frequent natural disasters, low level of income, and labor conditions. (3) Chinese poverty-stricken villages include six main subtypes, and most poverty-stricken villages are affected by multiple poverty-forming factors, reflected by a relatively high proportion of the three-factor dominant type, four-factor coordinative type, and five-factor combinative type. (4) There exist significant poverty differences in terms of geographical location and policy support, and the governments still need to carry out targeted poverty alleviation measures according to local conditions. The research can not only draw a macro overall poverty-reduction outline of impoverished villages in China, but also depict the specific poverty characteristics of each village, helping the government departments of pov-

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erty alleviation at all levels to mobilize all kinds of anti-poverty resources.

Keywords: poor village; multidimensional poverty measurement; poverty type; poverty factors; spatial econometric analysis

1 Introduction

Poverty is a global problem. As the largest developing country, China has a large population living in poverty, making poverty elimination a long-term process, which affects the effectiveness of the global poverty reduction work (Wang and Chen, 2017). Rural poverty has always been a focus of the Chinese government, which has worked to formulate poverty alleviation and development strategies (Duclos *et al.*, 2009; SCC, 2011; Lu, 2012). Since the reform and opening up, China's rural anti-poverty efforts have achieved remarkable results. However, a "bottleneck," where the rate of poverty reduction reduces and the pressure of poverty alleviation increases, eventually emerged. In 2011, China raised the poverty line and set a 2300 yuan per capita net income as a new national rural poverty alleviation standard, resulting in the fact that the number of poor people in China increased from 26.88 million to 128 million, marking a new stage for the Chinese anti-poverty campaign (Yang, 2012). At the end of 2016, there were still 128,000 poverty-stricken villages and 45,750,000 farmers living below the poverty line in China, according to 2016 China's poverty alleviation and development yearbook. Meanwhile, "taking targeted measures in poverty alleviation" mechanism has changed from a "flood irrigation for all regions" general support pattern to a "drip irrigation at certain points" specific one, accompanying with the target scale unit of poverty alleviation transferring from the county to the village. Taking targeted measures in village-level poverty alleviation that focused on the overall development of the whole village has been regarded as a key measure of rural poverty alleviation work in the new stage. Therefore, further investigations of the village-level poverty characteristic are needed to respond to national targeted poverty alleviation strategy, make every effort to improve the overall life quality of the poor, and enable the sustainable development of the villages (Grays, 2005; Yang, 2012; Wang and Qian, 2017).

2 Literature review

To date, many scholars have adopted regional poverty methodologies and multidimensional poverty theories to conduct a number of academic studies on rural poverty (Alkire and Foster, 2010; Guedes *et al.*, 2012; Betti *et al.*, 2015; Wang and Wang, 2016). It was also demonstrated that GIS is a useful tool to identify environmental factors that influence poverty and spatial statistics is an effective method in revealing similarities and dissimilarities of poverty in household and regional units (Thongdara *et al.*, 2012; Wang and Chen, 2017). Moreover, in terms of detecting poverty contributing factors, there are indeed diversified poverty contributing factors, indicating that poverty is driven not only by individual's own characteristics, but also by the environment where they live, i.e., economic development, social development and ecological environment. Therefore, some poverty factors analysis methods came from statistical regression, e.g., Orthogonal Least Squares (OLS) regression analysis and multiple linear regression (Thongdara *et al.*, 2012; Behruz *et al.*, 2014; Peirovedin *et al.*, 2016).

In China, many scholars and organizations focused on exploring the spatial distribution

and contributing factors of poverty. For example, Liu and Xu (2015) studied vulnerability – sustainable livelihoods geographical framework for county-scale multidimensional poverty identification and classification in Chinese rural areas. Luo *et al.* (2016) performed a GIS analysis on the spatial distribution pattern and evolution of local poverty-stricken villages in 11 poverty-stricken counties of Qinba (Qinling-Daba) mountainous area, and quantitatively analyzed their impact factors of poverty. With the help of Chinese household survey data, Olivia *et al.* (2011) examined the relationship between poverty and environmental variables in rural areas of Shaanxi. Pei *et al.* (2015) estimated the poverty level in Liupan mountainous area by measuring the poverty tolerance index, FGT index, and poverty index. Liu and Li (2015) studied poverty causes of Hubei ethnic regions in Wuling area using a linear regression model. Chen (2013) performed an in-depth analysis of the rural poverty mechanism from the perspective of transaction cost and designed a poverty alleviation strategy for the mountainous area. Wang *et al.* (2014) calculated village-level multidimensional poverty degree in Neixiang County using the “A-F” method proposed by Alkire and Foster (2010), and analyzed the village-level poverty characteristics and their spatial distribution pattern. Zhao (2015) analyzed the spatial factors of the poverty trap in contiguous poor areas by combining the TOPSIS model and so-called obstacle degree model in terms of geographical capital theory.

Generally speaking, the present China-related study focused on county-level poverty analysis, e.g., poverty degree, spatial distribution pattern, and the factors causing poverty. However, due to the relative lack of statistical information in China’s administrative villages, China’s comprehensive ‘Entire-village Advancement’ regional poverty reduction strategy still lacks a global quantitative classification on village-level regional poverty type. As for the spatial distribution of poverty-stricken villages from the perspective of China’s national level, the measurement and analysis of village-level regional poverty has been rare.

In view of this background, this paper will try to answer the following questions: in terms of poverty-stricken villages in China, how to measure their poverty degrees? How to determine their poverty types? How to examine their spatial distribution? How to understand China’s village-level poverty characteristics? That’s to say, this paper will take the poverty-stricken village as the regional research unit, adopting “entire-village advancement” data issued by the Chinese government during the 12th Five-Year Plan period of China (2011–2015), to construct a multidimensional integrated poverty model for measuring the poverty degree and the poverty type of poverty-stricken villages, as well as their spatial distribution across the country, so as to examine the national zoning pattern of poverty-stricken villages and provide technical support for the national strategy of overall poverty alleviation in 2020.

3 Study area and materials

3.1 Study area

Totally, there are 53,758 villages involved in this study, covering 13 contiguous destitute areas, 27 provinces, 1311 counties, as shown in Figure 1. From a historical point of anti-poverty view, these 13 contiguous destitute areas mostly belong to old revolutionary areas, ethnic minority areas, frontier areas, and have been considered as the main battlefield of poverty alleviation of China due to their “centralized contiguous” and “special difficult”

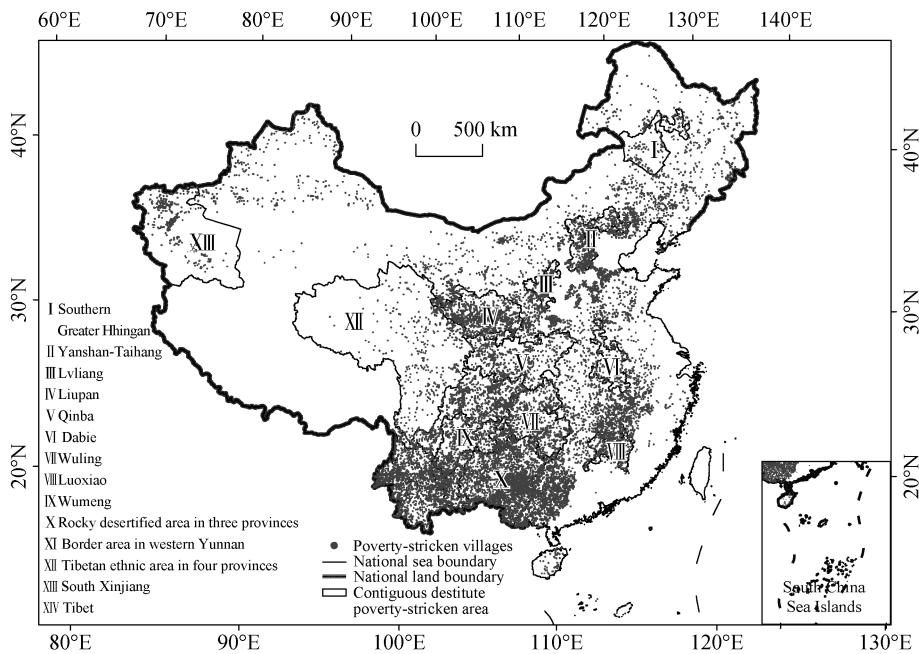


Figure 1 Distribution of the sampling sites in China

poverty characteristics (Wang and Chen, 2017). After decades of development, the problems of survival, food and clothing of rural residents in these areas have been basically solved, and the remarkable achievements have been gained in education, health care, public services, environmental protection, etc., however, there are still several critical problems that can be epitomized by weak infrastructure, social undertakings lagging behind, lack of public services and insufficiency of industrial development (Wang and Chi, 2016). In terms of physical geography, most of them are covered by the Loess Plateau, Qinghai-Tibet Plateau, southwest rocky desertified area, and other harsh natural conditions, facing the severe challenges of eventual storm fortification, financial trouble and poverty-relief as well as return to poverty. Poverty alleviation in these areas will determine the success or failure in China’s national anti-poverty strategies. Therefore, comprehensive development and evaluation means are especially needed to lift them out of poverty. In addition, what needs to be explained is that Tibet is excluded from the study due to regional data privacy.

3.2 Data description

There are two parts of data in this study, one is economic data and the other is geographical data. The economic data mainly comes from “Entire-village Advancement” archived village dataset, i.e., “village sheets”, issued by State Council Leading Group Office of Poverty Alleviation and Development of China in 2014. The “village sheets” list the basic monitoring information of each administrative village, including economic development, production and living conditions, infrastructure, education, medical facilities and social security, etc. Meanwhile, we acquired China statistics yearbook of the same period to support the further poverty analysis.

Geographical data used here is 1:250,000 national fundamental geographic dataset of

China, supporting the comprehensive evaluation and thematic poverty representation of poverty characteristics. Before being used in this study, all these data had been preprocessed in ArcGIS 10.2 by adopting geo-referencing, vectorization, removing coarse data, and so on.

4 Methods

China's current anti-poverty strategies claimed to take targeted measures in "Entire-village Advancement" poverty alleviation to promote village-level overall and comprehensive development, overcoming poverty targeting deviation and ineffective utilization of poverty alleviation resources (Wang and Chen, 2017). Meanwhile, poverty's overall situation in rural China has already changed fundamentally, lying in that poverty is no longer only caused by traditional economic lags, but mainly by spatial poverty contributing factors that comprehensively reflect economic disadvantage, social and political disadvantage, ecological disadvantage from three perspectives of economy, society and environment (Hentschel *et al.*, 2000; Higgins *et al.*, 2010; Liu *et al.*, 2016; Wang *et al.*, 2017). Therefore, as far as poverty-stricken villages are concerned, the examination on their poverty characteristics also shows a specialized demand on the spatial distribution of poverty and the relationship between poverty and surrounding environment (Hentschel *et al.*, 2000; Bird *et al.*, 2007; Wang and Chen, 2017). In this context, we conduct a multidimensional poverty detection from the combined views of spatial economics and new economic geography, and integrate a series of indicators to synthesize special development capital and then to determine whether there exist certain poverty types by measuring village-level multidimensional poverty degree and analyzing their poverty factors.

4.1 Village-level multidimensional poverty degree measurement

From the perspective of the harmonious and sustainable development of humans and land resource, both the geographical and socioeconomic factors affecting the development of poor villages were comprehensively screened to design a multidimensional village-level poverty index system, aiming at measuring comprehensive poverty level of each village, as well as providing data basis for poverty contributing factor analysis.

Therefore, for the comprehensive evaluation of relative poverty levels from the natural and socioeconomic aspects of each administrative village, we considered the basic requirements of comprehensive, objective, scientific nature and operability of index selection, and the fairness, multidimensional integration, policy relevance, data availability and other comprehensive needs, (Harun, 2011; Ravallion, 2011; Alkire and Santos, 2013; Liu *et al.*, 2016; Wang and Chen, 2017), a candidate set of multidimensional poverty assessment index systems for administrative villages – including factors such as nature, ecological environment, economics, and social security – was constructed. The candidate indices were selected according to the correlation of the indices and the requirements of the division index. Finally, a measurement index system of village-level multidimensional poverty was determined (Wang and Chen, 2017). As shown in Table 1, it consisted of 6 dimensions and 20 indices, i.e., X_1 – X_6 and X_{11} – X_{61} , respectively.

Then, we use the index grade classification method to normalize the different dimensional indices, and the index value is divided into grades 1–5 in the index system. A higher grade

Table 1 Village-level multidimensional poverty measurement indicators

Dimension	No.	Indicator	Indicator implication
Geographical environment (X_1)	X_{11}	<i>Distance from the nearest town's bazaar</i>	The distance from the village to the nearest town's bazaar (km)
	X_{12}	<i>Terrain type</i>	Terrain type of the village (namely, plain, hilly, plateau, basin)
	X_{13}	<i>Frequency of exposure to natural disasters</i>	The frequency of natural disasters in the village
Administrative village's feature (X_2)	X_{21}	<i>Village historical features</i>	Whether the village is an old revolutionary base spot, or ethnic minorities gathering one, or border one, or not
	X_{22}	<i>Population density</i>	Population density of the village (headcount/km ²)
Production and living condition (X_3)	X_{31}	<i>Per cultivated area</i>	Per cultivated area in the village (<i>mu</i>)
	X_{32}	<i>Road access ratio</i>	The ratio of natural villages traveling by motor vehicle roads to all natural villages in an administrative village (%)
	X_{33}	<i>Electricity access ratio</i>	The ratio of the households accessing to electricity to all the households in an administrative village (%)
	X_{34}	<i>Phone access ratio</i>	The ratio of households accessing to electricity to all the households in an administrative village (%)
		<i>Radio and television access ratio</i>	The ratio of households accessing to radio and television to all the households in an administrative village (%)
	X_{35}	<i>Safe drinking water access ratio</i>	The ratio of the households access to safe drinking water to all the households in an administrative village (%)
	X_{36}	<i>Sanitary toilet facilities access ratio</i>	The ratio of the households access to sanitary toilet facilities to all the households in an administrative village (%)
	X_{37}	<i>Dangerous building ratio</i>	The ratio of the households with dangerous buildings to all the households in an administrative village (%)
Labor force (X_4)	X_{41}	<i>Ratio of labor force</i>	The ratio of labor forces to all population in an administrative village
	X_{42}	<i>Ratio of labor-out</i>	The ratio of migrant labors to all labor forces in an administrative village
	X_{43}	<i>Ratio of illiterate labor forces</i>	The ratio of illiterate labors to all labor forces in an administrative village
		<i>"Yulu Plan" participation ratio</i>	The ratio of those labor forces participating in "Yulu Plan" to all the labor forces (%)
Medical facilities and social security (X_5)	X_{51}	<i>Clinics per one thousand people</i>	The clinic number that per one thousand people have in an administrative village
	X_{52}	<i>Doctors per one thousand people</i>	The number of doctors that per one thousand people have in an administrative village
	X_{53}	<i>Population ratio in the New Rural Co-operative Medical Insurance of China</i>	The ratio of population taking part in the new rural co-operative medical insurance of China to all population in an administrative village (%)
	X_{54}	<i>Population ratio in rural social endowment insurance</i>	The ratio of population taking part in rural social endowment insurance to all population in an administrative village (%)
Economic development (X_6)	X_{61}	<i>Per capita net income</i>	Per capita net income in an administrative village

indicates more severe poverty (Chen *et al.*, 2016). Further, a subjective and objective weighting method combining analytic hierarchy process (AHP) and entropy weight method (Wang and Chen, 2017), which takes into account the preferences of the decision maker, but also reduces the weight of the subjective randomness, was used to measure the importance of each dimension and index.

The last step is to use the integrated sum method to calculate the village-level multidimensional integrated poverty index (VPI) by the formula:

$$VPI = 20 \sum_{i=1}^n \left(\sum_{j=1}^m I_{ij} \omega_{ij} \right) \omega_i \quad (1)$$

where n indicates the number of dimensions, I_{ij} indicates the normalized index value of the i th dimension, m represents the value of the index corresponding to i dimensions, ω_{ij} represents the weighting of the index, ω_i represents the dimension weights, and 20 is the constant used to eliminate small digital effects and increase the difference between the data.

4.2 Poverty factors analysis

A poverty index contribution analysis and linear regression analysis of the index and the incidence of poverty were combined to explore the contributing factors to poverty in China's poverty-stricken villages. Different poverty index factors can effectively reflect the contribution of every poverty-stricken village; however, they can easily be affected by a subjective model design. Meanwhile, a linear regression analysis of the index and the incidence of poverty can statistically describe the differences in poverty factors more objectively, but cannot provide the specific causes of poverty in every poverty-stricken village and is more susceptible to the data dispersion limit. Therefore, this study combined the two methods to analyze the causal factors of poverty in Chinese poverty-stricken villages and perform cross-validation.

(1) Index contribution degree

Contribution degree C_{xij} (the contribution of index j to VPI) and contribution comprehensive ranking \overline{R}_{ij} were used to express the degree of influence of the expression index on the poverty of the poverty-stricken village, so as to analyze significant factors of poverty-stricken villages and their regional differences. The formula is described as follows:

$$C_{xij} = \frac{20\omega_{ij}I_{xij}}{VPI_x} \times 100\% \quad (2)$$

where C_{xij} represents the contribution degree index j for the i th dimension to poverty degree of the x th village of index I , ω_{ij} represents the weighting of index j for the i th dimension, I_{xij} represents the standardized score of index j for the i th dimension and the x th village, and VPI_x represents the village-level poverty index of the x th village.

To analyze the differences in poverty-contributing effects of the studied indicators in a given area, we used the formula

$$\overline{R}_{ij} = \sum_{x=1}^n R_{xij} / n \quad (3)$$

where R_{xij} represents the ranking of contribution degree the j th index among the contributing degrees of the 20 indices for the i th dimension and the x th village, n represents the number of studied sample villages, and \overline{R}_{ij} represents the average ranking of contributing degree of the j th index for the i th dimension among all indices.

(2) Linear regression analysis

We used linear regression analysis to study the interdependence of multiple variables,

which not only establishes a rigorous mathematical model for prediction, but also expresses the relationship between variables. With the incidence of poverty in poverty-stricken villages as the dependent variable and indicators in Table 1 as independent variables, the linear regression method was used to test the relationship between the incidence of poverty and the indices, which analyzed the major poverty-contributing factors complementarily to index contribution degree method.

4.3 Poverty type analysis

Based on significant factors for poverty from the index level for impoverished villages as described in the above sections, the Least Square Error (LSE) model was implemented to analyze the types of poverty in the poverty-stricken villages from the dimension level. The principle of the LSE model is to find the minimum variance between the sample and the actual distribution of the sample (Wang and Chen, 2017). The formula is described as follows:

$$S^2 = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 \quad (4)$$

where S^2 represents the variance, x_i represents the poverty contribution of a dimension of the poverty-stricken village, and y_i represents the poverty contribution of the poverty-stricken village in a given dimension.

By referring to Formula 2, the dimensions of the impoverished village were ranked in descending order of contribution to VPI. Then, the variance of each ranked contribution degree and contribution of each theoretical model was calculated and arranged in descending order (for the single-factor dominant type, only 1 dimension exists, and the contribution degrees of all other dimensions are 0). Finally, the theoretical model with the least variance was determined to be the type of poverty of the poverty-stricken villages. The dimensions with non-zero theoretical contributions were the poverty-contributing dimensions, demonstrating the poverty type (e.g., single-factor dominant type, dual-factor driving type, three-factor dominant type, four-factor coordinative type, five-factor combinative type, six-factor comprehensive type) and specific dimensions of poverty in poverty-stricken villages (e.g., geographical environment, administrative village characteristics, production and living conditions, labor conditions, medical and health social security, economic development).

4.4 Spatial econometric analysis

(1) Spatial kernel density estimation

As a non-parametric way to estimate the probability density function of a random variable from fundamental data smoothing problems, the objective of kernel density estimation (KDE) is to produce a smooth density surface of point events over space by computing event intensity as density estimation (Schnabel and Tietje, 2003; Serra-Sogas, 2003; Xie and Yan, 2008). Compared to spatial separation view, KDE is a more reliable and desirable hotspot analysis technique used for analyzing the first order properties of a point event distribution, and can aid in the determination of the number of clusters through the examination of contours at different levels of inclusion as means of looking for structure at different scales of spatial resolution (Lu, 1998; Xie and Yan, 2008). KDE can be calculated in a 2-D space as follows (Xie and Yan, 2008):

$$\lambda(s) = \sum_{i=1}^n \frac{1}{\pi r^2} k\left(\frac{d_{is}}{r}\right) \quad (5)$$

where $\lambda(s)$ is the density at location s , r is the search radius (bandwidth) of the KDE, n is the number of sampling points, and k is the weight of a point i at distance d_{is} to location s . k is usually modeled as a kernel function of the ratio between d_{is} and r . In this study, we used a kernel with a Gaussian function to explore the aggregation distribution of different poverty type.

(2) Theil-T difference analysis

To measure the effectiveness and efficacy of third-party departments on the anti-poverty development, *Theil-T* coefficient was introduced here to conduct inter-class and intra-class difference analysis. Compared with other diversity analysis (e.g., Gini coefficient and variable coefficient), *Theil-T* coefficient model could break down the overall differences (T_t) of the research area into inter-regional differences (T_r) and intra-regional differences (T_a), so that the gap or inequality between different types of counties can be better revealed (Theil and Sorooshian, 1979; Wang and Wang, 2016). The formulas are described as follows:

$$\text{Overall difference: } T_t = T_r + T_a \quad (6)$$

$$\text{Inter-regional difference: } T_r = \sum_{i=1}^n Y_i \log \frac{Y_i}{P_i} \quad (7)$$

$$\text{Intra-regional difference: } T_a = \sum_{i=1}^n Y_i \sum_{j=1}^n Y_{ij} \log \frac{Y_{ij}}{P_{ij}} \quad (8)$$

where n refers to the number of the classes after each village has been classified; Y_i represents the portion of the villages in Class i in the given indicator; P_i represents the ratio of the given villages in class i to the whole villages in the study area. Y_{ij} and P_{ij} represent the given indicator's poverty contribution portion of village j in the class i , and ratio of the village j to all villages in class i , respectively. The larger the *Theil-T Index*, the bigger the differences of poverty level, and vice versa.

5 Results

5.1 Comprehensive poverty distribution of impoverished villages

In terms of equal-interval classification, the village-level multidimensional poverty index (VPI) was classified into 5 poverty levels, i.e., mild, relative, medium, high, extreme poverty. As shown in Figure 2, poverty level of poverty-stricken villages follows a normal-right distribution, presenting an “olive-shaped” structure with a shape of “large middle, and small at two ends”. The peak point of VPIs is slightly higher than that of the standard normal distribution curve, indicating that there exist more villages with medium poverty than those with mild or extreme poverty. On the other hand, the VPI peak deviates from the standard normal distribution curve to the right, overall indicating that the poverty depth of the villages is relatively high.

Meanwhile, from Figure 3, it can be seen that China's poorest villages are mostly located in the western region, including Gansu, Yunnan, Guizhou, Guangxi, Hunan, Qinghai, Sichuan, and Xinjiang, listed by VPI in descending order. Poverty levels and poverty sizes of different counties are obviously increasing from east to west, and are closely related to the development level of the regional economy. We also find that poverty-stricken villages tend

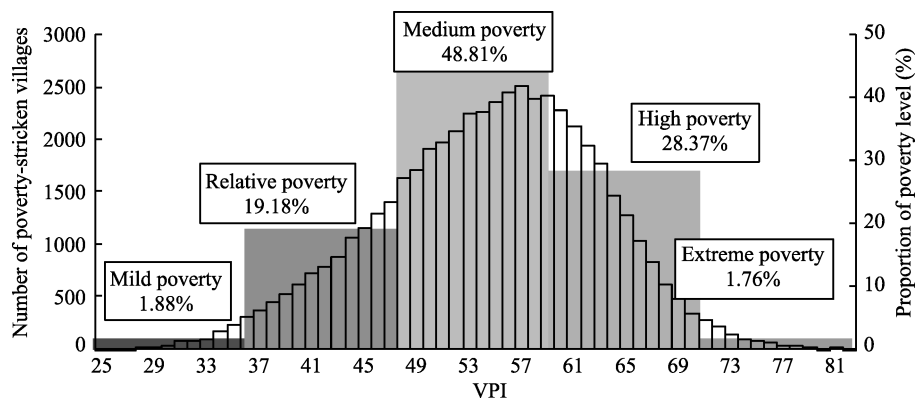


Figure 2 VPI frequency statistics of poverty-stricken villages in China

to be concentrated in areas with high VPI scores and are mostly located in contiguous poor areas. These areas featured the densest distribution of poverty-stricken villages, the most concentrated poor population, and the most severe poverty conditions. Dense aggregation of poverty-stricken villages was also found in the following contiguous destitute areas: Lvliang, Liupan and Tibetan areas in four provinces (Sichuan, Yunnan, Gansu and Qinghai), Wumeng, and Wuyi. In provinces such as Chongqing, Shaanxi, Henan, Hubei, Anhui, Hebei, Shandong, and Liaoning, noncontiguous distribution of poor areas are also observed. These results indicate the differences in both the scale of China's poverty-stricken villages and the distribution of poverty levels. With worsening poverty, the poverty-stricken villages tend to concentrate in remote locations with steep terrain and contiguous fragile ecology.

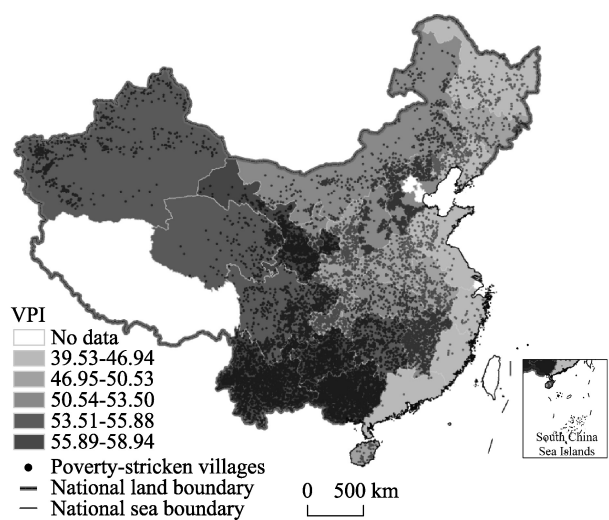


Figure 3 The spatial distribution of poverty-stricken villages in China

5.2 Causal factors of poverty in impoverished villages

5.2.1 General analysis of causal factors of poverty

Among all measured indicators for poverty-stricken villages in China, indices (ranked in descending order of contribution degree) include *road access ratio* (X_{32}), *terrain type* (X_{12}), *frequency of exposure to natural disasters* (X_{13}), *per capita net income* (X_{61}), *ratio of labor force* (X_{41}), *labor illiterate labor forces* (X_{43}), and *proportion of labor-out* (X_{42}). In order to comprehensively consider the individual differences among poverty-stricken villages, indices ranking 1–20 according to contribution degree to poverty were determined and listed in Table 2. It can be seen that: 1) From the analysis of poverty index contribution and average ranking trends, the primary reasons for the poverty of the poverty-stricken villages included

natural environment disadvantages, abominable terrain conditions, inconvenient traffic environment, and frequent natural disasters, all of which limit the development potential of the poverty-stricken villages. The second reason was related to disadvantages in human labor, including unbalanced personnel structure, relatively poor labor quality, and limited employment environment, all impeding the poverty alleviation of poverty-stricken villages.

Table 2 The statistics of rural poverty contributing factors

Indicator	X_{32}	X_{12}	X_{13}	X_{61}	X_{41}	X_{43}	X_{42}	X_{37}	X_{11}	X_{54}
Contribution degree (%)	14.82	12.80	9.50	8.25	7.95	6.97	6.22	5.73	5.31	4.26
Average ranking	2.61	2.59	4.89	5.82	5.35	6.88	7.61	7.72	8.14	9.94
<i>Beta</i>	-0.220	0.164	0.168	-0.363	-0.157	-0.191	-0.158	0.116	0.038	-0.093
Indicator	X_{36}	X_{21}	X_{31}	X_{35}	X_{34}	X_{22}	X_{53}	X_{33}	X_{52}	X_{51}
Contribution degree (%)	3.41	3.35	2.51	2.35	1.83	1.53	0.89	0.87	0.84	0.60
Average ranking	10.72	11.17	12.07	13.45	13.98	15.18	17.68	17.71	17.13	19.37
<i>Beta</i>	-0.081	/	-0.009	-0.060	-0.086	/	-0.035	-0.041	-0.035	-0.074

Limited market connectivity and inadequate infrastructure also affected the development of poverty-stricken villages. 2) By comparing the contribution and average ranking of the analyzed indicators, it can be seen that both showed generally similar trends, but with some differences in individual indicators. For example, the contribution of road access ratio (proportion of road construction) was higher than that of terrain type, while terrain type had a higher ranking, indicating that traffic problems more profoundly affect China's overall poverty, but terrain conditions are the primary cause for the development of the poverty-stricken villages. There is a similar relationship between the per capita net income and the proportion of the labor force, indicating that the difference in poverty was more reflected in income, while the internal influence was mainly contributed by labor force status.

In addition, linear regression analysis was used to analyze the influencing factors of poverty incidence, with *goodness-of-fit* of linear regression equation of $R^2 = 0.622$, $F = 6841.308$, $sig = 0.000$. Thus, the regression results were significant; the *t*-test suggested that indicators were significant at the 0.01 level. Type of poverty-stricken village and population density were excluded from the model due to lack of significance. As indicated in Table 2, the results of the *Beta* analysis of the linear regression standardized coefficient featuring the importance of indicators showed significantly positive and negative effects of the indicators on the incidence of poverty, which met our assumptions and was in line with the actual situation. The statistical results showed that the factors affecting the incidence of poverty were, in descending order, per capita net income (X_{61}), road access ratio (X_{32}), labor illiterate labor force (X_{43}), frequency of natural disasters (X_{13}), terrain type (X_{12}), ratio of migrant labor force (X_{42}), and ratio of labor force (X_{41}). The most significant poverty indicators impacting poverty-stricken villages were similar to the results of the index contribution and average ranking method, which shows that the modeling-based cause analysis results had good reliability and objectivity.

5.2.2 Main causes of poverty

From Table 2, the poverty contributing factors that most influenced the poverty conditions in poverty-stricken villages were selected for analysis. We found that the main factors leading to the poverty of poverty-stricken villages were road construction, natural disasters, income

level, and labor force (ranked in descending order of contribution degree).

(1) Road access status

From Figure 4a, it is evident that road construction was generally underdeveloped in poverty-stricken villages in China, especially in the southwest regions (Yunnan, Guizhou, Sichuan, and Chongqing), the central regions south of Hunan and Hubei, the western part of Xinjiang, and the northern part of Inner Mongolia. Road construction significantly impacted poverty. These areas are mostly plateau and mountainous areas, such as Hengduan Mountains in Sichuan and Yunnan, Yunnan-Guizhou Plateau in Yunnan, Guizhou and Guangxi, Qinling Mountains, Wuling Mountains, and Dabie Mountains; Greater Khingan Range in northern Inner Mongolia; and Tianshan Mountains in Xinjiang. Figure 4b shows that poverty caused by poor road construction (difficulty of access) was closely related to terrain-related poverty. Harsh terrain environment increased the cost of road construction accessing to the poverty-stricken villages, hindering poverty alleviation in local areas. These findings suggest that integrating various types of agricultural funds to improve the administrative road infrastructure is particularly important for speeding up the implementation of the whole village project.

(2) Natural disaster

Figure 4c shows that the poverty-stricken villages affected by serious natural disasters were mainly concentrated in Xinjiang, Inner Mongolia, Qinghai, Sichuan, Yunnan, and Jiangxi. Various types of natural disasters occur frequently in these areas, mainly including meteorological disasters such as drought, flood, cold wave, and dry-hot wind, and biological disasters such as animal epidemic situations and wheat disease. Comparing the distribution pattern of other influencing factors in Figure 4, we found that the impact of income and labor force on poverty was relatively small; the main cause of poverty in these areas was the limitation of the natural environment. It is the high degree of overlap between the rural poor areas and ecologically fragile areas prone to natural disasters that results in the high population vulnerability of these areas.

(3) Income level

From the spatial distribution of the contribution of income indicators shown in Figure 4d, it can be seen that the areas seriously affected by income level were concentrated in southern Xinjiang and the border area between Qinghai and Sichuan. A comprehensive comparative analysis of other poverty factors showed that the contribution degree distributions of labor quality index and income were most similar. The significant influence of income on the southern part of the Qinghai–Sichuan border area was related to the remote location and geographical isolation, as well as relatively conservative culture; all of these factors caused relatively low cultural quality for the local people and the resulting lower income levels. Overall, the cause of long-term poverty in poor areas of China is not limited to a relatively low level of income, but is influenced by multiple factors, including natural environment, social environment, and labor conditions, which have limited the development potential of poor rural areas and trapped them in long-term poverty.

(4) Labor force status

It can be seen from Figures 4e and 4f that the areas with poor labor conditions were mainly distributed in the western region – especially in both southern Xinjiang and Tibetan ethnic area in four provinces (Sichuan, Yunnan, Gansu and Qinghai). The two contiguous

destitute areas were located in deep inland areas, and the remote location restricted the development of infrastructure and basic education. The per capita education period in these areas was only around seven years. Meanwhile, the relatively closed geographical environment prevented communication with the outside world, and conservative and backward ideas remained. These factors led to the unbalanced local structure of the poor population and the low cultural quality of the labor force. A similar situation was also found in other areas of the poverty-stricken villages, mostly located in 14 contiguous poverty-stricken areas and surrounded by mountainous areas with a closed geographical environment.

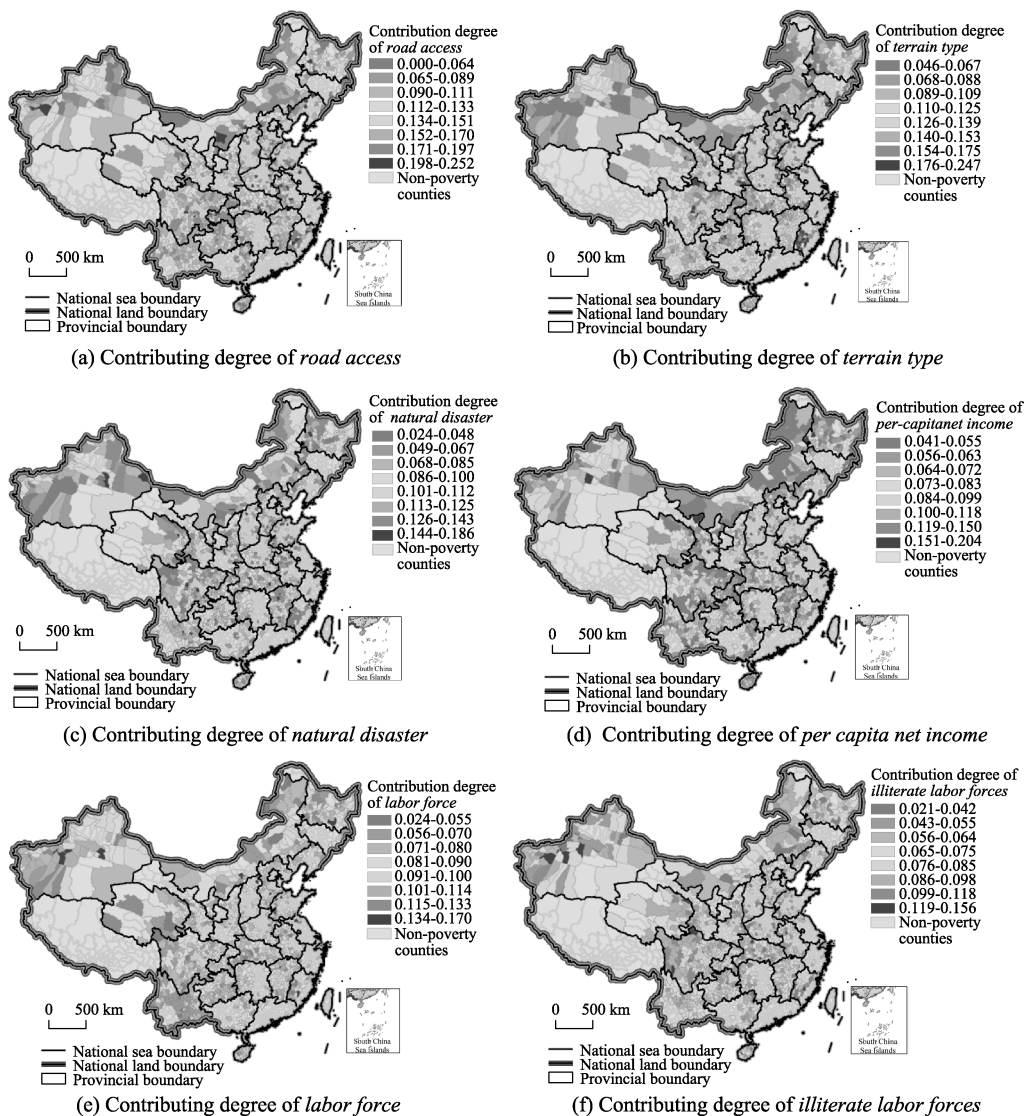


Figure 4 Spatial distribution of the main factors leading to rural poverty in China

5.3 Poverty type of impoverished villages

5.3.1 Overall analysis

In the present study, the LSE model was used to determine the types of poverty in the poverty-stricken villages of China, and the impacting degree on each dimension of poverty type

was analyzed. The results are presented in Table 3. It can be seen that the poverty type of underdeveloped villages in China can be divided into 6 categories: single-factor dominant type, dual-factor driving type, three-factor dominant type, four-factor coordinative type, five-factor combinative type, and six-factor comprehensive type. The three-factor dominant type is most widely distributed, covering over half of all studied poverty-stricken villages. Moreover, villages were usually affected by multiple poverty-causing factors, while the single-factor dominant type was only attributed to 0.14% of villages, indicating a complex poverty-contributing situation in China and suggesting that poverty alleviation should be realized by local-specific measures targeting the major problems of local areas. Targeted support should be provided by implementing the innovative methods of poverty alleviation and development proposed by the 13th Five-Year Plan released by the Chinese government in 2016.

Table 3 Distribution of poverty types and poverty contributing factors

Poverty type	Average VPI	Poor village ratio (%)	G-probability (%)	V-probability (%)	P-probability (%)	L-probability (%)	M-probability (%)	E-probability (%)
Single-factor dominant type	36.99	0.14	50.00	0.00	29.17	20.83	0.00	0.00
Dual-factor driving type	48.46	8.24	81.67	1.98	69.15	46.37	0.33	0.50
Three-factor dominant type	55.67	53.33	97.64	5.69	95.41	94.80	3.28	3.18
Four-factor coordinative type	56.28	28.99	98.34	33.92	96.45	98.12	32.59	40.58
Five-factor combinative type	54.34	8.36	99.40	79.17	98.00	99.23	65.43	58.78
Six-factor comprehensive type	51.58	0.94	100.00	100.00	100.00	100.00	100.00	100.00
Sum	55.08	100.00	96.63	20.59	93.71	92.09	17.64	19.36

Note: G-, V-, P-, L-, M- and E- respectively represent in turn geographical environment, village characteristic, production and living condition, labor force, medical facilities and social security, economic development. G-, V-, P-, L-, M- and E- probability denote the contributing degree of each dimension causing poverty in their corresponding poverty types, respectively.

5.3.2 Classification analysis

Poor villages with the same poverty type may have different subtypes due to internal differences in poverty-contributing dimensions, therefore, analysis of the inherent characteristics of each type of poverty and its subcategories can reveal the specific distribution of the poverty-stricken villages in China.

(1) Single-factor dominant type has only 0.14% of studied poverty-stricken villages. According to the different causes of poverty, this type can be further divided into geographical environment factor dominant, production and living condition dominant, and labor force dominant. No poverty-stricken village had administrative characteristics, medical and health insurance, or economic development as a dominant factor. Based on the probabilities of these factors, the ranking can be described as geographical environment > production and

living conditions > labor force. From Figure 5a, we can see that such poverty-stricken villages were mostly located outside of the contiguous poverty-stricken areas but near poor mountainous areas. Compared with the average VPI scores of different types of

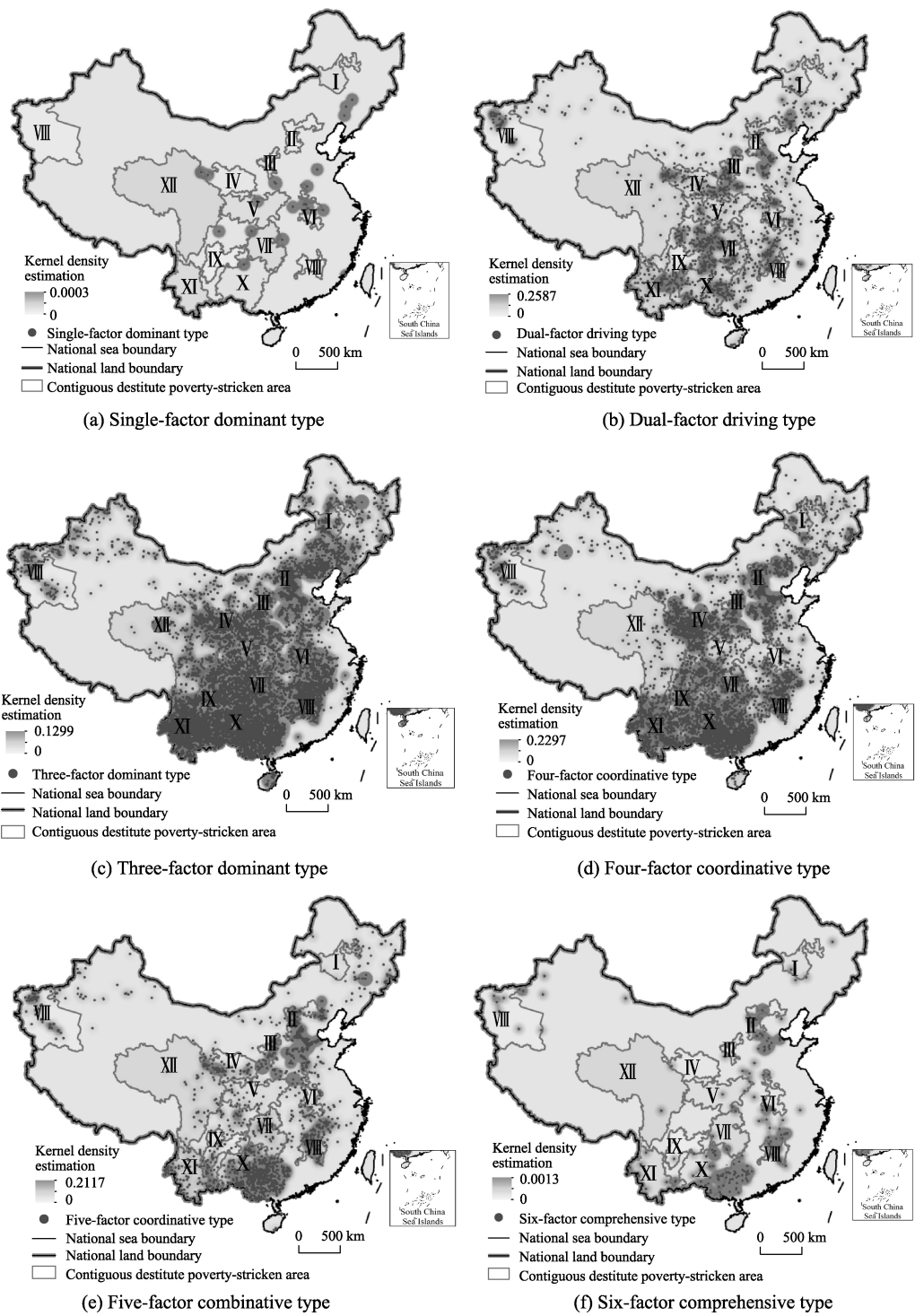


Figure 5 The spatial layout of different types of stricken-poverty villages in China

poverty-stricken villages in Table 5, the poverty degree of the single-factor dominant type was relatively low, indicating that very few “extreme” examples of poverty-stricken villages were formed due to a lack of resources; these suffered from a lack of adequately maintained geographical environment, production and living conditions, and labor resources. However, such impoverished villages were generally located outside of contiguous poverty-stricken areas, indicating relatively high potential poverty alleviation, which could be implemented by improving the shortage of certain resources.

(2) Dual-factor driving type, accounting for 8.24% of poverty-stricken villages, with a total of 12 dual-factor driving types, is summarized as follows: G-V, G-P, G-L, G-M, G-E, V-P, V-L, P-L, P-M, P-E, L-M, and L-E, among which G-P, G-L, and P-L subtypes were most widely distributed (probability ranking: G-P subtype > G-L subtype > P-L subtype), with combined coverage of 97.17% of Type 2. As shown in Figure 5b, poverty-stricken villages of this type were mainly located in Yanshan Mountain–Taihang Mountain, Lvliang Mountain, Dabie Mountain, Wuling Mountain, Luoxiao Mountain, rocky desertified areas in Yunnan–Guizhou–Guangxi, border area in western Yunnan and southern Xinjiang.

(3) Three-factor dominant type, accounting for over half (53.33%) of the overall poverty-stricken villages; the main type of poverty-stricken villages in China. A total of 19 subtypes can be divided due to combinations of poverty-forming factors, among which the G-P-L subtype accounted for the highest proportion (88.19%), followed by the G-V-L subtype (2.40%), G-V-P (1.77%), and G-P-M (1.72%); coverage of all remaining subtypes accounted for 5.92%. As shown in Figure 5c, this type of poverty-stricken village was widely distributed throughout China, with contiguous poverty-stricken areas as a center. The poverty level of this type of village was generally high, indicating that such areas are under the combined pressure of different disadvantages, including geographical location, ecology, and socioeconomic disadvantages, which together form a long-lasting poverty trap. The features of high degree of poverty and multiple disadvantages were also observed in the four-factor coordinative type and five-factor combinative type.

(4) Four-factor coordinative type, accounting for 28.99% of the studied villages, with 16 subtypes. The three main subtypes were G-V-P-L, G-P-L-M, and G-P-L-E, accounting for 92.94% of the four-factor coordinative type. This type presented the most severe degree of poverty among the six types of poverty-stricken villages and a highly concentrated distribution in China compared with the three-factor dominant type, occurring mainly in contiguous poverty-stricken areas.

(5) Five-factor combinative type, accounting for 8.36% of the studied villages, with 6 subtypes. The main subtypes, in descending order, can be described as follows: G-V-P-M-L > G-V-P-L-E > G-P-L-M-E > G-V-L-M-E > G-V-P-M-E > V-P-L-M-E, among which the first three accounted for 96.63% of this type. As indicated in Figure 5e, this type was mainly distributed in Guangxi, Jiangxi, Hebei, Henan, Shanxi, and Shaanxi. Cause analysis showed that these areas were located more deeply inland, with relatively good geographical location and natural environment conditions. However, compared with eastern coastal areas, these areas were disadvantaged in terms of transportation cost, infrastructure, public services, population structure, and social concept. The coexistence of advantages and disadvantages made the poverty-forming causes of these villages more complex.

(6) Six-factor comprehensive type, accounting for only 0.94% of the poverty-stricken vil-

lages, featuring multiple causes with equal contributing degrees. The average VPI of such poverty-stricken villages was 51.58, lower than the average level of Chinese poverty-stricken villages and representing a moderate to mild level of poverty. These villages were mostly located outside of contiguous poverty-stricken areas. The comprehensive condition indicates that although the development of this type of poverty-stricken village has been lacking, it is relatively easy to improve.

5.4 Poverty difference in poverty-stricken villages

5.4.1 Poverty difference in geographical location

In this paper, the Hu Huanyong Line (hereafter Hu Line) was introduced as a dividing line of geographical location for analysis of the comprehensive characteristic differences between impoverished villages in northwestern and southeastern China. The Hu Line was proposed by a famous Chinese geographer Hu Huanyong in 1935 and recognized as an important dividing line of China's population, geography, economy, climate, and terrain. It has been widely recognized and cited at home and abroad (Chen *et al.*, 2016).

(1) Difference in poverty status. As indicated in Figure 6a, poverty-stricken villages were mostly located southeast of the Hu Line. The distribution of poverty degree VPI in Figure 6b shows that the poverty degree was more severe in southeastern China. In addition, it can be seen from Figure 6 that only 13.49% of the poverty-stricken villages were located northwest of the Hu Line, with an average VPI score of 58.87, significantly higher than the average score (52.49) in the southeast. Cause analysis showed that due to differences in the process of "Whole-village Advancement," information missing has been found with northwest regions where poverty alleviation was more difficult to perform, resulting in the low poverty proportion in the southwest. On the other hand, since regions southeast of the Hu Line contributed 94% of the population and GDP value, and covered 43% of the national land (not including Hong Kong, Macao and Taiwan for now), the extreme unbalanced distribution of population and economics also led to China's poverty-stricken village on the northwestern side of the Hu Line with sparse distribution, high degree of poverty in its intensive distribution; and southeast with concentrated distribution and low poverty degree.

(2) Difference in poverty-forming causes. The six main poverty-forming causes

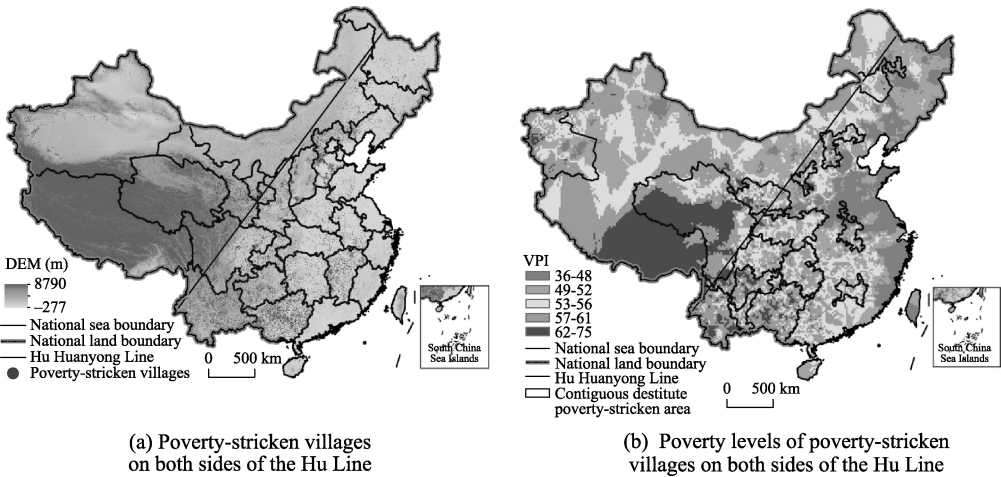


Figure 6 Poverty difference in geographical locations of China

mentioned above were analyzed, and the results are presented in Table 4. It can be seen that: 1) The contributing degree of road construction, terrain type, and frequency of natural disasters was higher southeast of the Hu Line than the northwest. 2) The per capita net income and the contribution of labor quality index were higher northwest of the Hu Line than southeast, indicating that the influence of income and labor force was more significant to the northwest. 3) The contribution rate of labor force was similar on both sides of the Hu Line. 4) The contribution ratio of the six main poverty-forming factors was generally higher southeast of the Hu Line than northwest, indicating that the poor areas were relatively concentrated in the southeast, making the formulation of poverty alleviation strategies easier. 5) *Theil* index comparison among the poverty-forming factors showed that the relative influence of the factors was: *income* > *labor quality* > *labor ratio* > *disaster* > *road construction* > *terrain*.

(3) Difference in poverty type. Comparison of poverty types of the poverty-stricken villages on the two sides of the Hu Line (Table 4) showed that: 1) The proportion of poverty-stricken villages of the single-factor driving type was only 0.05% in the northwest, compared with 0.43% in the southeast, suggesting that the poverty-forming causes in the northwest are more complex. 2) The skewed normal distribution for both sides of the Hu Line is shown in Figure 6, with the peak value of the southeastern part being more “concentrated” indicating that the poverty type of the southeastern was more “homogenized” than the northeastern counterpart. 3) T_a index comparison among the poverty-forming factors showed that the difference in poverty types for the both sides of the Hu Line was: *single-factor dominant type* > *five-factor combinative type* > *four-factor coordinative type* > *three-factor dominant type* > *dual-factor driving type* > *six-factor comprehensive type*.

Table 4 The statistics of poverty difference in geographical locations of China

Poverty characteristics		Geographical location differences				
		Northwest of the Hu Line	Southeast of the Hu Line	T_i	T_a	T_r
Poverty status	Number of villages	6942	44519	/	/	/
	Average VPI	57.87	52.49	0.331	0.046	0.285
Contribution degree of poverty-forming causes	Road access ratio (%)	12.78%	13.69%	0.320	0.013	0.307
	Terrain type (%)	11.39%	12.41%	0.320	0.012	0.308
	Frequency of exposure to natural disasters (%)	9.27%	9.79%	0.346	0.014	0.331
	Per capita net income (%)	8.49%	7.49%	0.317	0.031	0.287
	Labor force ratio (%)	8.48%	8.50%	0.344	0.010	0.334
	Illiterate labor forces (%)	7.59%	6.86%	0.349	0.028	0.321
Poverty type	Single-factor dominant type (%)	0.05%	0.43%	2.687	0.064	2.623
	Dual-factor driving type (%)	9.48%	10.63%	0.753	0.011	0.742
	Three-factor dominant type (%)	49.64%	54.38%	0.382	0.012	0.370
	Four-factor coordinative type (%)	30.33%	25.54%	0.506	0.036	0.470
	Five-factor combinative type (%)	9.83%	8.03%	0.814	0.040	0.774
	Six-factor comprehensive type (%)	0.67%	0.99%	1.274	0.001	1.273

Comprehensive analysis showed that regions northwest of the Hu Line were more landlocked and remotely located, with geographical location limitations such as higher transpor-

tation cost, more severe biological environment, and more dangerous terrain conditions, contributing to the higher degree of poverty and more complex poverty-causing factors, and the resulting higher pressure of poverty alleviation.

5.4.2 Poverty differences in policy support

“Whole-village Advancement” is an important innovation pattern in the development of the poverty alleviation work in China. It provides an important means for the promotion of new rural construction and development of poverty alleviation by fully integrating all kinds of development resources, improving the production and living conditions of farmers, and enhancing the rural ecological development (Wang and Chen, 2017). In this study, the poverty differences in policy support were examined in terms of the “Whole-village Advancement” implementation status of the villages.

(1) Difference in poverty conditions. Table 5 shows that the average VPI scores of poverty-stricken villages where “Whole-village Advancement” has been implemented were lower than the national average, indicating that the development of these poverty-stricken villages was above average national development. The average VPI of poverty-stricken villages where “Whole-village Advancement” is currently implemented was higher than the national average, but is expected to decrease over time due to the currently applied poverty alleviation policy. The VPI scores of villages where the policy has not yet been implemented were between the above two, which may be attributed to the fact that “Whole-village Advancement” is more likely to be implemented in places with deeper poverty and higher priority. The lower degree of poverty in villages where “Whole-village Advancement” was implemented compared with villages where the policy was not yet implemented also suggested the significance of the policy. A comparison of VPI scores among different groups in Tables 4 and 5 showed that the differences in political support were lower than geographical

Table 5 The statistics comparison in policy support in terms of “Whole-village Advancement”

Poverty characteristics		Policy support differences (“Whole-village Advancement”)					
		Already implemented	Being implemented	Not yet implemented	T_a	T_r	T_c
Poverty status	Number of villages	8264	19967	23230	/	/	/
	Average VPI value	54.16	55.63	54.92	0.619	0.018	0.601
Contribution degree of poverty-forming causes	Road access ratio (%)	13.64%	14.65%	14.80%	0.651	0.014	0.636
	Terrain type (%)	13.92%	12.57%	13.07%	0.638	0.020	0.618
	Frequency of exposure to natural disasters (%)	9.84%	9.66%	9.31%	0.661	0.018	0.643
	Per capita net income (%)	7.77%	8.34%	7.84%	0.626	0.023	0.603
	Labor force ratio (%)	8.30%	7.95%	8.08%	0.663	0.019	0.644
	Ratio of illiterate labor forces (%)	6.86%	6.98%	6.85%	0.655	0.021	0.633
Poverty type	Single (%)	0.22%	0.06%	0.18%	2.728	0.021	2.706
	Two-factor driving (%)	9.97%	7.22%	8.50%	1.208	0.028	1.181
	Three-factor dominant (%)	48.71%	55.49%	53.11%	0.745	0.016	0.729
	Four-factor coordinative (%)	32.15%	27.82%	28.88%	0.852	0.022	0.830
	Five-factor combinative (%)	8.19%	8.44%	8.35%	1.304	0.022	1.282
	Six-factor comprehensive (%)	0.76%	17.31%	0.98%	1.974	0.004	1.970

differences, indicating that poverty was mainly influenced by the limitations of geographic resources, and suggesting that poverty alleviation will be a long process.

(2) Difference in poverty-forming factors. 1) Comprehensive comparison among the three groups of poverty-stricken villages (ones where “Whole-village Advancement” policy has been implemented, is being implemented, and has not yet been implemented) showed that, with the progress of the policy, the road construction, income, and quality of labor increased gradually. 2) Terrain constraints, natural disasters, and the proportion of the labor force showed little improvement over a short period under “Whole-village Advancement” policy. 3) *Theil* index comparison among the poverty-forming factors showed that the T_r coefficient was the highest for the contribution degree of per capita net income index, indicating that “Whole-village Advancement” worked efficiently to improve income in poor areas.

(3) Difference in poverty types. Among villages that already implemented “Whole-village Advancement,” the proportion of single-factor dominant type and dual-factor driving type was the highest, and the proportion of five-factor combinative type and six-factor comprehensive type was the lowest, indicating that “Whole-village Advancement” procedures improved some of the development constraints of poverty villages, and the development conditions of the poverty-stricken villages are gradually improving.

Comprehensive analysis showed that the implementation of “Whole-village Advancement” helped improve the development environment of the poverty-stricken villages and increase the income of the poor areas, and is therefore an important step in China's poverty alleviation work.

6 Policy implications

Aiming at the problems of reducing the poverty rate, the “elite capture” of the financial resources in the countryside, the low utilization rate of poverty alleviation resources and the insufficiency of poverty alleviation means, one of the goals of China's national targeted poverty alleviation strategy is to realize the accurate identification, targeted aid, precise management and accurate assessment of the impoverished village. To accurately implement the poverty alleviation work, we must first overcome the three difficult problems of “support who”, “who will help” and “how to help”.

The relevant research in this paper can provide some technical support and practice help for accurate recognition of poverty-stricken villages. First, using VPI multidimensional poverty measurement model and GIS spatial analysis technology, the relative poverty degree and its spatial distribution of poverty-stricken villages can be more finely obtained on the basis of “whether it is poverty-stricken or not”, to better solve the problem of “supporting who” and their priority. Second, through quantitative analysis to the causes of poverty and poverty types, it can dig into the causes of poverty at the village-level scale, further reveal the distribution characteristics and formation mechanism of the spatial poverty trap, so as to adopt more targeted measures to maximize the utilization of poverty alleviation resources and to solve the problem of “how to help” better. Third, through the research on national large-regional poor village, it can not only draw a more macro overall poverty outline of impoverished villages in China, but also depict the specific poverty characteristics of each village, which can help the government departments of poverty alleviation at all levels to

mobilize social poverty alleviation, social poverty alleviation and industry poverty alleviation resources, and provide guidance to help solve the problem of “who will be supported”.

For example, it is found from the results of the paper that, for the poverty “hardest hit”, Gansu, Yunnan, Guizhou and other regions, need properly “tilt” national financial resources that play the role of macroeconomic regulation and redistribution of benefits. The poverty-stricken villages in rural China are poor in many factors, and most of them have restricted factors, such as bad access condition, poor natural environment, low income and low labor cultural quality. Therefore, according to the poverty characteristics of impoverished villages, the corresponding supporting strategies should be formulated to optimize the use of poverty alleviation resources. Through the integration of all kinds of development resources, the “Whole-village Advancement” work can effectively improve the rural development by integrating all kinds of development resources, and further implementation of similar poverty alleviation strategies are also needed.

7 Discussion and conclusions

In this study, we designed a comprehensive multidimensional poverty measurement model, analyzed the poverty-forming factors and poverty types using the index contribution model and LSE model, and characterized the differences among poverty-stricken villages in different geographical locations and policy support conditions. The results showed that: (1) The areas with the highest VPI, in descending order, are Gansu, Yunnan, Guizhou, Guangxi, Hunan, Qinghai, Sichuan, and Xinjiang. The poverty level of a poverty-stricken village is related to the level of regional economic development. Spatially, there is obvious territoriality in the distribution of poverty-stricken villages, and the villages are concentrated in contiguous poverty-stricken areas. (2) The main factors contributing to the poverty of poverty-stricken villages include *road construction*, *terrain type*, *frequency of natural disasters*, *per capita net income*, *labor force ratio*, and *cultural quality of labor force*. The main causes of poverty included underdeveloped road construction conditions, frequent natural disasters, low level of income, and confined labor conditions. (3) Chinese poverty-stricken villages include six main subtypes: single-factor dominant type (0.14% of poverty-stricken villages), dual-factor driving type (8.24%), three-factor dominant type (53.33%), four-factor coordinative type (28.99%), five-factor combinative type (8.36%), and six-factor comprehensive type (0.94%). The results indicate that most Chinese poverty-stricken villages are affected by multiple poverty-forming factors, reflected by the relatively high proportion of the three-factor dominant type, four-factor coordinative type, and five-factor combinative type. (4) Significant differences were observed in poverty-stricken villages located on different sides of the Hu Line. The number of poverty-stricken villages in the northwest region is relatively small, but with a higher overall level of poverty and more complex causes for poverty. The proportion of poverty caused by multiple factors was higher as well, resulting in higher poverty alleviation pressure. The number of poverty-stricken villages in the southeast was larger, but with a relatively lower poverty level, more concentrated poverty-forming causes, and better potential of alleviating poverty. (5) The work of “Whole-village Advancement” has achieved certain poverty alleviation effect, promoted the local development environment and improved the road access, income, labor quality and other development constraints, but still need to further local conditions to carry out targeted work.

Due to a lack of data sources and the limitations of data acquisition, our study sample did not include non-impovertised villages, so we were not able to analyze the differences between poor and non-impovertised villages. Hopefully, this will be improved in future studies.

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