Hindawi
Complexity
Volume 2024, Article ID 7012402, 23 pages
https://doi.org/10.1155/2024/7012402

Research Article

Spatial Identification and Distribution Pattern of the Complexity of Rural Poverty in China Using Multisource Spatial Data

Zhenyu Qi, Jinghu Pan, and Yaya Feng

College of Geography and Environmental Science, Northwest Normal University, Lanzhou 730070, China

Correspondence should be addressed to Jinghu Pan; panjh_nwnu@nwnu.edu.cn

Received 15 August 2022; Revised 21 January 2024; Accepted 6 April 2024; Published 30 April 2024

Academic Editor: Daniel Maria Busiello

Regional poverty is one of the most serious challenges facing the world today. Poverty, antipoverty, and poverty alleviation are the focus of the attention of scholars and the public. This paper takes China's counties as the research unit, selects the influencing factors of poverty from natural and socio-economic factors, establishes an evaluation index system, simulates the natural poverty index and socio-economic poverty eradication index of each county, and clarifies the distribution characteristics of spatial poverty using GIS spatial analysis and BP artificial neural network. The results indicate that natural factors are the main cause of poverty in Chinese counties, with 710 counties having a high natural poverty index, accounting for nearly 30% of the total number of counties in the country. The national county-level natural poverty index shows a clear strip distribution pattern along latitude and longitude, with a strip distribution from north to south and from west to east; socio-economic factors have played a certain role in poverty alleviation, with as many as 1521 counties with low socio-economic poverty alleviation indices, accounting for approximately 64% of the total number of counties in the country. The spatial distribution of the county-level socio-economic poverty alleviation index is relatively fragmented. Through spatial scanning statistics, a total of 44 county poverty pressure index risk clusters reached a statistical significance level, involving 243 counties and districts. In poverty reduction practice, the internal counties and districts of contiguous poverty-stricken areas should strengthen cooperation and exchange. In the process of poverty alleviation and development, targeted poverty alleviation and economic development should be carried out based on the poverty-dominant type and self-development ability of the county, in order to improve efficiency. Regions that are relatively prosperous and have taken the lead in poverty reduction should play a leading and exemplary role in strengthening the radiation power of regional central cities. The prominent feature of this study is the comprehensive utilization of multisource data and the use of new spatial analysis methods (flexible spatial scanning method is widely used in the field of infectious disease prevention and control research). By constructing a multidimensional poverty measurement system that includes natural and social factors, it distinguishes the differences between the factors that cause poverty and the factors that eliminate poverty in regional poverty. At the same time, the flexible spatial scanning detection method was used to detect the differentiation mechanism of poverty spatial patterns.

1. Introduction

Regional poverty is one of the most serious challenges facing the world today. Poverty, antipoverty, and poverty alleviation are the focus of attention of scholars and the public [1]. Since the reform and opening up, the Chinese government has implemented a series of policies to reduce poverty. The number of poor people in rural areas is rapidly decreasing. However, the epidemic is still raging around the world since the beginning of 2020. The epidemic of SARS-CoV-2 has closed borders in many countries around the world, suspended flights, disrupted traffic, closed factories, and closed stores. The global economy has experienced the largest negative growth in decades. And the impact on the world is far from over. Agence France-Presse reported in October epidemic of SARS-CoV-2 has hit the American middle class hard and has pushed 8 million people back into poverty. According to a study released in March 2021 by the Pew Research Center [2], an independent polling agency in the United States, the epidemic of SARS-CoV-2 has caused at least 32 million middle-class Indians to return to poverty. According to the estimates of the United Nations Economic Commission for Latin America (CEPAL), the poverty rate in Latin America will increase by 4.4 percentage points to 33.7% in 2020, and the number of poor people will increase by 28.7 million. The extreme poverty rate rose by 2.5 percentage points to 13.5%. The number of people living in extreme poverty increased by 16 million, and nearly 83.4 million people faced food crisis. While the poverty rate has risen, social stratification has accelerated [3]. The epidemic has had a greater impact on socially disadvantaged groups. On the one hand, due to poor health and hygiene protection conditions, these groups are more vulnerable to the epidemic; on the other hand, unemployment and income decline have a greater negative impact on life. Although the epidemic is basically under control in China, it still occurs frequently in some areas, and the prevention and control situation is still very severe. Preventing the pressure from returning to poverty due to the epidemic has also become a major task of China's national governance in the next stage; at the same time, the identification of poor areas has been questioned and criticized by scholars and the public due to the lack of scientific and reasonable identification methods. According to different targeting scales, poverty identification can be divided into two types, respectively, family or individual identification and geographic identification. Geographic identification refers to poverty identification carried out by geographic units of different scales. At this stage, China's poverty is still very large, and the remaining poor population is spatially distributed. It has obvious regional characteristics, which inevitably determines that in the long-term future, the targeting of poverty alleviation projects must still be based on regional targeting. The identification of the traditional poor areas is mainly based on a single indicator, but it only depends on a single indicator cannot accurately identify poverty areas and their characteristics, failing to achieve the goal of "precision poverty alleviation" in space, causing the phenomenon of "there is no assistance". If we simply measure poverty based on statistical data such as income, we often lack a geospatial perspective and cannot intuitively clarify the regional characteristics that caused poverty and the influencing mechanism of spatial geography on poverty. Under the background of the country's vigorous promotion of "precision poverty alleviation", it is of great theoretical value and profound realistic significance to identify poor areas from a spatial perspective and multiple dimensions, and to classify them and propose differentiated countermeasures for poverty alleviation.

Since the 1990s, more and more attention has been paid to the research and application of the results of spatial poverty in the world. From the perspective of social, economic, ecological environment, and other multidimensional space, exploring the endowment of geographical resources, regional spatial characteristics, spatial trap, spatial dependence of poverty, and so on have become hot topics in the field of poverty research at home and abroad. At the research scale, with the application of GIS and remote sensing technology, the development of statistical methods, and the enrichment of micro data, the study of poverty geography is being developed by focusing on the formation mechanism of the macro-level poverty trap and the combination of low-level equilibrium shifting to multiple scale combination including micro, meso, and macro. In research methods, attach importance to regional poverty appraisement, and quantitative analysis of regional poverty influencing factors. In the research content, pay close attention to the identification of spatial poverty traps, research on the coupling relationship between multidimensional geographic factors and rural poverty, regional poverty appraisement, regional targeting, assessment, and so on. In the formulation of poverty alleviation policies, it is often difficult for policy makers to observe and obtain the real attribute characteristics of poor families, which will restrict the effectiveness of the precision poverty alleviation policy to a certain extent [4]. Due to the nesting, correlation, and influence of different spatial scales, individual or family poverty on the microscale is often affected by economic result on the medium and macro-scale. Therefore, it is still necessary to carry out research on poverty space from the perspective of meso- and macro-scale. At present, most of the related research studies take provincial or prefecture-level cities as the research object, and it is rare to target more detailed nationwide research on the regional unit [5].

Based on this, this paper takes the county as the basic unit, abandons the traditional method of relying solely on statistical data for poverty measurement, and uses GIS, artificial neural network, and multisource spatial data to obtain the spatial complexity distribution of the natural poverty index, socioeconomic poverty reduction index, and poverty pressure index at the county level in China. For the first time in the field of poverty research, the Flexible spatial scanning detection method was used to identify deeply impoverished counties. Quantitative analysis was conducted on the impact of natural poverty factors and socioeconomic poverty reduction factors on county poverty. Simulate the relationship between county environmental conditions and the occurrence of poverty and its spatial pattern, and explore the main factors leading to poverty in deeply impoverished counties, aiming to find out the current situation of poverty in the country, and providing scientific references for proposing differentiated poverty reduction suggestions and improving the regional accuracy of poverty alleviation policies. From a multidimensional perspective, this paper abandons the traditional method of simply relying on statistical data such as income to measure poverty. By using GIS, artificial neural network, and multisource spatial data, this paper quantitatively analyzes the impact of natural poverty causing factors and social and economic poverty alleviation factors on regional poverty, and simulates the relationship between regional environmental conditions and the occurrence of poverty and its spatial pattern, which can help to understand the current situation of poverty. Improve the precision of regional targeting of poverty alleviation policies to provide scientific reference. The findings of this study could provide valuable implications for formulating China's poverty alleviation strategy after 2020, thereby contributing to global poverty alleviation and development.

2. Related Work

The famous British economist Rountree first proposed the concept of poverty at the beginning of the 20th century. He explained poverty from the perspective of the most basic living needs of human beings. He believed poverty is a state in which the total income of a family cannot meet the most basic living needs of the family members [6]. Since only the single indicator of minimum living security expenditure is used as the basis for dividing poverty, it is called single-dimensional poverty. Based on the definition of single-dimensional poverty, the World Bank proposes to use the criteria of "1.25 US dollars per day" and "1 US dollars per day" as the basis for determining the international poverty status [6]. There are three poverty line standards in China, namely "1984 standard", "2008 standard", and "2010 standard", and the corresponding poverty lines are 200 yuan, 865 yuan, and 2300 yuan, respectively. As far as the current domestic scholars' research on poverty is concerned, the meaning of single-dimensional poverty mainly refers to income poverty, that is, under certain environmental conditions, the overall income of individuals, families, and social groups cannot meet the minimum requirements of people's basic living needs and resources, so they are classified as poor.

In the 1980s, the research on poverty was further extended and expanded, and scholars' understanding of poverty gradually developed from one dimension to multidimensional, from simple income poverty to multiple dimensions of material, rights, and abilities. The theory of multidimensional poverty originated from Amartya Sen, who won the Nobel Prize in Economics in 1998. He believed that poverty is the deprivation of basic feasible capabilities of human beings [7]. The problem of human poverty is not only the poverty of economic income, but also the poverty of infrastructure and public services, as well as the poverty of subjective feelings of social welfare. The definition of multidimensional poverty is thus come.

In the 1950s, space economists Harris [8] and Myrdal [9] proposed that the social and economic development of backward areas has a certain relationship with the local geographical location. By the 1990s, the research and application of the theory of spatial poverty had received extensive attention from researchers, and the understanding of geographic capital also appeared in the study of spatial poverty. Geographical capital is the collection of natural, social, and economic capital formed by the agglomeration of natural, social, and economic capital in a certain geographical location. The lack of geographic capital in a certain area leads to the formation of a spatial poverty trap, which leads to spatial poverty; that is, spatial poverty is the regional poverty caused by the lack of natural environment, social economy, and other geographical capital. The research on spatial poverty is mainly to reveal the degree of influence of geographic capital on the spatial distribution of poverty.

Usually, poverty is divided into absolute poverty and relative poverty. Under the influence of the concept of single-dimensional poverty, many scholars have carried out research on the accuracy of identifying individuals with income poverty by formulating different poverty lines, and proposed many methods, such as the Engel Coefficient Method, the Income Ratio Method, the Martin Method, the Linear Expenditure System Model Method, and so on. Domestic scholars compared the poverty line measurement methods proposed by foreign scholars, and believed that the method suitable for China's actual poverty measurement was the Martin Method.

Economic growth is an important guarantee for poverty eradication. Although the economically developed areas have strong financial support and a sound social public service system [10], a sound social public service system will automatically allow higher-income groups to drive the development of low-income groups by providing jobs and increasing consumption through the "trickle-down effect", thereby establishing an environment where social groups can enjoy benefits fairly [11]. However, more and more studies have shown that income can only reflect one aspect of human development and poverty, and cannot fully reflect poverty in other dimensions besides income. With the proposal of the conception of multidimensional poverty, many scholars have correspondingly conducted research on the identification and measurement of poverty from the perspective of multidimensional and multiindicators. Hagenaars [12] added the dimension of leisure on the basis of single-dimensional poverty, and identified and measured poverty from the two aspects of leisure and income, which laid the foundation for subsequent scholars' related research. Nussbaum [13] used 10 dimensions such as physical health, life, thought, real perception, interpersonal relationship, and environmental awareness to explore the problem of ability poverty in issues such as social justice and human rights. Watts proposed the first distribution-sensitive poverty index, which is called the Watts index. After that, Charkravarty [14] extended the Watts index to the Watts multidimensional poverty index based on axiomatic conditions, and was widely used in countries around the world. Callander et al. [15] constructed a multidimensional poverty measurement index system from three dimensions of income, health, and education, and identified the poverty-stricken individuals at different stages in the central area, the transition area between the city center and the suburbs, and the three suburban areas in Australia. Luzzi and others [16] used the principal component analysis method to determine the optimal dimension for measuring poverty, and eliminated the multicollinearity effects between indicators of different dimensions and between indicators of the same dimension, and used cluster analysis to explore the impact of each dimension on the unbalanced effects among different groups.

Among the research studies on poverty in the world, Chinese scholars' research on multidimensional poverty not only compares foreign multidimensional poverty measurement methods, but also measures China's poverty from multiple dimensions. Li [17] firstly measured and analyzed the poverty situation in rural China from multiple dimensions. Wang and Alkire [18–20] used the AF method to measure and identify China's multidimensional poverty, and further studied the decomposition of regions, dimensions, and urban and rural areas. Zou and Fang [21] studied the fuzzy set method for measuring average ability deprivation, the efficiency method, and the measurement method based on the input-output theory, and discussed the existing problems and future development trends of multidimensional poverty measurement.

In the 1990s, Jalan and Ravallion [22] conducted a survey on farmers in four southern provinces, including Guangxi and Guangdong, and the results showed that spatial differences in factors such as topography, medical care, education, and road network density would cause some areas to fall into persistent poverty. Ravallion and Lokshin [23] found through their research on poverty in Bangladesh that geographical factors have a great influence on poverty, and location environment is the decisive factor leading to poverty. Minot et al. [24], Epprecht et al. [25], and others studied the distribution of spatial poverty in Vietnam and found that the poor are mainly concentrated in inland mountainous areas, and terrain and road density are the main influencing factors of spatial poverty. Curtis et al. [26] and others found that the high incidence of child poverty in the United States is concentrated in the southern Appalachian Mountains, remote areas, and northern plains Indian aboriginal agglomeration areas, and race and employment are the main factors causing poverty.

In summary, there are many studies on spatial poverty by domestic and foreign scholars. In their research, the measurement objects include both the impoverished population and administrative units, and the research scale includes both macro and relative micro levels. The research methods are also different. However, the rural impoverished population in China exhibits a wide range and relatively concentrated spatial distribution pattern, with a multilevel organizational structure and spatial agglomeration distribution pattern of impoverished households, impoverished villages, impoverished counties, and impoverished areas. With the deepening of China's poverty alleviation work, the complexity and difficulty of rural poverty problems continue to emerge, and the promotion of precision poverty alleviation strategy is facing unprecedented pressure and challenges. Therefore, in the formulation of poverty reduction and elimination policies, decision-makers often find it difficult to observe and obtain the true characteristics of impoverished families, which can to some extent constrain the effectiveness of precision poverty alleviation policies. However, traditional methods for identifying poverty-stricken areas and calculating the number of impoverished people mainly focus on single factors such as income, which is often unable to accurately identify impoverished individuals and their poverty characteristics, and rarely consider geographical factors. Therefore, there is a lack of geographical spatial perspective, which cannot intuitively clarify the regional characteristics of poverty and the impact mechanism of spatial geography on poverty. The results obtained are often not well matched with other spatial data. There is currently no relevant research on using flexible spatial scanning detection to identify poverty risks in impoverished areas.

There are not many studies on the mechanism of spatial differentiation of poverty. Minot and Baulch [27] and others studied the spatial distribution of poverty in Vietnam using the small-area estimation method, and put forward corresponding poverty reduction policy recommendations. Katsitadze [28] studied the causes of poverty and the distribution of spatial poverty in Georgia in the post-Soviet era and proposed corresponding poverty reduction methods. Li et al. [29] and others used household survey data from 22 counties in 13 provinces to study how to implement targeted poverty reduction methods.

In this paper, two research methods are used: artificial neural networks and spatial scan metrology. Artificial neural network (ANN) is a network that is widely interconnected by a large number of neurons. It is an abstraction, simplification, and simulation of the human brain neuron network from the perspective of information processing. It reflects the basic characteristics of the human brain. Its research began in the early 1940s. The psychologist McCulloch and the mathematical logician Pitts established a neural network and mathematical model, referred to as the MP model, and the development process was from the initial development climax to 1969. The book "Perceptron" in 2009 proposed that perceptrons cannot solve the problem of higher-order predicates, which greatly affected the research on artificial neural networks. There was a low tide period until the BP algorithm was proposed in 1986, which marked the artificial neural network. Another research climax is coming. The research content includes theoretical research, technical research, and applied research. This paper focuses on applied research.

In the past ten years, the research work of artificial neural networks has become more and more in-depth, and great progress has been made in practical applications, For example, in the fields of automation, prediction, and estimation, biology, medicine, and economics, many practical problems that modern computers cannot solve have been very successfully solved. At present, there are many models of artificial neural networks, and learning algorithms are emerging one after another. However, from the perspective of its application, there are only more than ten kinds of research studies, among which BP (back propagation) neural network is the most representative [30]. Its applications are involved in various fields. In the research on poverty identification and measurement; on the whole, there are few studies using the BP neural network method to analyze spatial poverty.

Identifying spatial agglomerations has always been the core goal of space science and spatial statistics. Currently, there are three methods: general, focused, and agglomeration identification [31] to identify and test the existence of spatial agglomerations. Global Moran's I and Local Moran's I are the most widely used general and focused identification test methods, respectively. The non-random geographic process produces spatial agglomeration. Compared with the former two, the agglomeration identification test uses the likelihood ratio test [32] to evaluate the spatial agglomeration situation of geographical phenomena without prior knowledge or assumptions. Naus and Naus [33] first proposed the scanning statistic model in 1965. This agglomeration detection test can not only detect whether a phenomenon or event exists in a certain area, but also can accurately locate and determine the size of the aggregation area [34]. Before 1995, researchers generally used scanning windows of fixed shape and size, but due to the different regional population densities and the indeterminacy of the distribution scale of geographical events, the identification results were far from the actual situation. In 1995, Kulldorff and Nagarwalla [32] and others proposed a generalized mathematical model based on likelihood ratio test, which corrects for nonuniform population density and uses variable-sized circular or elliptical scanning windows [35], but it cannot detect irregularly shaped agglomerations; in 2005, Tango and Takahashi [36, 37] and others proposed a flexible spatial scanning measurement method on the basis of circular scanning measurement. A collection of geographically connected regions, different regions are scanned with a dynamically changing irregular scanning window, and the scanned region is limited to a smaller neighborhood of the starting region.

This method can not only detect whether a phenomenon or event is clustered in a certain area, but also can accurately locate and determine the scale of the cluster area, which is mostly used for risk prediction and assessment of diseases, but the related research on spatial poverty has not been seen, so this paper uses this method to detect the risk of poverty in poor areas.

3. Methods and Data Sources

3.1. Methods

3.1.1. BP (Back Propagation) Neural Network. To evaluate the poverty status of a region, multiple indicators need to be considered at the same time to form a comprehensive evaluation index system. The problem of spatial poverty is generally characterized by spatiality, nonlinearity and uncertainty due to the simultaneous interaction of natural and socioeconomic factors. So it is not possible to use a simple linear method for causal analysis. BP (back propagation) neural network is a multilayer feedforward artificial neural network using an error back propagation algorithm, with the advantages of simple model construction and a rich training algorithm. This paper uses the BP neural network to simulate the natural impoverishing poverty index (NII) and social economic poverty alleviation index (SEPAI) in MATLAB R2012b. Take each natural and social economic factor (Table 1) as the input layer, NII and SEPAI as the output layer, and the number of nodes in the hidden layer is determined by the formula $n = \sqrt{n_i + n_0} + a$ (n is the number of nodes in the hidden layer. n_i and n_0 are the number of nodes in the input layer and output layer, respectively. In this paper, n_i and n_0 are 6 and 1, respectively, and a are constants between 1 and 10). Finally, the number of nodes in the hidden layer is determined according to the above formula through many experiments. After repeated tests, it is finally determined that the number of nodes in the implicit layer of NII and SEPAI in the simulation process is 5. Traditional BP algorithm (such as traingdx) has a slow convergence speed and is easy to fall into local minimum, while L-M optimization algorithm (Levenberg–Marquardt) uses the derivative of error to replace the derivative of mean square error of traditional BP algorithm, and uses batch processing in the training process, which greatly improves the convergence speed and convergence, so the training function used in this paper is L-M optimization trainlm algorithm function. Finally, the Poverty Pressure Index (PPI) is put forward. According to NII and SEAPI, the PPI of the study area is determined. The expression is

$$\mathrm{PPI} = \mathrm{NII} * (1\text{-}0.2 * \mathrm{SEAPI}). \tag{1}$$

In the formula: 0.2 is social economic poverty alleviation coefficient, which means that 20% SEPAI is used to eliminate or alleviate local poverty.

3.1.2. Flexscan Measurement Method. The purpose of using the Flexscanning measurement method in this paper is to detect poverty-stricken counties with a high risk of poverty, and to further identify and determine the deep-poor counties that need to be focused on in the future. The key to the Flexscanning statistics of the average risk is to detect the abnormal situation of poverty occurrence at the three scales of province, city, and county, that is, to detect whether the poverty pressure index at the three scales of province, city, and county has a statistical significance of aggregation, its precise location and the magnitude of poverty risk. Currently, there are two methods for Flexscanning statistics, SaTScan, and Flexible. The former uses a dynamic circular or elliptical scanning window to analyze the risk of poverty. The size and position of the scanning window are dynamically changed, which can avoid the subjective influence caused by human selection; the latter mainly uses the dynamic irregular scanning window to analyze the size of the risk of poverty occurrence. Based on the irregularity of the boundaries of administrative divisions at all levels, this paper adopts Flexible. The theoretical poverty pressure index is calculated according to the Poisson distribution, and then the log-likelihood ratio test statistic (Log Likelihood Ratio Test Statistic) (LLR for short) is constructed using the actual poverty pressure index and the theoretical poverty pressure index. Finally, the scanning window with the largest LLR is selected as the high-poverty aggregation window [36], the provinces, cities, and counties included in the window are determined, the relative risk of the corresponding study area is calculated, respectively, and the Monte Carlo method is used. Calculate the P value of the LLR to determine whether it is statistically significant.

Assuming that the Flexscan statistics S is the largest likelihood ratio among all possible scan windows Z, then [34]

Table 1: Appraisement index system of rural spatial poverty.

First-level index	Second-level index	Unit	Data type
Natural environment	Net primary productivity (NPP) X_1	gc/m^2	Raster data
	Catchment index X_2	—	Observation data
	Terrain fragmentation X_3	m	Spatial grid
	Average height X_4	m	Spatial grid
	Average slope X_5	—	Spatial grid
	Vegetation Humidity Index (GVMI) X_6	—	Raster data
Social economy	Per capita public financial revenue X_7	Yuan/person	Statistics data
	Per capita household savings balance X_8	Yuan/person	Statistics data
	Per capita net income of farmers X_9	Yuan/person	Statistics data
	Illiteracy rate X_{10}	%	Statistics data
	Bed number per 10000 of health institutions X_{11}	Bed	Statistics data
	Average nighttime light X_{12}	_	Raster data

$$S = \frac{(\max/Z)\{L(Z)\}}{L_0} = \frac{\max}{Z}\left\{\frac{L(Z)}{L_0}\right\}. \tag{2}$$

In the formula (2): $L(Z)$ is the likelihood function value of the scan window Z, and L_0 is the likelihood function value obtained based on the null hypothesis [34].

The likelihood ratio of the Poisson model is

$$\text{LLR} = \frac{L(Z)}{L_0} = \frac{[n(Z)/u(Z)]^{n(Z)}[N - n(Z)/u(G) - u(Z)]^{n(G)-n(Z)}}{[N/u(G)]^{n(G)}}. \tag{3}$$

In the formula: $n(Z)$ is the actual poverty pressure index in the scanning window Z; μ (Z) is the ideal value of the poverty pressure index in the scanning window Z obtained according to the null hypothesis; N is the poverty pressure index in the research area; μ (G) is the ideal value of the poverty pressure index in the research area obtained according to the null hypothesis, and μ $(G) = N$.

3.2. Data

3.2.1. Administrative Boundary Vector Diagram. As this paper mainly studies rural poverty, for the convenience of research, if there are several municipal districts in a city, it is necessary to combine all municipal districts and name them as "urban areas", and then conduct statistical analysis as a unit. Thus, a total of 2,389 county-level research units were obtained nationwide. Data of Taiwan Province, Hong Kong, and Macao SAR are temporarily unavailable and are not included in the scope of study.

3.2.2. Digital Elevation Model. The DEM grid resolution is 90 m (Figure 1). Using DEM in ArcGIS software, the relevant data and the county administrative boundary vector map are superposed to obtain the terrain fragmentation, average elevation, average slope, and composite terrain index of each county.

3.2.3. NPP Data. NPP data obtained from NASA's MODIS product website (https://ladsweb.nascom.nasa.gov). It is a synthetic product of MOD17A3 with 1 km resolution in 2013. The MOD09A1 product used to calculate GVMI is also downloaded from this website.

3.2.4. Precipitation Data. The precipitation data in 2013 is taken from China Meteorological Data Network (https://data.cma.cn/).

3.2.5. Nighttime Light Data. The night light data in 2013 is from NOAA's National Geographic Data Center (https://ngdc.noaa.gov/eog/download.html), which is a stable lighting product.

3.2.6. Social-Economy Statistical Data. The social-economy statistical data were collected from the China Regional Economic Statistics Yearbook published in 2014, and some missing data were obtained from the 2014 statistical yearbooks of provinces and cities (2013 data). The Digital Elevation Model (DEM) data was obtained from the United States Geological Survey (USGS) website (https://lta.cr.usgs.gov/HYDRO1K)The grid resolution is 90 meters (Figure 1). Using the DEM in the ArcGIS software, the relevant data is superimposed with the vector diagram of county administrative boundaries, and the terrain fragmentation, average elevation, average slope, and synthetic terrain index of each county are statistically obtained. The sources of the data are shown in Table 2.

3.3. Index System of County Poverty Appraisement. A comprehensive and in-depth analysis of regional poverty appraisement needs to start from the perspectives of economy, society, nature, and ecological environment, and systematically characterize regional poverty manifestations (economic status and hard status), livelihood capabilities (social status and soft status), and sustainable development capabilities (natural environment and potential state). When selecting an indicator, it is necessary to comprehensively consider the basic principles of comprehensiveness, scientificity, conciseness, rationality, and operability of the indicator. It can meet the poverty alleviation requirements of

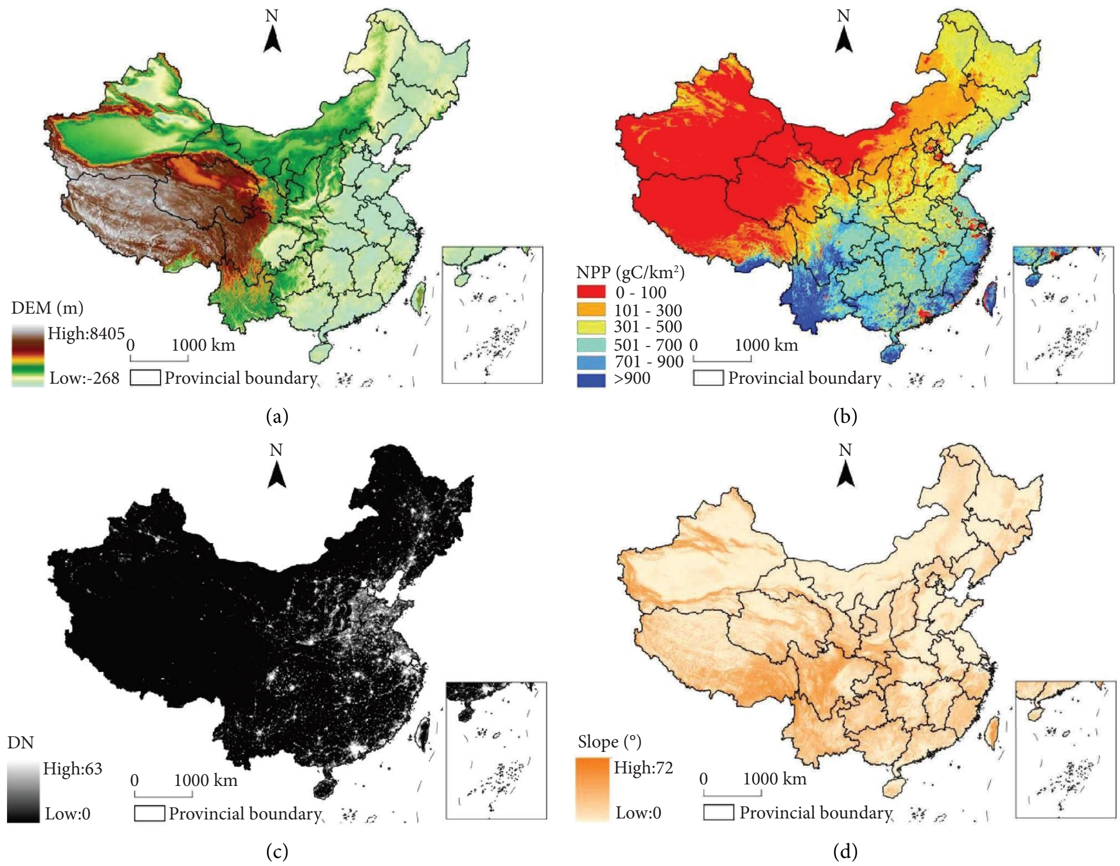

Figure 1: Spatial distribution of some rasterization index. (a) DEM. (b) NPP. (c) Nighttime light. (d) Slope grade.

Table 2: The sources of the data.

Data set name	Data source
The administrative boundary vector diagram	The 1 : 4,000,000 database of National Geographic Center for Basic Data (https://www.ngcc.cn/ngcc/html/1/index.html)
Digital elevation model (DEM) data	U.S. Geological survey (USGS) website (https://lta.cr.usgs.gov/HYDRO1K)
NPP data	NASA's MODIS product website (https://ladsweb.nascom.nasa.gov)
The data of the amount of precipitation	China Meteorological Data Network (http://data.cma.cn/)
The nighttime light data	National Geophysical Data Center of the U.S. National Oceanic and Atmospheric Administration (https://ngdc.noaa.gov/eog/download.html)
Social-economy statistical data	The China Regional Economic Statistics Yearbook published in 2014

multidimensional comprehensiveness and fairness of spatial poverty identification, the pertinence of research objects, policy relevance, and availability of evaluation data on the national scale at the same time. By referring to relevant literature [38] and the actual situation of poverty-stricken counties in China, and taking into account the monitoring needs of the core indicators of the current national comprehensive poverty alleviation strategy, this paper is guided by the theory of spatial poverty and the theory of man-land relationship, and takes the county-level administrative division as the research object. Meanwhile, it combines objective factors such as the natural ecological environment to alleviate poverty and the dynamic relationship of mutual effect between poverty and the natural environment, ecology, resources, society, economy, and other factors to establish a candidate set of multidimensional poverty appraisement index systems including natural, ecological environment, socioeconomic, and other indicators. On this basis, candidate indicators are screened according to the relevance and discrimination of the indicators, and factors that a variance expansion factor VIF greater than 10 are eliminated, and the impact of multicollinearity is reduced. The appraisement index system shown in Table 1 is finally obtained.

To study the spatial distribution pattern of rural poverty at county level in China, firstly we must identify the factors causing poverty and poverty alleviation, as well as the degree of each factor's impact on spatial poverty. In this paper, we use correlation analysis to identify the factors that cause poverty and eliminate poverty. The cause of poverty is the factor that leads to poverty. The factors caused poverty are negatively related to the degree of poverty. The greater the numerical value of the indicators that caused poverty, the more severe the degree of poverty. There is a positive correlation between poverty alleviation factors and the degree of poverty. The higher the value of poverty alleviation indicators, the lower the degree of poverty. Correlation analysis is performed on each selected indicator and per capita GDP to measure the factors that caused poverty and poverty alleviation factors that affect the spatial distribution of rural poverty in the county. Judging the factors causing poverty and poverty alleviation factors according to the results of related analysis, the size of the numerical value indicates the degree of poverty.

The NPP in the indicator system is used to reflect the strength of the productivity of the county ecosystem. The terrain fragmentation is characterized by the standard deviation of the high average at different points in each county. The compound Topographic Index (CTI) is a function of the upstream confluence area (FA) and landscape slope (slope). The calculation formula is [38]

$$\mathrm{CTI} = \mathrm{In}\left(\frac{\mathrm{FA}}{\tan(\mathrm{slope})}\right). \tag{4}$$

The catchment index is introduced to represent the availability of water resources in a county. The calculation formula is

$$\mathrm{AW} = \frac{(\mathrm{CTI} * \mathrm{AP})}{10000}. \tag{5}$$

In this formula, AW is the catchment index; and AP is the annual precipitation. If a county has flat terrain, large catchment area and abundant rainfall, its AW will be large. On the contrary, if the terrain slope is large or the catchment area is small, and the precipitation is scarce, then the AW is small.

The Global Vegetation Moisture Index (GVMI) can reflect the information of vegetation and soil moisture comprehensively, and indicate the good or bad of the ecological environment of the county. The calculation formula is [39]

$$\mathrm{GVMI} = \frac{(\mathrm{NIR} + 0.1) - (\mathrm{SWIR} + 0.02)}{(\mathrm{NIR} + 0.1) + (\mathrm{SWIR} + 0.02)}. \tag{6}$$

In the formula, NIR and SWIR are, respectively, the near infrared band (Band 2) and short infrared band (Band 6) of MODIS data product MOD09A1. The spatial resolution of MOD09A1 data product is 500 m, and the temporal resolution is 8 d synthesis. The spatial resolution of 500 m is resampled to 1 km, and the corresponding GVMI of 8d is obtained according to formula (3), and then the monthly GVMI is obtained by using the maximum synthesis method (MVC), and finally the annual average value is obtained.

The nighttime light remote sensing data adopts NPP-VIIRS data with high spatial resolution, and adopts invariant target area method [40] and neighborhood filtering method to eliminate the abnormal values in the original NPP-VIIRS nighttime light image. All the spatial data use the Albers equivalent conical projection coordinate system, and the spatial resolution is resampled to 1 km, which is convenient for calculation and analysis. The spatial distribution is shown in Figure 1.

The flowchart of this paper is shown in Figure 2.

4. Results

4.1. Correlation Analysis of Poverty Influencing Factors. In order to obtain the degree of impact of selected indicators on poverty pressure at county level, some scholars do a correlation analysis on each factor and per capita GDP or farmers' per capita net income. Considering that per capita GDP is the most important indicator for measuring the socioeconomic development status. This paper uses Person correlation analysis. On the one hand, further understand the main influencing factors of the degree of poverty in the study area, determine the linear correlation between each variate and per capita GDP, and judge whether each indicator is the impoverishing poverty factor or a poverty alleviation factor, and the nature of the impact of each indicator on poverty; on the other hand, ensure the accuracy of training and simulation of BP neural networks. Due to the large number of samples, this paper adopted a sampling method, and selected 200 samples at equal intervals for analysis after ranking GDP per capita of all county-level. Table 3 shows the influence of all factors selected in this paper on county-level spatial poverty. A negative correlation coefficient indicates that the factor is an impoverishing poverty factor; otherwise, it is a poverty alleviation factor. From the significant level test results, it can be seen that each factor having a significant impact on regional poverty. Except for the significance level of the catchment index X_2 and illiteracy rate X_{10}, which is greater than 0.01, the others are less than 0.05.

There is a negative correlation between the net primary productivity of vegetation in natural factors, degree of terrain fragmentation, average slope, average elevation, vegetation humidity index, and per capita GDP. Socioeconomic factors are positively correlated with per capita GDP. Among them, average slope, per capita public financial income, per capita savings balance, per capita net income of farmers, the number of beds per 10,000 people in the health institutions, and the average nighttime light index showed a significant correlation.

4.2. Simulation and Analysis of Natural Impoverishing Index. Natural Impoverishing Index (NII) refers to the degree of impact of natural geographic elements on poverty. In this paper, the degree of terrain fragmentation, elevation, average slope, NPP, GVMI, and catchment index are used as the input layer, and NII is used as the output layer to build a BP neural network. The number of input layer nodes is 6 and the number of hidden layer nodes is 5 and the number of output layer nodes is 1. A $6 \times 5 \times 1$ network topology is constructed. The reasonableness of the training samples directly affects the quality of the neural network training results. Therefore, the training level is of great importance.

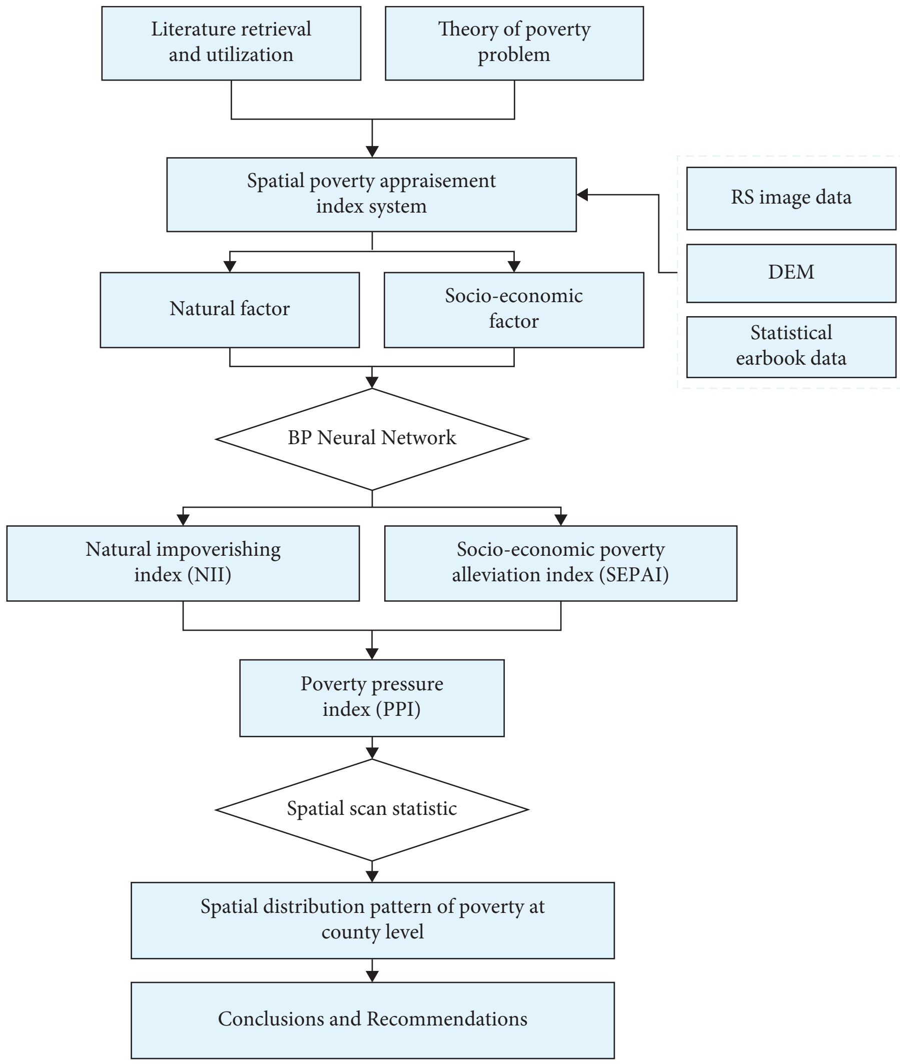

FIGURE 2: The flowchart.

TABLE 3: Results of correlation analysis.

	X_1	X_2	X_3	X_4	X_5	X_6
Correlation coefficient	−0.086	0.050	−0.155	−0.176	−0.279	−0.145
Significance level	0.004	0.243	0.015	0.006	0.000	0.021
	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
Correlation coefficient	0.890	0.727	0.764	0.020	0.501	0.421
Significance level	0.000	0.000	0.000	0.388	0.000	0.000

According to the maximum and minimum ranges of all sample data, and the distribution characteristics of the data, this paper uses the natural breakpoint method to classify. The advantage is that the variance between classes is the largest and the variance within the class is the smallest. Finally, NII is divided into 5 levels. The degree of poverty in the order of levels 1 to 5 is low, lower, average, high, and higher, and the specific evaluation criteria are shown in Table 4. The neural network is constructed and trained according to the above determined evaluation level criteria. The output layer neuron uses a purelin transfer function, and the training function uses the optimized L-M algorithm trainlm function. The basic parameters of network training are: the learning rate is 0.01, the maximum time of training is 10,000, and the minimum error is 0.001.

According to the above network and evaluation criteria, the data of the samples to be analyzed in each county input trained network, and is simulated 7 times by the BP neural network to reach the preset accuracy with an error of 0.09%. The BP neural network was trained well. After the network was run, the results of simulating Natural Impoverishing Index of each county were obtained. Using breakpoint method in ArcGIS to display the results spatially, obtains the spatial distribution pattern of the natural impoverishing poverty index NII (Figure 3). As can be seen from Figure 3, if you draw a straight line from Yingjiang, Yunnan to Gaizhou, Liaoning, the Natural Impoverishing Index NII happens to be bounded by this line, and is divided into two parts that are very different. The counties with lower NII are almost all

Table 4: Evaluation standard of natural impoverishing index.

NPP	Catchment index	Degree of terrain fragmentation	Elevation	Average slope	GVMI	Classification
1	1	0.0656	0.0520	0.0792	1	1 (low)
0.5530	0.5609	0.1564	0.1500	0.1860	0.7457	2 (lower)
0.4005	0.3681	0.2887	0.2992	0.3194	0.5780	3 (average)
0.2785	0.2441	0.5460	0.5632	0.5308	0.4508	4 (high)
0.1579	0.1423	1	1	1	0.2937	5 (higher)

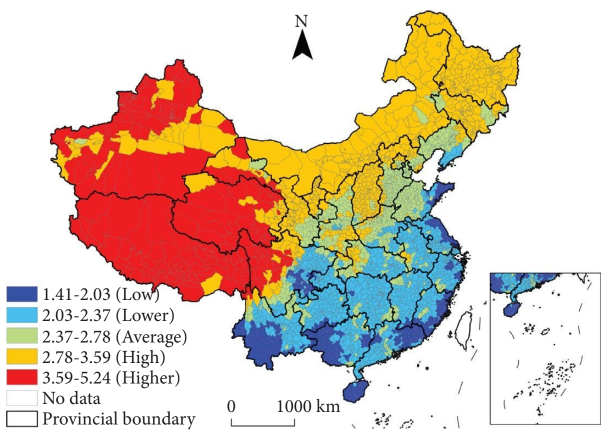

Figure 3: Spatial distribution of natural impoverishing index.

located on the east side of the Yingjiang-Gaizhou line, while the counties with higher NII are distributed in the west of the line. On the whole, the distribution of NII in counties across the country shows a clear pattern of zonal distribution with latitude and longitude: NII is arranged in a stripe pattern from north to south and from west to east. There are 278 counties with lower NII (NII°<°2.03), mostly distributed in provinces and regions south of 26°north latitude; there are as many as 780 counties with lower NII (2.37°≤°NII°<°3.59), except for some counties in the Bohai Rim, all of them are located south of 35°north latitude. The above-mentioned counties and districts have lower elevations, high vegetation coverage, superior natural conditions, and ample rainfall, which is beneficial to the development of agriculture. At the same time, the vegetation productivity is high, and is rich in products. There are 539 counties with higher NII (3.59°≥°NII°>°2.78), concentrated in areas north of 33°north latitude; among them, there are 171 counties with higher NII (NII°>°3.59), all of which are located in the northwest and southwest areas west of 104° east longitude; the county with the highest NII is Yecheng County, Xinjiang, with a value of 5.238. The counties with high and higher NII are concentrated on the first and second steps of China's terrain, in which the landform undulates terribly, and the climate is arid or alpine, and the natural environment is harsh as well as the vegetation coverage is low and geological disasters are frequent, and the soil is barren.

Statistics show (see Table 5) that the average natural poverty index of 680 poverty-stricken districts and counties in 14 contiguous areas of dire poverty determined by the Outline of Poverty Alleviation and Development in China's Rural Areas (2011–2020) issued by Central Committee of the Communist Party of China and the State Council of the People's Republic of China is 2.83, which is higher than the average natural poverty index (2.56) of all 2389 districts and counties across the country. In terms of the divided area (Table 5), in 14 contiguous areas of dire poverty, Tibet has the highest natural poverty index (4.34), followed by the Kashgar region, Khotan region, and Kizilsu Kirgiz Autonomous Prefecture in the southern Xinjiang, namely 3.66, and the Tibetan areas (3.61) in Gansu Province, Qinghai Province, Sichuan Province, and Yunnan Province. The mountain area in western Yunnan has the lowest natural poverty index (1.99). The natural poverty index in southern regions such as Wuling Mountain, Wumeng Mountain, desertification region in Yunnan Province, Guizhou Province, Guangxi Zhuang Autonomous Region, Luoxiao Mountain, and so on is generally lower than the national average, while the natural poverty index in northern regions such as Liupan Mountain, the southern foot of Daxing'an Mountains, Yanshan Taihang Mountain, Lvliang Mountain, Qinba Mountain, and so on is generally lower than the national average.

In terms of provinces, the average NII value of all counties in Hainan Province is the lowest, only 1.77, and the provinces with a smaller average NII value include Fujian (2.05), Guangxi (2.09), Zhejiang (2.09), and Yunnan (2.10). Tibet has the highest average NII value in all counties, and provinces with an average NII value > 3 also include Xinjiang (3.74), Qinghai (3.67), and Heilongjiang (3.05). In terms of the coefficients of variation of the NII values of every province, Sichuan has the largest coefficient of variation (0.22), followed by Xinjiang (0.18) and Yunnan (0.17), indicating that each county within the jurisdiction of the provinces has huge differences in natural impoverishing condition, and the distribution is the most uneven. The coefficient of variation of the NII value in Heilongjiang Province is the smallest, only 0.04, followed by Ningxia and Inner Mongolia, whose coefficients of variation are 0.05.

4.3. Simulation and Analysis of Socio-Economic Poverty Alleviation Index. The Socio-Economic Poverty Alleviation Index (SEPAI) refers to the extent to which socio-economic factors influence poverty reduction. This paper selects six indicators, respectively, per capita public financial income, per capita household savings, farmers' per capita net income, illiteracy rate, the number of beds per 10,000 people in the health institution and the average light intensity of nighttime

Table 5: Poverty indices of 14 contiguous specially poor areas of China.

Poverty index	NII	SEPAI	PPI
Liupan Mountains area	2.82	0.82	2.64
Qinba Mountains area	2.72	1.06	2.68
Wuling Mountain area	2.29	0.94	2.26
Wumeng Mountain area	2.33	0.60	2.95
Stony desertification area in Yunnan, Guangxi, and Guizhou	2.10	0.67	2.26
Mountain area in western Yunnan	1.99	0.86	2.82
South Foothills of the Greater Khingan Range	2.99	0.79	2.09
Yanshan-Taihang Mountains area	2.91	1.02	2.44
Lvliang Mountains area	2.84	0.94	2.33
Dabie Mountain area	2.39	0.68	1.95
Luoxiao Mountain area	2.29	0.87	2.01
Tibetan areas of Sichuan	3.61	0.92	3.15
Kashgar, Khotan, and Kizilsu Kirgiz in southern Xinjiang	3.66	0.99	3.00
Tibet	4.34	—	—

light to be used as the input layer, and SEPAI is used as the output layer to construct the BP neural network. The number of nodes in the input layer is six, and the number of nodes in the hidden layer is five, and the number of points in the output layer is 1. Construct a $6 \times 5 \times 1$ Network Topology. According to the maximum and minimum ranges of all sample data and the distribution characteristics of the data, the natural breakpoint method is used to classify. SEPAI is divided into 5 levels, and the degree of poverty alleviation is low, lower, average, high, and higher in the order of level 1 to level 5 (see Table 6). The neural network construction and training method is the same as the simulation method of NII.

According to the above network and evaluation standards, the sample data of each county to be analyzed was input into the trained network, and the BP neural network was simulated 9 times to achieve a preset accuracy with an error of 0.08%. After the network operation, the results of simulated social and economic impoverishing index of each county were obtained. After spatializing the results using the natural breakpoint method in ArcGIS, the spatial distribution pattern of the socio-economic impoverishing index is obtained (Figure 4). As can be seen from Figure 4, compared with more regular spatial distribution of natural impoverishing index in county areas, the spatial distribution of the socio-economic impoverishing index is more fragmented and chaotic, and the regularity is not strong. There are only 172 counties with higher SEPAI (SEPAI>3.04), which are mainly concentrated in the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei, Liaodong Peninsula, Shandong Peninsula, and other places. The highest SEPAI is in municipal district of Shanghai Beijing and Shenzhen, and Ordos Dongsheng District, with SEPAI of 4.679, 4.272, 4.227, and 4.220, respectively. There are 236 counties with higher SEPAI ($3.04 \geq \text{SEPAI} > 2.09$), which are mainly distributed in the periphery of high-level SEPAI counties. There are as many as 687 counties with very low SEPAI ($\text{SEPAI} < 0.81$), which is distributed nearly approximating in space to the shape of "π". There are 834 counties with lower SEPAI ($0.81 \leq \text{SEPAI} < 1.34$) and with the largest number, which distributed throughout the country.

Statistics show that the average socio-economic poverty alleviation index of 680 poverty-stricken districts and counties in 14 contiguous poor areas with special difficulties identified by the state is 0.83, which is far lower than the average socio-economic poverty alleviation index of all 2389 districts and counties throughout the country (1.35). In terms of the divided area, among the 14 contiguous poverty-stricken areas, the socio-economic poverty alleviation index in the Wumeng Mountains area is the lowest (0.60), followed by stony desertification area in Yunnan, Guangxi, and Guizhou (0.67) and the Dabie Mountains area (0.68). Qinba Mountain area (1.06) and Yanshan-Taihang Mountain area (1.02) have the highest socio-economic poverty alleviation index, but they are still far below the national average level. In terms of provinces, Guizhou Province has the lowest average SEPAI value in each county, and Zhejiang Province has the highest average SEPAI value. From the perspective of the coefficients of variation in the SEPAI values of each province, Guangdong and Ningxia have the largest coefficients of variation, followed by Henan and Guizhou, indicating that the socio-economic development conditions of the counties and districts governed by these provinces are very different and the distribution is the most uneven. Zhejiang province has the smallest coefficient of variation in SEPAI values, followed by Inner Mongolia and Shanxi. Compared with the coefficient of variation of NII, the coefficient of variation of SEPAI in each province is much higher than the coefficient of variation of NII, even in Zhejiang province with the smallest coefficient of variation in SEPAI. It is as high as 0.41, which indicates that the differences in the socio-economic poverty alleviation index among counties in China are much larger than the differences in a natural impoverishing index.

4.4. Analysis of Poverty Stress Index. Using the natural impoverishing index and the socio-economic poverty alleviation index, the poverty pressure index of each county is calculated according to formula (4), and comprehensive consideration of natural and socio-economic factors can better reflect the regional poverty status and spatial distribution characteristics. The natural breakpoint method was

Table 6: Evaluation standards socio-economic poverty alleviation index.

Per capita public financial income	Per capita household savings	Farmers' per capita net income	Illiteracy rate	The number of beds per 10,000 people in the health institution	Average light intensity of nighttime light	Level
0.0364	0.0531	0.0453	0.1834	0.0845	0.0254	1 (low)
0.0951	0.1118	0.0964	0.2473	0.1443	0.0873	2 (lower)
0.1925	0.2094	0.2021	0.3262	0.2358	0.1986	3 (average)
0.5077	0.3902	0.4310	0.5363	0.4052	0.4509	4 (high)
1	1	1	1	1	1	5 (higher)

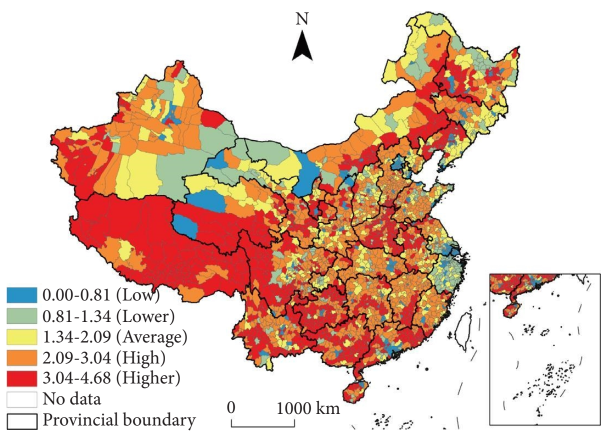

Figure 4: Spatial distribution of socio-economic poverty alleviation index.

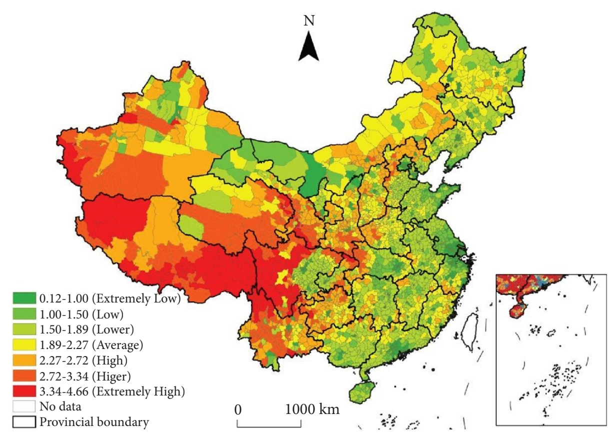

Figure 5: Spatial distribution of poverty pressure index.

used to classify the results spatially, and the spatial distribution pattern of the poverty pressure index was obtained (Figure 5). From Figure 5, it can be seen that the national poverty pressure index PPI is bounded by the "Heihe-Baise" line, and is divided into different east and west parts. The counties with lower PPI are almost all located on the east side of the "Heihe-Baise" line, while the counties with higher PPI are located on the west side of the line. Overall, the poverty pressure index shows a spatial distribution pattern "large dispersion, small aggregation" and there is a significant differences between east, middle, and west. There are 80, 85, and 308 counties with extremely high, high, and higher PPI, respectively, accounting for 20% of the total counties; counties with PPI > 2 have a total of 873 Counties, accounting for 37% of the total counties and these counties should be the key counties for poverty alleviation and poverty alleviation work. Due to the lack of statistical data, there are 28 counties and counties with no data.

Statistics show that the average poverty pressure index of 680 poverty-stricken counties in 14 contiguous poor areas with special difficulties is 2.64, which is much higher than the average poverty pressure index (1.95) of all 2,361 districts and counties in the country. In terms of the divided area, the poverty pressure index of the three regions in southern Xinjiang is the highest among the 14 contiguous special hardship areas (3.00), followed by the Wumeng Mountains area (2.95) and the western Yunnan border mountains area (2.82); Dabie Mountain area (1.95) and Luoxiao Mountain area (2.01) have the lowest poverty pressure index, which is the same as or slightly higher than the national average level. In terms of provinces, Qinghai Province has the highest average PPI of 2.79. The provinces with higher average PPI also include Yunnan (2.52), Gansu (2.47), Xinjiang (2.47), Sichuan, and Guizhou (2.35). The county's PPI average is the lowest in all counties of Jiangsu Province (1.18), and the provinces with an average PPI is less than 1.5 also include Zhejiang (1.42), Guangdong, and Hainan (1.47). From the coefficient of variation of the PPI value of each province, Zhejiang has the largest coefficient of variation of 0.40, followed by Chongqing (0.37) and Guangdong (0.35). Although Zhejiang and Guangdong have the highest levels of economic development in the country, the degree of poverty pressure in the counties and districts in the province is quite different. The development level of Chongqing's urban function core area, developing area, and new areas is high, which is very different from northeast Chongqing and southeast Chongqing. The coefficient of variation of the PPI value was the smallest, only 0.17, followed by Guizhou and Hainan, with coefficients of variation of 0.18 and 0.19, respectively.

The corresponding spatial weight matrix was constructed using the Rook standard. The global Moran's I value of the poverty pressure index in China's counties was calculated to be 0.33 with the support of GeoDA software. It passed a 1% significance test, indicating that the poverty pressure index in China's counties has a higher agglomeration effect in space. Counties and districts with higher PPI have higher PPI in the surrounding counties; counties and districts with lower PPI have lower PPI. According to the spatial autocorrelation of districts and counties with neighboring districts and counties, at 5% level of significance, the districts and counties throughout the country are divided into 4 types, as shown in Figure 6: high-high aggregation (HH), low-low aggregation (LL), low-high agglomeration (LH), and high-low agglomeration (HL). As can be seen from Figure 6, the significant number of each type is LL (565) > HH (475) > LH (49) > HL (48). The pressure of self-poverty is high and HH-type counties with high poverty pressure in the surrounding counties accounted for 20% of the country's total counties, which indicates that the distribution of poverty in China's counties is still very wide, and can be called "poverty-type" counties. HH-type contiguous large area is distributed in the Northwest and Southwest. The number of LL-type counties that the pressure of self-poverty is small and the poverty pressure in surrounding counties is also small accounts for about 23.9% of the total. It is not as continuous as the HH-type in space, and can be called "rich" counties. However, LH-type districts and counties with high poverty pressures in the surrounding counties are often embedded in HH-type distributions and fill in the blanks, which is called Peach orchards-type County. The HL-type counties that the pressure of self-poverty is high, and the poverty pressure in surrounding counties is small is distributed around LL-type, which is called "shadow-type". These counties are mostly distributed near the economically developed metropolitan areas, covered by the aura of the metropolitan areas, and should be highly concerned.

The problem of spatial poverty in China's counties in the new period is more caused by natural factors, and socio-economic factors can play a certain relief role in spatial poverty in counties. The harsh natural environment in some counties has greatly restricted the regional socio-economic development. Studies have shown that regions with higher poverty pressures have correspondingly higher natural impoverished index. For example, the natural condition of the three regions and states of Xinjiang in the west, the Qinghai-Tibet Plateau, and the Loess Hilly and Gully Areas is harsh, and the terrain is undulating, and the climate is dry or cold, and disasters are frequent; the ecological environment in Yunnan, Guizhou, and Guizhou karst areas is fragile, and rocky desertification is serious, and the area of arable land in rural areas is small, and the lack of water and land resources, which make the contradiction between human and land sharp. Social development level in the above-mentioned area is also relatively backward, and the transportation infrastructure is poor; the industrial structure is often single, and the contrast between economic development and resource advantages is large, lacking regional endogenous growth mechanisms, relying more on foreign aid, and lacking self-blood-making capacity. The low eastern coastal areas, the central plains, and the individual industrial and mining cities in the west have relatively superior natural conditions, good climatic conditions, and relatively abundant water and land resources. The regions have strong self-

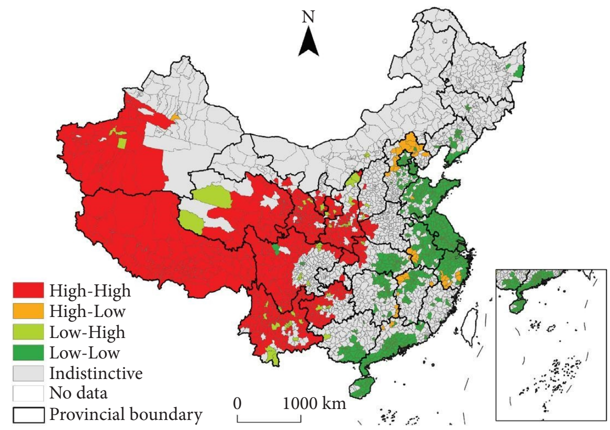

Figure 6: The local spatial autocorrelation pattern of poverty pressure index in China.

development capabilities, developed industries and agriculture, and generally have complete industrial chains. The level of third industries is also higher, absorbing labor force employment, and has a significant role in stimulating the development of surrounding areas; moreover, these places have convenient transportation, complete infrastructure, complete social and public services, and a socio-economic poverty alleviation index is naturally high.

In this paper, after the merger of 592 key poverty-stricken counties and 680 counties in 14 contiguous poor areas with special difficulties, duplicate counties were eliminated, and the rest of poverty-stricken counties is 832 in total (hereinafter collectively referred to as national-level impoverished counties). The poverty pressure index calculated in this paper is arranged in order of counties, and 832 counties and districts are also selected for comparison with national-level impoverished counties. In terms of the number of counties and districts, 566 counties identified in this paper are consistent with national-level poverty counties (Figure 7). The provinces with large numbers of differences are mainly Henan, Hunan, Guangxi, and so on. From the perspective of spatial distribution, this paper finds that the districts and counties under higher poverty pressure show a high degree of coupling with ecologically fragile areas, and mountainous areas, plateaus, hills, and restricted development areas have become the areas with the highest concentration of poverty pressure. Compared the districts and counties with high poverty pressure obtained in this paper with national-level poverty counties, we can find that:

(1) It has a high coincidence in spatial distribution, especially in a large number of poverty-stricken areas such as northwest, southwest, north China, and the contiguous poor areas with special difficulties as well as poverty-stricken districts and counties obtained in this paper are often distributed in the core area of the country's concentrated contiguous poverty-stricken areas.

(2) From this paper, we can obtain that the spatial distribution characteristics are discrete in the poverty-stricken districts and counties in some

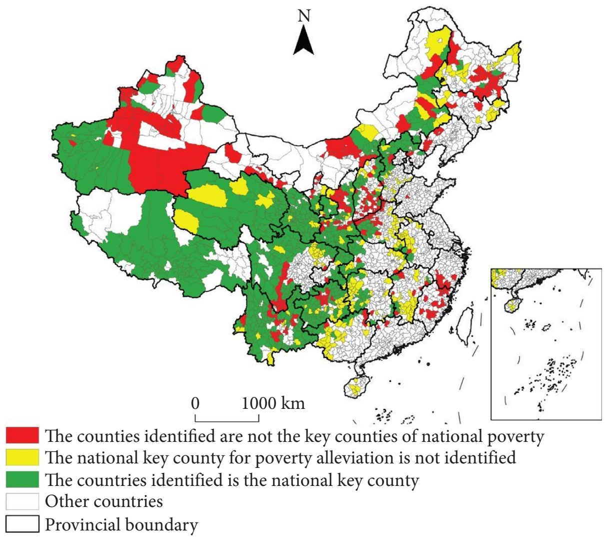

Figure 7: Comparison between identified in this study and state-supported impoverished counties.

provinces such as central and northeast China. For example, in Shanxi, Jiangxi, Heilongjiang, and Anhui provinces, according to the spatial distribution of national-level poverty counties, these districts and counties are all concentrated in continuous distribution.

(3) The poverty-stricken districts and counties have a decreasing trend from west to east and from south to north. Compared with the spatial distribution of national-level poverty counties, the poverty-stricken districts and counties proposed in this paper are concentrated in the southwest and northwest regions. This also shows that these districts and counties are the key and difficult areas for China's poverty alleviation work in the future, and other districts and counties are relatively better. The poverty alleviation pressures in the poor areas and counties located in the plain area are not great, and they have basically reached the level of poverty alleviation.

(4) Some poverty counties are distributed in the east and the key ecological function areas. In this paper, several poverty counties are identified in the mountainous regions of Zhejiang and Fujian. Some poverty counties are also distributed in important ecological function areas such as the Qilian Mountains area, regions on the middle and upper reaches of the Yellow River, and northern Xinjiang. These are not listed into the list of national poverty counties.

4.5. Analysis of Spatial Scanning Detection. In the research of this chapter, the poverty pressure index of the province, city, and county are obtained, respectively, and the regions with high, high, and extremely high poverty pressure index are divided into the poverty-stricken areas identified in this paper. On this basis, this section will use the spatial scanning measurement method to analyze and study the poverty-stricken areas identified above under the three scales, and further obtain the areas that are more difficult to reduce poverty in the poverty-stricken areas. Based on the irregularity of the boundaries of administrative division units and the actual situation of the distribution of poverty-stricken areas, this paper first calculates the theoretical poverty pressure index of each scanning window according to the Poisson distribution, and then constructs the logarithm of the test statistic according to the actual and theoretical poverty pressure index. Likelihood Ratio (Log Likelihood Ratio, LLR), LLR is used to evaluate the abnormal degree of poverty pressure index in the scanning window [37]. Generally speaking, the larger the LLR value, the higher the abnormal degree of poverty stress index in this window. Usually, the window with the largest LLR is defined as the window with the highest abnormal degree of poverty stress index, and then the statistical significance level (P) of this window is evaluated.

Since the probability distribution of the scan statistic is extremely complex, this paper uses the Monte Carlo method proposed by Kulldorff and others to calculate the P value of the test statistic. Scanning statistics can be used to evaluate not only the window with the largest LLR, but also other windows with larger LLR for statistical significance, and try to find all outlier regions [36]. In order to avoid the identified poverty risk clusters from being too large and save the scanning time, the LLR with restriction statistical type is selected in this paper. The default Alpha value is 0.2, and the scanning results of poverty risk clusters are visualized by ArcGIS 10.2 software.

According to the above principles, the log-likelihood ratio LLR of the test statistic at the county scale is constructed, and the spatial scanning results are shown in Figure 8.

Through spatial scanning statistics, a total of 44 county-level poverty pressure index risk clusters that reached statistical significance were obtained (Figure 8), with a maximum value of 5.77, a minimum value of 0.00, a mean value of 3.21, and a standard deviation of 1.75. The 44 clusters involved a total of 243 counties and districts. Xinjiang, Tibet, Qinghai, Gansu, Sichuan, Yunnan, and other provinces have many high-risk poverty counties.

According to the list of key counties for national poverty alleviation and development work issued by the State Council Leading Group for Poverty Alleviation and Development, 592 poverty-stricken counties have been identified nationwide. Contiguous areas with special difficulties, a total of 680 counties, are the main battlefields for poverty alleviation in the new stage (Figure 9). In this paper, the duplicate counties and districts are eliminated after merging the two, there are a total of 832 poverty-stricken counties (hereinafter collectively referred to as national-level poverty-stricken counties).

The above 243 high-risk poverty counties are superimposed with 832 national-level poverty-stricken counties, and 208 are both national-level poverty-stricken counties and high-risk poverty-stricken counties identified in this paper, which are called deep poverty counties in this paper. These places should be the areas with the most difficulty in

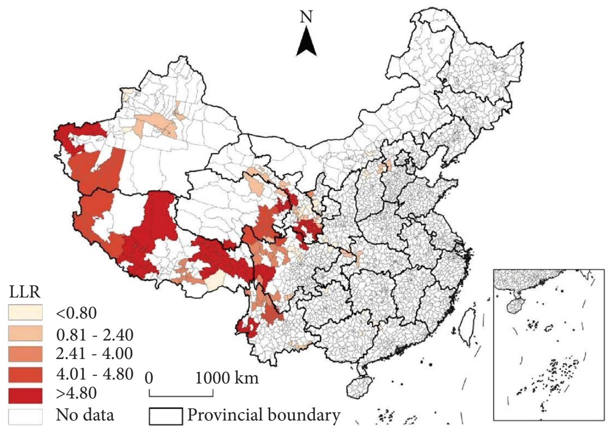

Figure 8: The spatial distribution of high risk clusters of poverty at county level.

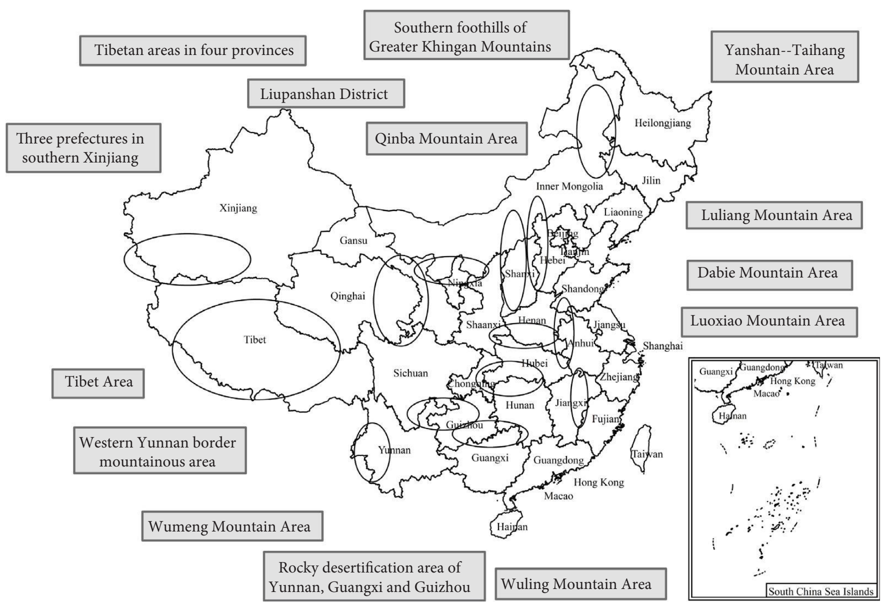

Figure 9: The sketchmap of 14 contiguous special poverty-stricken areas of China.

getting rid of poverty in the near future and in the future are also the areas that need to benefit most from poverty alleviation and poverty reduction policies. The spatial distribution of these areas is shown in Figure 10.

As can be seen from Figure 10, the overall spatial distribution pattern of the deeply impoverished counties mostly occurs in the border areas of adjacent provinces, such as Xinjiang and Tibet, Tibet and Sichuan, Sichuan and Yunnan, Sichuan and Qinghai, Gansu, and Sichuan, and Gansu and Sichuan. The border areas of Qinghai, Gansu and Ningxia, Shaanxi and Sichuan, Hubei and Chongqing, Shanxi, Hebei, and Inner Mongolia. Regional economies often expand to the periphery around provincial capitals or regional central cities. The junction of administrative regions, especially the inter-provincial junction area, has become the edge of the national, especially the provincial government's regional development strategy. The economic foundation of these places is very weak, and they cannot enjoy the radiation drive of big cities. The gap between the provinces is growing, and some of them have even become the regions with the most extensive poverty, the deepest poverty, and the most difficult poverty alleviation in their provinces.

From the perspective of the area, the area with the largest number of deeply impoverished counties is Tibet, with 43 counties, accounting for 20.7% of the total number of deeply impoverished counties, followed by Tibetan areas in the four provinces (37), and western Yunnan border mountainous areas (34). Liupan Mountains (26), Wumeng Mountains (15), and Qinba Mountains (12); there are no deeply impoverished counties in the southern foothills of the Daxing'an Mountains, Dabie Mountains, and Luoxiao Mountains, and there are Wuling in a small number of areas: Mountain area (1), Luliang Mountain area (3), and Yanshan Taihang Mountain area (6). Although the three prefectures in southern Xinjiang are not the areas with the largest number of deeply impoverished counties, they are the areas with the greatest poverty risk, with an average risk of 4.93 (see Table 7). The areas with higher poverty risk include

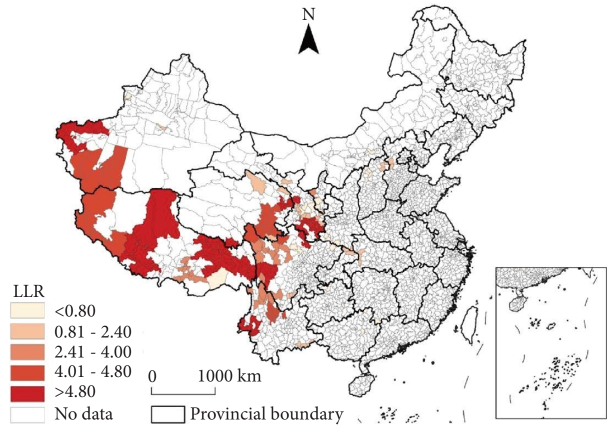

Figure 10: The spatial distribution of “Stubborn” poverty-stricken counties.

Tibet (4.50), Tibetan areas in the four provinces (3.99), and mountainous areas in western Yunnan (3.82). The poverty risk in Lvliang Mountain areas was the lowest (0.44), followed by Yunnan- Guangxi-Guizhou rocky desertification area (1.17) and Yanshan Taihang Mountain Areas (1.35).

In terms of provinces (see Table 8), the province with the largest number of deeply impoverished counties is Yunnan, including 45 counties, accounting for 21.6% of the total number of deeply impoverished counties, followed by Tibet (43), Sichuan (30), and Gansu (27); Inner Mongolia and Hunan have the least number, both of which are 1, and Guangxi (2), Chongqing (2), Hubei (2), Ningxia (3), Hebei (3), Shaanxi (4), Guizhou (7), and Shanxi (8). Although Xinjiang is not the province with the largest number, it is the province with the greatest risk, at 4.94. The provinces with higher risk include Qinghai (4.59), Tibet (4.50), Yunnan (3.42), Gansu (3.23), and Sichuan (3.22); Guangxi had the smallest risk at 0.19, followed by Inner Mongolia (025), Hunan (0.47), Shaanxi (0.80), Ningxia (0.83), and Shanxi (0.94).

5. Discussion

In recent years, China has successively proposed policy models for poverty alleviation and targeted poverty alleviation in concentrated poverty-stricken areas in terms of poverty alleviation policies. However, from the perspective of implementation effects, the poverty alleviation models in the various concentrated areas are basically similar, or even identical, to policy units, it is too large and lacks targeted, and can be “landed” policy measures [41]. At present, the design concept of precision poverty alleviation is still at a stage suitable for solving the problem of food and clothing for farmers and individuals, and applicable policy units are small, and lack of long-term mechanism for getting rich in rural areas. Under the background of strengthening the top-level design and scientific deployment of national poverty alleviation policies in the new era, it is necessary to innovate and implement policy transformation in poverty alleviation strategies, but the premise of scientifically identifying poor areas is that formulate differentiated poverty alleviation policies.

The analysis results show that there is a high correlation and rationality between the selected indicators and per capita GDP. The poor topography, ecology, climate, and other natural factors are the factors that lead to poverty, while the socio-economic factors are the factors to eliminate and alleviate poverty. Although there is a positive correlation between catchment index and per capita GDP, and it should be determined as poverty alleviation factor, but considering that the smaller the value of catchment index, the more significant the impact on poverty is, it is reasonable to classify it as the impoverishing poverty factor. In this paper, the main factors related to poverty level are selected from natural poverty factor and socio-economic poverty alleviation factors, and regression equation is established. Regression analysis results also show that the poor natural factor as the core of the ecology and terrain is the main impoverishing factor, but social and economic development is the main poverty alleviation factors. Natural factors are not easy to change, and poor ecological environment conditions are often the main factors leading to poverty.

Regarding the relationship between the economy and poverty, it is generally believed that the more economically backward the region, the poorer it is. So the economic factors are classified as the cause of poverty. However, this paper considers that the economic factors are the factors that eliminate or alleviate poverty; it is only in counties with slow economic development. The impact of economic factors on the alleviation or alleviation of poverty is not particularly obvious, which leads to the uneven development of the economy and the subsequent emergence of relative poverty, but its role in alleviating poverty is undeniable. Related scholars [42, 43] believe that the main achievements in poverty alleviation through investigation attributes to the economic growth. The relevant analysis results of this paper also confirm this.

The problem of spatial poverty in China’s counties in the new period is more caused by natural factors, and socio-economic factors can play a certain relief role in spatial poverty in counties. The harsh natural environment in some counties has greatly restricted the regional socio-economic development. Studies have shown that regions with higher

Table 7: The number and value of "Stubborn" poverty-stricken counties located in 14 contiguous special poverty-stricken areas of China.

Areas	No.	Risk average	Areas	No.	Risk average
Liupan Mountains	26	2.70	Yanshan and Taihang Mountain area	6	1.35
Qinba Mountains	12	2.86	Lvliang district	3	0.44
Wuling Mountains	1	1.77	Dabie Mountain area	0	0.00
Wumeng Mountains	15	2.14	Luoxiao mountains	0	0.00
Rocky desertification area in Yunnan, Guangxi, and Guizhou	9	1.17	Four provinces Tibetan areas	37	3.99
West Yunnan border mountains	34	3.82	Three prefectures in southern Xinjiang	12	4.93
The mountains at the southern foot of the great	0	0.00	Tibet region	43	4.50

Table 8: The number and value of “Stubborn” poverty-stricken counties located in the various provinces and autonomous regions in China.

Provinces	No.	Risk average	Area	No.	Risk average
Hebei	3	1.08	Guizhou	7	1.05
Shanxi	8	0.94	Yunnan	45	3.42
Inner Mongolia	1	0.25	Tibet	43	4.50
Hubei	2	1.77	Shaanxi	4	0.80
Hunan	1	0.47	Gansu	27	3.23
Guangxi	2	0.19	Qinghai	17	4.59
Chongqing	2	1.77	Ningxia	3	0.83
Sichuan	30	3.22	Xinjiang	13	4.94

poverty pressures have correspondingly higher natural impoverished index. For example, the natural condition of the three regions and states of Xinjiang in the west, the Qinghai-Tibet Plateau, and the Loess Hilly and Gully Areas is harsh, and the terrain is undulating, and the climate is dry or cold, and disasters are frequent; the ecological environment in Yunnan, Guizhou, and Guizhou karst areas is fragile, and rocky desertification is serious, and the area of arable land in rural areas is small, and the lack of water and land resources, which make the contradiction between human and land sharp. Social development level in the above-mentioned area is also relatively backward, and the transportation infrastructure is poor; the industrial structure is often single, and the contrast between economic development and resource advantages is large, lacking regional endogenous growth mechanisms, relying more on foreign aid, and lacking self-blood-making capacity. The low eastern coastal areas, the central plains, and the individual industrial and mining cities in the west have relatively superior natural conditions, good climatic conditions, and relatively abundant water and land resources. The regions have strong self-development capabilities, developed industries and agriculture, and generally have complete industrial chains. The level of third industries is also higher, absorbing labor force employment, and has a significant role in stimulating the development of surrounding areas; moreover, these places have convenient transportation, complete infrastructure, complete social and public services, and a socio-economic poverty alleviation index is naturally high.

For the high-risk areas of poverty identified by the spatial scanning at the county scale, the spatial distribution of the three prefectures in southern Xinjiang, Tibet, Qinghai, and Yunnan has a high consistency. The deeply impoverished counties identified at the county scale account for 25% of the total number of impoverished counties, and these counties should be the primary focus in poverty alleviation practice.

In this paper, after the merger of 592 key poverty-stricken counties and 680 counties in 14 contiguous poor areas with special difficulties, duplicate counties were eliminated, and the rest of poverty-stricken counties is 832 in total (hereinafter collectively referred to as national-level impoverished counties). The poverty pressure index calculated in this paper is arranged in order of counties, and 832 counties and districts are also selected for comparison with national-level impoverished counties. In terms of the number of counties and districts, 566 counties identified in this paper are consistent with national-level poverty counties (Figure 7). The provinces with large numbers of differences are mainly Henan, Hunan, Guangxi, and so on. From the perspective of spatial distribution, this paper finds that the districts and counties under higher poverty pressure show a high degree of coupling with ecologically fragile areas, and mountainous areas, plateaus, hills, and restricted development areas have become the areas with the highest concentration of poverty pressure. Compared the districts and counties with high poverty pressure obtained in this paper with national-level poverty counties, we can find that:

(1) It has a high coincidence in spatial distribution, especially in a large number of poverty-stricken areas such as northwest, southwest, north China, and the contiguous poor areas with special difficulties as well as poverty-stricken districts and counties obtained in this paper are often distributed in the core area of the country’s concentrated contiguous poverty-stricken areas.

(2) From this paper, we can obtain that the spatial distribution characteristics are discrete in the poverty-stricken districts and counties in some provinces such as central and northeast China. For example, in Shanxi, Jiangxi, Heilongjiang, and Anhui provinces, according to the spatial distribution of national-level poverty counties, these districts and counties are all concentrated continuous distribution.

(3) The poverty-stricken districts and counties have a decreasing trend from west to east and from south to north. Compared with the spatial distribution of national-level poverty counties, the poverty-stricken districts and counties proposed in this paper are concentrated in the southwest and northwest regions. This also shows that these districts and counties are the key and difficult areas for China’s poverty alleviation work in the future, and other districts and counties are relatively better. The poverty alleviation pressures in the poor areas and counties located in the plain area are not great, and they have basically reached the level of poverty alleviation.

(4) Some poverty counties are distributed in the east and the key ecological function areas. In this paper, several poverty counties are identified in the mountainous regions of Zhejiang and Fujian. Some poverty counties are also distributed in important ecological function areas such as the Qilian Mountains area, regions on the middle and upper reaches of the Yellow River, and northern Xinjiang. These are not listed into the list of national poverty counties.

Existing literature rarely examines the distribution pattern of poverty within the meso-scale region. Chinese scholars’ research on spatial differences in poverty at the district and county level is mostly qualitative analysis, and quantitative analysis results are rare. After superimposing the planning maps of counties and national main functional areas, it is found that the distribution of poor counties is highly consistent with the distribution of important ecological functional areas in China. These poor areas are high in Natural Impoverishing Index and far from regional central cities. It has the characteristics of marginality and closedness, which hinders the input of material and energy outside the zone, and its internal resources and environmental carrying capacity have a smaller space for "potential tapping". In addition, the socio-economic poverty alleviation index is low, and the infrastructure facilities are lagging behind, and outside the zone, the slow diffusion of advanced technologies has reduced the efficiency of the use of resources and the environment, which made the economy highly dependent on the environmental background of regional resources. For the aforementioned poor counties, they can be further divided into two types: ecologically fragile and ecological conditions to be improved. For the former, in the process of poverty alleviation and development, we must focus on promoting ecological migration, and moderately promote local poverty alleviation in areas with suitable conditions. For the latter, we should continue to improve the local poor production and living conditions, and steadily promote poverty alleviation and development in accordance with the principle of "pointed development and protection on the surface" to improve the quality of people's livelihood.

The fact that there is a significant spatial correlation in poverty pressure in counties suggests that we are practicing poverty reduction. The internal counties and districts in the successive poverty-stricken areas, should strengthen cooperation and exchanges, and abandon the traditional concepts of "Benefit Oneself at Others' Expense"; while the phenomenon of large internal differences within the more economically developed provinces has inspired us that we should be targeted to carry out poverty alleviation and economic development to improve efficiency in accordance with the poverty-dominated types and self-development capabilities of counties; areas that are relatively rich and take the lead in reducing poverty should take the lead in demonstration and strengthen the radiative power of regional central cities [44].

Zhou's study [45-51] reveals that such factors as complex geographical environment, fragile ecological environment, frequent natural disasters, endemic disease prevalence, and aging of social subjects have indeed affected and even aggravated rural poverty in China. There is a high spatial overlap between individual poverty and regional poverty. Poverty causing factors are complex, and there are regional and individual differences. The practice of targeted poverty alleviation in rural areas mainly involves industrial development, resettlement assistance, financial development, education development, medical security, land consolidation and other aspects, and has built an endogenous sustainable mechanism to promote regional development. Du's study [52] reveals that although the floating population has increased the per capita income of families by 8.5% to 13.1%, the overall impact on poverty is not significant, because most poor people do not migrate. Wang's study [53–55] made it clear that the poverty level, type and cause of poverty in each poor village are the premise and guarantee for China to take targeted measures in its poverty alleviation strategy. The main factors affecting the poverty level in China's rural poor villages include road construction, terrain type, natural disaster frequency, per capital net income, labor force ratio, and labor force cultural quality. Underdeveloped road construction conditions, frequent natural disasters, low income levels, and poor working conditions are the main causes of poverty. Liu's study [56] Establish multidimensional poverty geographic identification index system and integrated methods to identify rural poverty in China and reveals that In comparison to the income poor and the designated poor counties, the multidimensionally poor counties were not only worse in single-dimensional and composite scores, but also having multiple disadvantages and deprivations. Zhou's study [57] on the basis of the digital elevation model (DEM) data and geographic information science (GIS) spatial analysis method, it reveals that the complex conditions of the natural topography have a positive driving effect on the spatial distribution of the poverty-stricken counties.

The innovation or research feature of this paper is to comprehensively use data from multiple sources and multiple spatial analysis methods to carry out research from multiple scales. Distinguish the poverty-inducing and poverty-reducing factors (including natural environmental factors, social factors and economic development factors) affecting regional poverty, use an artificial neural network to simulate the spatial pattern of poverty, and use geographic detectors and spatial scanning detection methods to detect the differentiation mechanism of the spatial pattern of poverty. Traditional methods of identifying poor areas and measuring poor populations mainly focus on a single factor such as income, often fail to accurately identify poor individuals and their poverty characteristics, and rarely take into account geographical factors. Therefore, they lack a geographical spatial perspective and cannot intuitively clarify the regional characteristics of poverty and the impact mechanism of spatial geography on poverty. The results obtained often do not match well with other spatial data. This paper focuses on the "spatialization" of poverty, which intuitively reflects the differences in the distribution of poverty in space. In practice, the research method of this paper can provide new ideas and methods for the quantitative and multidimensional measurement of regional poverty in the new era, and the research conclusions can also provide scientific reference for the formulation and implementation of regional poverty reduction policies.

This study is limited by the availability of data. In the construction of the indicator system, some important indicators based on the county scale (such as new rural social endowment insurance, medical insurance, administrative villages connected to the Internet, tap water, and cable TV) are difficult to obtain official data, and may have omissions. As far as the whole country is concerned, there are great differences in the level of social and economic development in the east, middle, and west, and the extent to which social and economic factors alleviate poverty is also different.

When calculating the poverty pressure index in this paper, it is subjective to use 20% of the social and economic poverty reduction index to eliminate or alleviate local poverty on the basis of reference to existing research results.

6. Conclusions

(1) Natural factors are the main cause of poverty in China's counties at this stage. The distribution of Natural Impoverishing Index in counties across the country shows a clear pattern of zonal distribution with latitude and longitude, and they are arranged in a stripe pattern from north to south, and from west to east. There are 710 counties with higher Natural Poverty Index (NII > 2.78), accounting for nearly 30% of the total counties in the country. These counties or areas have large undulations and low-quality cultivated land resources; or low vegetation cover, serious soil erosion; or the cold-dry climate and frequent natural disasters.

(2) Socio-economic factors play a role in alleviating poverty, and the spatial distribution of the socio-economic poverty alleviation index in counties across the country is relatively fragmented. As many as 1521 counties with lower socio-economic poverty alleviation index (SEPAI < 1.34) account for about 64% of the total counties nationwide. These counties have low levels of socio-economic development and the infrastructures, such as transportation and so on, are backward, and social and public services are weak. The coefficients of variation of the socio-economic poverty alleviation index in the counties within each province are much higher than the coefficients of variation of the Natural Poverty Index, indicating that the differences in the socio-economic poverty alleviation index in China's counties are much greater than the difference in the Natural Poverty Index.

(3) The national poverty pressure index is bounded by the "Heihe-Baise" line, with significant differences between east region and the central and west region, showing a spatial distribution pattern of "large dispersion, small aggregation". The poor counties identified in this paper and the key poverty-relief counties identified by the state have a higher coincidence in spatial terms, and the characteristics of a high degree of coupling with ecologically fragile areas.

Based on the above conclusions, there are several policy suggestion:

(1) Poverty caused by natural factors can be mainly divided into areas constrained by ecological environment and areas caused by terrain factors. To achieve a win-win situation between regional economic development and ecological environment construction in ecologically constrained poverty-stricken areas, it is necessary to take the path of green poverty reduction. On the one hand, we will promote comprehensive management projects for mountains, rivers, forests, fields, and lakes in key areas such as the control of sandstorms in Beijing and Tianjin, the control of rocky desertification in karst areas, and the protection of the sources of the Yangtze, Yellow, and Lancang rivers in Qinghai. This will curb the trend of soil desertification and degradation in pastoral areas and poverty-stricken areas where agriculture and animal husbandry are combined, and alleviate land desertification and rocky desertification. On the other hand, exploring the establishment of upstream and downstream ecological compensation mechanisms and increasing ecological compensation efforts is of great significance for synchronously achieving ecological environment protection and poverty alleviation in these regions. According to the needs of ecological environment protection and the characteristics of ecosystems in various regions, we will appropriately expand ecological engineering construction and provide employment opportunities and income for poverty alleviation targets through the use of work as a substitute for relief. Reasonably determine a group of ecological public welfare positions, so that poverty alleviation targets can increase their income by providing ecological public welfare services, and create a beautiful countryside that is livable and suitable for business. For areas that are not suitable for the development of agriculture and have become impoverished due to terrain factors, on the one hand, we can develop standardized animal husbandry at a moderate scale in this type of poverty-stricken area according to local conditions, and strive to explore planting and breeding models that are suitable for local development, such as combining agriculture and animal husbandry, balancing food and grass, and ecological circulation. On the other hand, we should base ourselves on resource endowments, fully utilize local unique natural resources such as land, energy, natural landscapes, and biology, as well as ethnic, cultural, and other cultural resources, develop rural tourism industry according to local conditions, transform resource advantages into industrial and economic advantages, and drive economic development.

(2) Socio-economic factors leading to poverty are mainly divided into income constrained poverty-stricken areas and areas with inconvenient transportation leading to poverty. Economic income constrained poverty-stricken areas should promote employment poverty alleviation and industrial poverty alleviation based on local conditions. Firstly, we should establish a sound public employment service system that covers both urban and rural areas, conduct large-scale vocational skills training, promote multichannel transfer of employment for migrant workers, and improve the quality of

employment; encourage the establishment of environmentally friendly enterprises in rural areas, achieve rural economic diversification, and provide more employment opportunities; strengthen support and guidance services, implement rural employment and entrepreneurship promotion actions, vigorously develop rural characteristic industries such as culture, technology, tourism, and ecology, and revitalize traditional crafts. This can broaden the channels for farmers to increase their income, not only increasing the economic income of low-income rural residents, but also expanding the income of middle-income rural groups. The overall income level can be improved, and the poverty alleviation plan can be achieved as soon as possible. In areas far from the city center of prefecture level cities with inconvenient transportation conditions that lead to poverty, rural infrastructure and public service facilities are not perfect enough, making it difficult to meet the basic living needs of farmers such as consumption, medical care, and education. On the one hand, we should accelerate the improvement of infrastructure such as rural roads, water and electricity, environmental protection, and information networks, promote major water conservancy projects for water-saving and water supply, and ensure the safety of drinking water; strengthen the construction of rural social security system, improve the unified basic medical insurance system, basic pension insurance system, and minimum social security system for urban and rural residents. In terms of rural public health services, it is necessary to strengthen the construction of the grassroots medical and health service system, and support the improvement of conditions in township health centers and village clinics. On the other hand, by enhancing basic education capabilities, increasing vocational education efforts, and improving the quality of higher education, we can block the intergenerational transmission of poverty, improve the basic cultural quality of the impoverished population, and enhance the labor skills of impoverished families. Finally, for extremely remote areas with harsh terrain and blocked transportation, poverty alleviation through relocation can be adopted. Based on soil and water resources, economic development environment, and urbanization process, relocation and resettlement methods can be selected according to local conditions.

Data Availability

In this paper, the administrative boundary vectors from China national center for basic geography data, Digital Elevation Model (Digital Elevation Model, DEM) data acquisition from the United States geological survey (USGS) website (https://lta.cr.usgs.gov/HYDRO1K), NPP data acquisition from NASA's MODIS products website (https://ladsweb.nascom.nasa.gov) precipitation According to from China meteorological data network (https://data.cma.cn/). Night light Data from the National Atmospheric and Oceanic Administration of the National Geographic Data Center (NOAA's National Geophysical Data Center, https://ngdc.noaa.gov/eog/download.html). The socioeconomic statistics were summarized by the China Regional Economic Statistics Yearbook published in 2014.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 42071216).

References

[1] K. Labar and F. Bresson, "A multidimensional analysis of poverty in China from 1991 to 2006," *China Economic Review*, vol. 22, no. 4, pp. 646–668, 2011.

[2] Pewresearch, "In the pandemic, India's middle class shrinks and poverty spreads while China sees smaller changes," 2021, https://www.pewresearch.org/fact-tank/2021/03/18/in-the-pandemic-indias-middle-class-shrinks-and-poverty-spreads-while-china-sees-smaller-changes.

[3] Economic Commission for Latin America and the Caribbean, "Social panorama of Latin America 2020," 2021, https://www.cepal.org/en/publications/46688-social-panorama-latin-america-2020.

[4] M. Ravallion and Q. Wodon, "Poor areas, or only poor people?" *Journal of Regional Science*, vol. 39, no. 4, pp. 689–711, 1999.

[5] J. H. Pan and Y. X. Hu, "Spatial identification of multidimensional poverty in China based on nighttime light remote sensing data," *Economic Geography*, vol. 36, no. 11, pp. 124–131, 2016.

[6] World Bank, "Poverty net," http://go.worldbank.org/RQBDCTUXWOPermanentURL.

[7] A. Sen, *Development as freedom*, Oxford University Press, New York, NY, USA, 1999.

[8] C. D. Harris, "The market as a factor in the localization of industry in the United States," *Annals of the Association of American Geographers*, vol. 44, no. 4, pp. 315–348, 1954.

[9] G. Myrdal, *Economic Theory and Under-developed Regions*, Harper and Brothers Publishers, New York, NY, USA, 1957.

[10] L. Meng, "Evaluating China's poverty alleviation program: a regression discontinuity approach," *Journal of Public Economics*, vol. 101, pp. 1–11, 2013.

[11] G. M. Fisher, "The development of the orshansky poverty thresholds and their subsequent histoy as the official US poverty measure," *Social Security Bulletin*, vol. 55, no. 3, pp. 3–14, 1992.

[12] A. Hagenaars, "A class of poverty indices," *International Economic Review*, vol. 28, no. 3, pp. 583–607, 1987.

[13] M. Nussbaum, "Capabilities as fundamental entitlements: sen and social justice," *Feminist Economics*, vol. 9, no. 2, pp. 14–28, 2003.

[14] S. R. Chakravarty, J. Deutsch, and J. Silber, "On the Watts multidimensional poverty index and its decomposition," *World Development*, vol. 36, no. 6, pp. 1067–1077, 2008.

[15] E. J. Callander, D. J. Schofield, and R. N. Shrestha, "Capacity for freedom–using a new poverty measure to look at regional differences in living standards within Australia," *Geographical Research*, vol. 50, no. 4, pp. 411–420, 2012.
[16] G. F. Luzzi, Y. Flückiger, and S. Weber, "A cluster analysis of multidimensional poverty in Switzerland," in *Quantitative Approaches to Multidimensional Poverty Measurement*, N. Kakwani and J. Silber, Eds., pp. 63–79, Palgrave Macmillan UK, London, UK, 2008.
[17] X. Y. Li, J. Z. Ye, X. M. Zhang, L. X. Tang, and T. Zuo, "Report on rural poverty situation in China," *Journal Of China Agricultural University (Social Sciences Edition)*, vol. 1, pp. 1–8, 2004.
[18] X. L. Wang and S. Alkire, "Multidimensional poverty in China: estimation and policy implications," *Chinese Rural Economy*, vol. 12, pp. 4–10, 2009.
[19] S. Alkire, *Choosing Dimensions: The Capability Approach and Multidimensional Poverty*, Chronic Poverty Research Centre, New York, NY, USA, 2007.
[20] S. Alkire and J. Foster, "Counting and multidimensional poverty measurement," *Journal of Public Economics*, vol. 95, no. 7–8, pp. 476–487, 2011.
[21] W. Zou and Y. Fang, "How to measure poverty: from unidimensional to multidimensional," *Social Sciences Abroad*, vol. 2, pp. 63–69, 2012.
[22] J. Jalan and M. Ravallion, *Spatial Poverty Traps?*, World Bank, Development Research Group, Washington, DC, USA, 1997.
[23] M. Ravallion and M. Lokshin, "Testing poverty lines," *Review of Income and Wealth*, vol. 52, no. 3, pp. 399–421, 2006.
[24] N. Minot, B. Baulch, and M. Epperecht, "Poverty and inequality in Vietnam: spatial patterns and geographic determinants," *Research reports*, vol. 54, no. 1, pp. 153-154, 2006.
[25] M. Epprecht, D. Müller, and N. Minot, "How remote are Vietnam's ethnic minorities? An analysis of spatial patterns of poverty and inequality," *The Annals of Regional Science*, vol. 46, no. 2, pp. 349–368, 2011.
[26] K. J. Curtis, P. R. Voss, and D. D. Long, "Spatial variation in poverty-generating processes: child poverty in the United States," *Social Science Research*, vol. 41, no. 1, pp. 146–159, 2012.
[27] N. Minot and B. Baulch, "Spatial patterns of poverty in Vietnam and their implications for policy," *Food Policy*, vol. 30, no. 5–6, pp. 461–475, 2005.
[28] N. Katsitadze, "The problem of overcoming poverty in post-soviet Georgia," in *Proceedings of the SASE's 27th Annual Meeting*, London, UK, July 2015.
[29] Y. Li, B. Su, and Y. Liu, "Realizing targeted poverty alleviation in China," *China Agricultural Economic Review*, vol. 8, no. 3, pp. 443–454, 2016.
[30] L. Huang, "BP neural network algorithm improvement and application research," Msc. Thesis, Chongqing Normal University, Chongqing, China, 2008.
[31] J. Besag and J. Newell, "The detection of clusters in rare diseases," *Journal of the Royal Statistical Society: Series A*, vol. 154, no. 1, pp. 143–155, 1991.
[32] M. Kulldorff and N. Nagarwalla, "Spatial disease clusters: detection and inference," *Statistics in Medicine*, vol. 14, no. 8, pp. 799–810, 1995.
[33] J. I. Naus and J. I. Naus, "The distribution of the size of the maximum cluster of points on a line," *Journal of the American Statistical Association*, vol. 60, no. 310, pp. 532–538, 1965.
[34] F. Yin, "A study on the applicability of space-time scan statistic in early warning of infectious disease," Doctoral dissertation, Sichuan University, Chengdu, China, 2007.
[35] P. F. Guo, H. Y. He, T. Zhang, X. Zhao, Q. Ren, and X. S. Li, "Preliminary exploration on the application of scan statistics in the epidemiology of endemic diseases," *Modern Preventive Medicine*, vol. 38, no. 2, pp. 215–218, 2011.
[36] T. Tango and K. Takahashi, "A flexibly shaped spatial scan statistic for detecting clusters," *International Journal of Health Geographics*, vol. 4, no. 1, pp. 11–15, 2005.
[37] K. Takahashi, M. Kulldorff, T. Tango, and K. Yih, "A flexibly shaped space-time scan statistic for disease outbreak detection and monitoring," *International Journal of Health Geographics*, vol. 7, no. 1, p. 14, 2008.
[38] R. Sørensen, U. Zinko, and J. Seibert, "On the calculation of the topographic wetness index: evaluation of different methods based on field observations," *Hydrology and Earth System Sciences*, vol. 10, no. 1, pp. 101–112, 2006.
[39] P. Ceccato, N. Gobron, S. Flasse, B. Pinty, and S. Tarantola, "Designing a spectral index to estimate vegetation water content from remote sensing data: Part 1," *Remote Sensing of Environment*, vol. 82, no. 2–3, pp. 188–197, 2002.
[40] B. L. Yu, K. Shi, Y. J. Hu, C. Huang, Z. Q. Chen, and J. P. Wu, "Poverty evaluation using NPP-viirs nighttime light composite data at the county level in China," *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 8, no. 3, pp. 1217–1229, 2015.
[41] K. Zhou and C. S. Wang, "Spatial-temporal pattern of poverty-stricken areas and its differential policies for poverty alleviation in China," *Bulletin of the Chinese Academy of Sciences*, vol. 31, no. 1, pp. 101–111, 2016.
[42] J. Huang, Q. Zhang, and S. Rozelle, "Determinants of rural poverty reduction and pro-poor economic growth in China," *Indiana: Poorest and Hungry Assessments Analyses and Actions*, 2009.
[43] X. G. Kang, *The Poverty and Anti-poverty Theory of China*, Guangxi People's Press, Nanning, China, 1995.
[44] Y. S. Liu and J. T. Li, "Geographic detection and optimizing decision of the differentiation mechanism of rural poverty in China," *Acta Geographica Sinica*, vol. 72, no. 1, pp. 161–173, 2017.
[45] Y. S. Liu, J. L. Liu, and Y. Zhou, "Spatio-temporal patterns of rural poverty in China and targeted poverty alleviation strategies," *Journal of Rural Studies*, vol. 52, pp. 66–75, 2017.
[46] Y. Z. Guo, Y. Zhou, and Y. S. Liu, "Targeted poverty alleviation and its practices in rural China: a case study of Fuping county," *Journal of Rural Studies*, vol. 93, pp. 7-8, 2019.
[47] Y. S. Liu, Y. Z. Guo, and Y. Zhou, "Poverty alleviation in rural China: policy changes, future challenges and policy implications," *China Agricultural Economic Review*, vol. 10, no. 2, pp. 241–259, 2018.
[48] Y. Zhou, Y. Z. Guo, Y. S. Liu, W. X. Wu, and Y. R. Li, "Targeted poverty alleviation and land policy innovation: some practice and policy implications from China," *Land Use Policy*, vol. 74, pp. 53–65, 2018.
[49] Y. Zhou, Y. R. Li, and Y. S. Liu, "The nexus between regional eco-environmental degradation and rural impoverishment in China," *Habitat International*, vol. 96, Article ID 102086, 2020.
[50] Y. Zhou and Y. S. Liu, "The geography of poverty: review and research prospects," *Journal of Rural Studies*, vol. 93, pp. 408–416, 2022.
[51] Y. Zhou and H. Huang, "Geo-environmental and socioeconomic determinants of poverty in China: an empirical analysis based on stratified poverty theory," *Environmental Science and Pollution Research*, vol. 30, no. 9, pp. 23836–23850, 2022.

[52] Y. Du, A. Park, and S. G. Wang, "Migration and rural poverty in China," *Journal of Comparative Economics*, vol. 33, no. 4, pp. 688–709, 2005.

[53] Y. H. Wang, Y. F. Chen, Y. Chi, W. J. Zhao, Z. W. Hu, and F. Z. Duan, "Village-level multidimensional poverty measurement in China: where and how," *Journal of Geographical Sciences*, vol. 28, no. 10, pp. 1444–1466, 2018.

[54] Y. H. Wang and Y. F. Chen, "Using VPI to measure poverty-stricken villages in China," *Social Indicators Research*, vol. 133, no. 3, pp. 833–857, 2017.

[55] Y. H. Wang and W. P. Qi, "Multidimensional spatiotemporal evolution detection on China's rural poverty alleviation," *Journal of Geographical Systems*, vol. 23, no. 1, pp. 63–96, 2021.

[56] Y. H. Liu and Y. Xu, "A geographic identification of multidimensional poverty in rural China under the framework of sustainable livelihoods analysis," *Applied Geography*, vol. 73, pp. 62–76, 2016.

[57] L. Zhou and L. Y. Xiong, "Natural topographic controls on the spatial distribution of poverty-stricken counties in China," *Applied Geography*, vol. 90, pp. 282–292, 2018.