

# Poverty Measurement and Evaluation at the County Level in China: From the Perspective of Nighttime Light Data

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Precise poverty alleviation is an important task for the party and the country. Accurately measuring and identifying poverty-stricken areas is of great significance for the formulation and implementation of targeted poverty alleviation policies. In order to solve the problems of the single basis of poverty identification and insufficient consideration of the diversity of poverty causes, nighttime light data was measured and used to build a multidimensional poverty evaluation index system based on the pentagonal framework of livelihoods. The research result shows that the distribution of multidimensional poverty-stricken counties identified by nighttime light data has a high degree of coincidence with the fourteen contiguous poverty-stricken areas designated by the state, and the distribution of multidimensional poverty-stricken counties has significant spatial agglomeration. At the same time, poverty alleviation work needs to pay attention to the multidimensional poverty phenomenon in economically developed areas in the future, in order to solve the problem of uneven and uncoordinated regional development. This research can provide data resources and method references for the future, including continuous monitoring of poverty areas and the assessment of poverty alleviation effects, as nighttime light data is rich in data, easy to obtain, and has a wide coverage.

Keywords: multidimensional poverty; assessment; nighttime light data

## 1. INTRODUCTION

Eradicating poverty is a major issue that needs to be solved in order to build a well-off society in China. Since the 1980s China's poverty alleviation and development work has accomplished world-renowned achievements, but it still faces huge problems and challenges. A major problem in the study of poverty is the identification of the subject of poverty. First of all, identifying the size of the poverty-stricken area is not based on scientific standards, it is

allocated from the top to the bottom based on the calculation results of poverty reduction departments at all levels. This makes the indicators not necessarily consistent with reality. Secondly, the "Outline of China's Rural Poverty Alleviation and Development (2011–2020)" (hereinafter referred to as the new *Outline*) delineates eleven contiguous areas of extreme poverty, including the Liupan Mountain District and Tibet, that have clearly implemented special policies. There are a total of fourteen contiguous and extremely poverty-stricken areas (hereinafter referred to as "contiguous and poverty-stricken areas") in three areas and prefectures in the provinces, Tibet, and southern Xinjiang. The practice of

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ensuring “concentration and continuity” objectively led to the existence of poverty-stricken and non-poverty-stricken communities in the special hardship areas, while the scattered and unconnected poverty-stricken villages (households) were therefore excluded. Third, in the process of identifying poverty-stricken villages (houses) based on the obtained poverty indicators in various places, there may be situations in which the really poverty-stricken villages (houses) are excluded from recognition due to the data quality problems of the indicators themselves [1]. In addition, in terms of poverty measurement, the identification of poverty-stricken areas in China is mainly based on economic indicators such as per capita GDP, general public budget income per capita, and net income per capita of rural residents. The identification criteria of the poverty-stricken are single and cannot comprehensively reflect the multiple dimensions of poverty [2].

Based on the above understanding, this paper constructed a multidimensional poverty assessment index system based on the pentagon of livelihoods. Nighttime light data was introduced into the calculations to ensure the objectivity of the data. After the verification of the Hebei Province, the multidimensional poverty situation in counties across the country in 2015 was identified and evaluated. This provided a useful technical method for the accurate identification and evaluation of “precision poverty alleviation”. The research paper is arranged as follows: first, a literature review from three different aspects: the concept of poverty development, poverty measurement methods, and data sources; second, the sources and processing methods of the data sources, especially the nighttime light data, are introduced; third, the multi-dimensional poverty index is calculated according to the indicator system, and verified with the nighttime light index; fourth, the research results are analyzed and the spatial distribution of the multidimensional poverty area in the country measured. Finally, the research conclusions and prospects are presented.

## 2. LITERATURE REVIEW

The understanding of the concept of “poverty” has undergone a process of development and change. For a long time, what people called “poverty” actually referred to “economic poverty” or “income poverty”, and its typical identification standard is the “poverty line”. With the development of theory and practice, people began to realize that poverty is a complex and comprehensive social phenomenon. In addition to income, poverty also involves the lack of multiple dimensions such as education, health, housing, and public goods. After the introduction of Amartya Sen’s theory of poverty [3], some scholars and international organizations have gradually changed the quantitative evaluation criteria for poverty from a simple minimum life requirement to comprehensive evaluation from economic, social, cultural, and educational perspectives [4, 5]. Since then, many scholars have also proposed various multidimensional poverty measurement index systems, such as Watts multidimensional poverty index, AF poverty “double critical value” method, HPI method, and MPI method, and these have been widely used in multidimensional poverty measurement [6–9].

In terms of poverty measurement methods, the Sustainable Livelihoods Approach (SLA) is an integrated analysis framework that explains poverty around the complex problems and factors that cause poverty and gives multiple solutions [10]. The vulnerability-sustainable livelihood analysis framework of the British International Development Agency (DFID) has been widely used in different sustainable analysis frameworks proposed by various organizations and institutions [11]. The livelihood capital owned by households in this framework mainly includes five aspects, namely financial, natural, human, material and social capital. The combination of the amount and structure of various types of capital constitutes a “livelihood pentagon”. The lack of some capital or the imbalance between portfolios will greatly reduce or deform the “livelihood pentagon”, thus affecting the assessment results [12].

In terms of basic data sources for poverty measurement, current comprehensive socioeconomic survey data are mostly used in multidimensional poverty measurement, such as health and nutrition survey data, various independent household survey data, and statistical yearbook data. These data are greatly affected by survey methods, survey cycles and coverage areas. There are certain limitations in terms of data availability, comprehensiveness, accuracy, and timeliness. Improvements are urgently needed by introducing new data sources. Due to its rich data, easy access, and wide coverage, nighttime light data has been widely used in socio-economic parameter estimation, urbanization monitoring, ecological environment, and health effects research [13]. Some domestic and foreign scholars have used nighttime light data to study the problem of poverty: Ebener et al. proposed using nighttime light data to measure poverty and health [14]; Noor et al. used DMSP/OLS nighttime light data to measure poverty in Africa [15]; Wang et al. used DMSP/OLS data to measure poverty in China [16] at the provincial level; Yu et al. compared the poverty index and average light data in concentrated contiguous poverty areas [17] at the county level; Pan Jinghu et al. used NPP/VIIRS nighttime light data to estimate the poverty situation in Chinese counties [18] in 2012. The above research shows that it is feasible to conduct large-scale and long-term dynamic multidimensional poverty identification and assessment using nighttime light data.

## 3. MATERIALS AND METHODS

### 3.1 Data Sources and Processing

The first-generation nighttime light data from the National Oceanic and Atmospheric Administration (NOAA) was adopted as the DMSP/OLS nighttime light data. This data has some shortcomings, including a lack of online calibration, insufficient spatial resolution (about 2700 m), signal oversaturation, and a single band [19, 20]. NPP/VIIRS nighttime light data adopted NOAA second generation nighttime light data products. Compared with DMSP/OLS data, its spatial resolution is improved to 15 arc seconds (about 740 m), there is no data oversaturation, the production time period is shorter (updated monthly), and it can be obtained for free. This paper uses the 2015 NPP/VIIRS nighttime light image data,

**Table 1** China’s Multidimensional Poverty Index Evaluation System.

Target layer	Criterion layer	Index layer	
		Index description	Unit
Multi-dimensional poverty index	Financial capital	GDP per capita (X1)	RMB Yuan
		Rural disposable income per capita of residents (X2)	RMB Yuan
		Local fiscal revenue per capita (X3)	RMB Yuan
	Natural capital	Annual precipitation (X4)	mm
		Total sown area of crops (X5)	hectare
	human capital	Proportion of students (X6)	%
	Physical capital	Ratio of machine harvesting area to total planting area (X7)	%
		Rural electricity consumption per capita (X8)	KWH
		Number of medical beds per capita (X9)	bed/ten thousand person
	Social capital	Urbanization rate (X10)	%
Ratio of per-capita disposable income of rural residents and urban residents		%	

which has been subjected to various pretreatments such as high albedo correction and negative correction. After the nighttime light data of China was taken out, the data was first converted into a map projection and resampled into 500 m raster data. The data is then checked and outliers are rejected.

The precipitation data used in this study was obtained from the China Meteorological Data Network and resampled to 500 m of spatial raster data. Administrative division data was obtained from the National Basic Geographic Information Center. For other socio-economic data, *China County Statistical Yearbook (County-Level) (2016)* was referenced.

### 3.2 Evaluation Model Construction and Verification

(1) Construction of multidimensional poverty index evaluation system based on livelihood pentagon

According to the DFID’s sustainable livelihood analysis framework and referring to existing related research, based on the principles of effectiveness, comparability, systematicness and operability, 11 indicators that can reflect the five livelihood capitals were selected to build China’s multidimensional poverty index evaluation system (as shown in Table 1).

The currently used multidimensional poverty measurement methods, such as the A-F poverty “double critical value” method mentioned above, and the HPI method, are not very sensitive to the choice of weights. The same weight value or subjective methods, such as expert scoring, are used to determine weights by most studies. Different indicators have different degrees of impact on poverty. If the evaluations adopt the same weight, the importance of different indicators cannot be reflected well. However, the expert consultation method depends on the knowledge level and experience of experts to work out whether the weight is reasonable or not, which makes it subjective. Therefore, this paper adopts the entropy method, an objective weighting method, to determine the weight.

Therefore, the calculation formula for the Multidimensional Poverty Index (MPI) is:

$$MPI = \sum_{i=1}^{11} w_i \times x_i \tag{1}$$

In the formula, MPI is a multidimensional poverty index, which is used to comprehensively evaluate the multidimensional poverty situation. The higher the value, the less prone to multidimensional poverty; the lower the value, the more severe multidimensional poverty is.  $x_i$  is the value of the  $i$ -th index after normalization, and  $w_i$  is the weight value of the  $i$ -th index.

This paper took the counties of Hebei Province as a sample area of multidimensional poverty modeling for verification to test the rationality of this evaluation method. The place selected has a certain representation. The result is as follows: according to the list of key counties of the state for poverty alleviation and development (hereinafter referred to as “poverty-stricken counties”), some areas of Hebei Province are located in the “Yan-Taihang Mountain Contiguous Poverty-stricken Area”. Among the 170 county-level administrative units, there are 39 poverty-stricken counties, accounting for about 30%. In addition, Hebei Province surrounds Beijing and has undergone a series of macroeconomic layout adjustments, including “Beijing-Tianjin Region” and “Bohai-Rim”. The total economic volume has increased by more than ten times in the past 20 years, and the economy has grown rapidly. However, there are also problems of large regional differences and uneven economic development.

According to the calculation results of the Hebei Province, counties with higher MPI values are mainly concentrated in Shijiazhuang, Langfang, Tangshan, Cangzhou, and Handan. However, counties with lower MPI values are mainly concentrated in Zhangjiakou, Chengde, and Qinhuangdao. By comparing the results with the distribution of poverty-stricken counties and the location of the Yanshan-Taihang Mountain contiguous poverty-stricken area, it is found that most of the counties with low MPI values belong to the poverty-stricken counties or are in the contiguous poverty-stricken area. The calculated results are in agreement with the actual situation, which indicates that the indicator system is accurate.

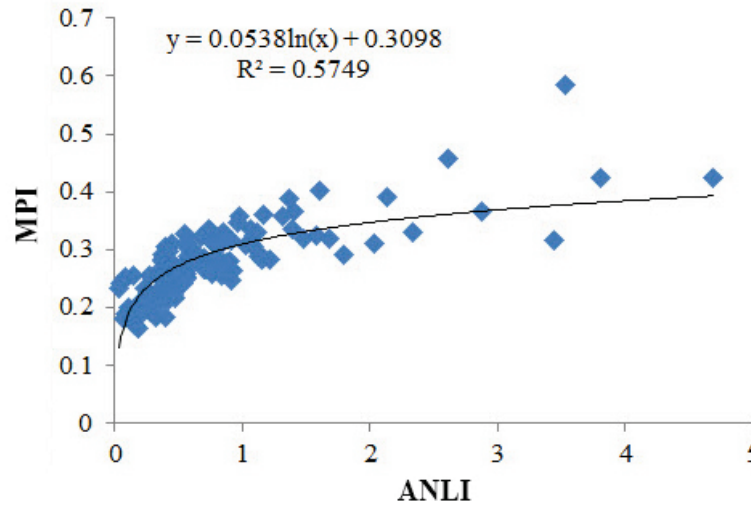
(2) Construction of the nighttime light index

**Table 2** Fitting results of TNLI and MPI.

Way of regression	Linear	Index	Logarithm	Power
$R^2$	0.4567	0.3717	0.3717	0.2829

**Table 3** Fitting results of ANLI and MPI.

Way of regression	Linear	Index	Logarithm	Power
$R^2$	0.5897	0.5243	0.5749	0.5946



**Figure 1** Regression results of ANLI and MPI

A series of studies have shown that the total light (total intensity) or average light-time intensity of an area can reflect the area’s light characteristics [18]. This paper adopts two types of nighttime light indexes: the Total Nighttime Light Index (TNLI) and the Average Nighttime Light Index (ANLI) to study its relationship with MPI. The calculation formula is as follows.

$$TNLI = \sum_{i=1}^n DN_i \tag{2}$$

$$ANLI = \frac{TNLI}{n} \tag{3}$$

Among them,  $DN_i$  is the pixel radiation value of the  $i$ -th grid unit in the area;  $n$  is the number of grids in the area;  $TNLI$  is the total light index of the area; and  $ANLI$  is the average light index in the area.

(3) Fitting of MPI and nighttime light index

After the above calculations, the MPI value and two nighttime light indices TNLI and ANLI were obtained. In order to find the optimal model, various methods were used to perform fitting regression. The fitting results are shown in Tables 2 and 3. It can be seen that the determination coefficient  $R^2$  of the fit between ANLI and MPI is better than that of TNLI as a whole. Therefore, ANLI and MPI were adopted for fitting in this paper.

It can be seen from Table 3 that the values of the determination coefficients are similar even when using various methods for fitting. After testing the four models one by one, the optimal fitting model is a logarithmic model (Figure 1). The relevant test parameters of the regression model are:

correlation coefficient  $R = 0.7582$ , determination coefficients  $R^2 = 0.5749$ ,  $F = 170.42$ ,  $t = 13.05$ ,  $DW = 1.23$ . All of these passed the 1% significance test. The standard residuals of all observations also fall into the double standard error band.

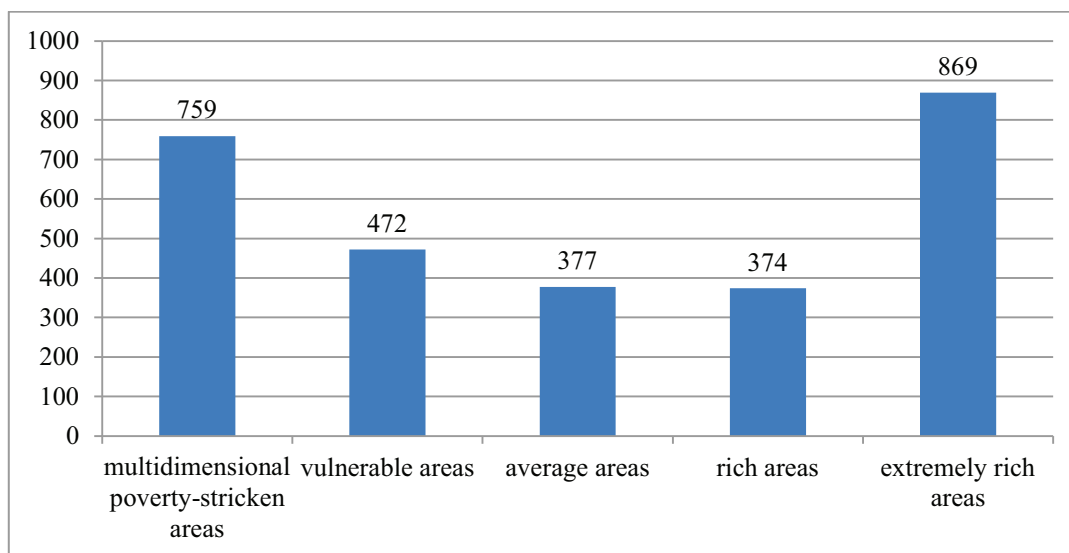
(4) MPI value estimation and error test of counties in China

The MPI value of each county can be calculated according to the regression model established by the sample area data, using the ANLI value of each county in the country. In order to facilitate the description and analysis, this paper divides the obtained MPI value into five levels from high to low according to the distribution characteristics of the data using the natural breakpoint method, these levels are extremely rich areas, rich areas, average areas, vulnerable areas and multidimensional poverty-stricken areas. The distribution is shown in Figure 2.

To test the accuracy of the model, the MPI values and MPI estimates of each county in Hebei Province were used for error testing. The relative error calculation formula is as follows.

$$Relative\ error = \frac{MPI - MPI_e}{MPI} \times 100\% \tag{4}$$

In the formula, MPI is a multidimensional poverty index calculated using a comprehensive evaluation index system. “MPI estimate” is a multidimensional poverty index estimated using nighttime light data. After the calculation, the relative error of MPI estimates in each county of Hebei Province is 7.87%. Since there are few related researches using NPP/VIIRS nighttime light data at present, this paper adopts the accuracy of other scholars using NPP/VIIRS data to estimate the other parameters for comparison. Gao Yi et al. used NPP/VIIRS data to invert the population grid data with



**Figure 2** Distribution of Multidimensional Poverty Identification Results in China

an error of 41% [21]; Chai Ziwei et al. used NPP/VIIRS data to estimate the GDP of 60 towns in the Pearl River Delta region with an average error rate of 15% [22]; Pan Jinghu et al. used NPP/VIIRS data to estimate the multidimensional poverty index of counties in Shaanxi Province with the average relative error rate of 12.51% [18]. The above comparison results show that the model constructed in this study has certain accuracy and reliability, and can be used for national estimation.

#### 4. RESULTS

According to the above results, the extremely rich areas and wealthy areas of the country are mainly concentrated in the Bohai Rim region, the Yangtze River Delta region, the Pearl River Delta region, the southeast coast, and the Sichuan Basin. There are no poverty-stricken counties in Beijing, Tianjin, Shanghai, Jiangsu and Shandong. It is worth noting that several multidimensional poverty-stricken counties have also been identified in some economically developed provinces such as Guangdong Province and Zhejiang Province. This shows that the problem of uneven and uncoordinated regional development is still more prominent in poverty alleviation.

There were 745 multidimensional poverty-stricken counties identified in this study, most of which were located in northwest China, Tibet Autonomous Region, Qinba Mountain Area, Wuling Mountain Area and other places. By comparison with the list of poverty stricken counties, 344 poverty stricken counties were identified as multidimensional poverty-stricken counties, and the remaining poverty stricken counties that were not identified as multidimensional poverty were mainly distributed in Hebei, Shanxi, Henan, Anhui, and Guizhou. The distribution of the multidimensional poverty-stricken counties was then compared with the distribution of fourteen consecutive special hardship areas delineated by the new Outline. It can be seen that: first, the distribution of multidimensional poverty-stricken counties generally coincides with the fourteen contiguous poverty-stricken areas. A total of 406 multidimensional poverty

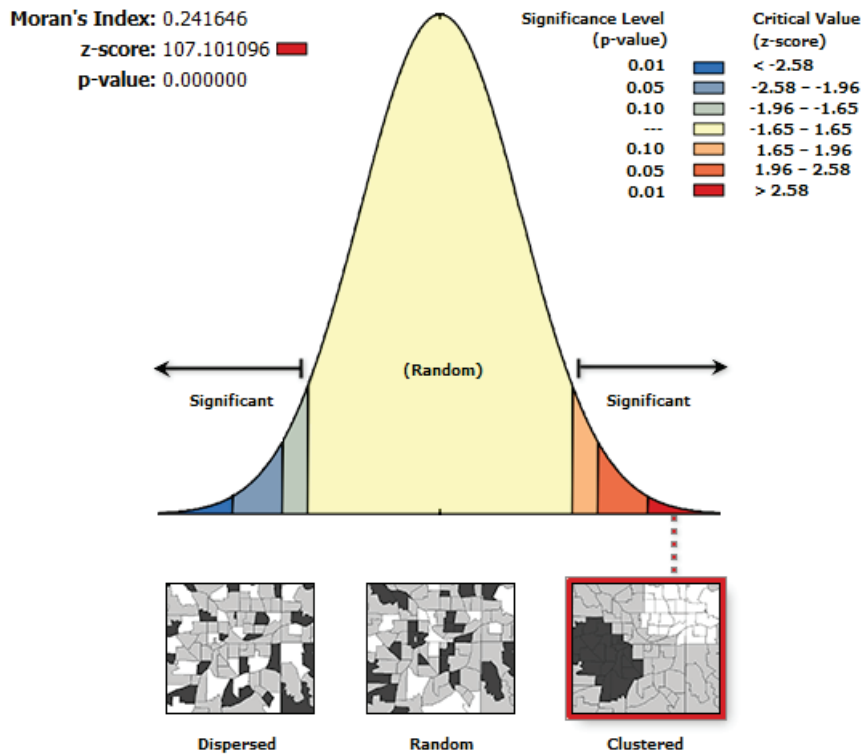
counties are in the contiguous poverty-stricken areas. Second, there are counties with high MPI values in even the most poverty stricken areas. Some counties with low-level poverty have also been included in the “continuous poverty stricken areas”, because of the principle of “concentrated poverty stricken areas” which must be followed when planning. Third, among the fourteen consecutive poverty-stricken areas, more than 97% of the counties in Tibet and Tibetan areas in the four provinces were identified as multidimensional poverty-stricken counties. 70%–80% of the counties (cities and districts) included in the rocky desertification areas of Guizhou, Guangxi, Yunnan, the western border mountainous areas of Yunnan, the three regions or states in southern Xinjiang, and the Qinba mountainous areas are identified as multidimensional poverty counties. The areas with lower percentages of multidimensional poverty-stricken counties were identified as: 40% in Lvliang Mountain Area, 24% in Yan-Taihang Mountain Area, and 19% in Dabie Mountain Area.

According to the new *Outline*, 14 consecutive poverty-stricken areas cover a total of 638 counties (cities and districts) nationwide, while a total of 592 poverty-stricken counties. There are a total of 824 county-level administrative units in the country that belong to a series of extremely poverty-stricken areas or poverty-stricken counties. Among the multidimensional poverty-stricken counties identified in this study, 509 coincide with the above counties (Table 4). The remaining 241 multidimensional poverty-stricken counties are in neither poverty-stricken counties nor contiguous poverty-stricken areas. These counties are mainly distributed in Xinjiang Uygur Autonomous Region, Inner Mongolia Autonomous Region, Heilongjiang Province, Jiangxi Province, Hunan Province, Guangxi Province, and Gansu Province. It can be seen from the results that simply using income as the identification standard or delineating poverty-stricken areas according to the principle of concentration and continuity does not reflect the actual situation well. Some areas may have different levels of multidimensional poverty, but they have not been identified as poverty-stricken counties or classified as



**Table 4** Coincident multidimensional poverty-stricken counties.

Province	count	Province	count
Tibet Autonomous Region	72	Hubei Province	20
Yunnan Province	62	Heilongjiang Province	14
Sichuan Province	57	Jiangxi Province	14
Shanxi Province	33	Chongqing Municipality	9
Gansu Province	33	Hebei Province	7
Qinghai Province	32	Jilin Province	6
Hunan Province	29	Shanxi Province	5
Guangxi Zhuang Autonomous Region	28	Henan Province	4
Inner Mongolia Autonomous Region	26	Ningxia Hui Autonomous Region	4
Guizhou Province	25	Anhui Province	3
Xinjiang Uygur Autonomous Region	25	Hainan Province	1



Given the z-score of 107.10, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

**Figure 3** Global Space Autocorrelation Calculation Results

poverty-stricken areas. It is also worth noting that because this paper uses the regional average nighttime light index ANLI to estimate the MPI value, and the population density around the Tarim Basin in Xinjiang and central and western Inner Mongolia is very low, the nighttime light index in these areas may not be representative. The corresponding MPI estimation accuracy is low.

In order to explore the spatial distribution characteristics of multidimensional poverty in China, this study further conducted a spatial autocorrelation analysis on MPI estimates in counties across the country. First the global Moran index is calculated. The calculation result shown in Figure 3 is that the global Moran index is 0.24, and the Z score is 107, which is much larger than the critical value when the confidence level

is 99%. This shows that the Z value is positive and significant, that is, there is a positive spatial autocorrelation, and similar observations tend to be spatially clustered. The results of global spatial autocorrelation analysis show that in 2015, the distribution of multidimensional poverty-stricken counties in China had significant spatial agglomeration between similar values, that is, counties with higher MPI values were significantly aggregated in geographical space, and counties with lower MPI values were geographically spaced.

The global assessment of spatial autocorrelation often masks abnormal local conditions or small-scale local instabilities. Therefore, based on this, local statistics are used to detect the local spatial concentration of MPI in each county. The calculation results are shown below. The test results show that

the Z value of the Bohai Rim region, the Yangtze River Delta, the Pearl River Delta, and the southeast coast is significant at a significance level of 0.01. Statistically speaking, the county areas adjacent to these counties have a high probability that their MPI values are not in a randomly distributed state, but tend to be surrounded by areas with the same high MPI value. As a result, the spatial concentration of high MPI values and high values is formed. Based on this, it can be recognized that these regions tend to be spatially distributed. By the same token, the Z-values of Tibet, Xinjiang, Qinghai, Yunnan, and Guizhou are also significant at a significance level of 0.01, which indicates that the MPI values of these areas also tend to be the characteristics of spatial agglomeration surrounded by low values.

## 5. CONCLUSION

In order to solve the problems of single poverty identification in China's current poverty alleviation work and research, and insufficient consideration of the diversity of poverty causes this paper builds a multidimensional poverty assessment index system based on the "Pentagon of Livelihoods" and selects Hebei Province as a sample area for verification. A regression model between the multidimensional poverty index and the nighttime light index was constructed, and the multidimensional poverty situation and spatial distribution characteristics at the county level in China were estimated in 2015. The study showed:

- (1) Nighttime light data has the characteristics of rich data, easy acquisition, and wide coverage. First, nighttime light data is available free of charge over the years from the National Oceanic and Atmospheric Administration. The relationship between nighttime light data and MPI can be used to simulate and verify poverty on a small scale. The method is simple, feasible and reliable, and can provide reference for data resources and methods for continuous monitoring of poverty areas and evaluation of poverty alleviation effects in the future.
- (2) Multidimensional poverty assessment based on the livelihood pentagon model of counties across the country shows that the distribution of multidimensional poverty-stricken counties in China coincides with the 14 contiguous special poverty zones designated by the state. The distribution of multidimensional poverty counties has significant spatial agglomeration between similar values. At the same time, in the work of poverty alleviation, the multidimensional poverty phenomenon in economically developed areas in the future needs to be taken seriously, and the problems of uneven and uncoordinated regional development need to be addressed.
- (3) Although this study is based on a livelihood pentagon model and uses the entropy method to calculate the index weights for objective evaluation, the establishment of an evaluation index system and the selection of evaluation indicators are still empirical and semi-theoretical. Measures to further optimize the MPI indicator system

to enhance policy pertinence and regional applicability need further study. The problem of abnormal lighting data in some areas that affects the accuracy of the estimation needs to be further optimized.

## 6. ACKNOWLEDGMENT

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