MULTI-DIMENSIONAL POVERTY IDENTIFICATION AND EVOLUTION ANALYSIS IN HEBEI PROVINCE BASED ON NIGHTTIME LIGHT REMOTE SENSING DATA

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KEY WORDS: nighttime light remote sensing data; analytic hierarchy process (AHP); multi-dimensional poverty index (MPI); hot spot analysis; spatiotemporal evolution

ABSTRACT:

This paper explores the use of spatiotemporal geographic information and advanced technology to effectively address the issue of poverty reduction and development. The focus is on Hebei Province, where multi-dimensional poverty identification and spatiotemporal evolution analysis are conducted using nighttime light remote sensing data. The study establishes a Multi-dimensional Poverty Index (MPI) system based on the regional average nighttime light index (ANLI) extracted from data spanning 2010, 2014, and 2018. A coupled regression model confirms the correlation between MPI and ANLI. Visualization and analysis are performed using GIS technology, Moran's I, and Getis's G* to interpret the identification results. From the experimental results, MPI established in this paper fits well with ANLI, which can be used for poverty identification and monitoring. The established multi-dimensional poverty model can identify multi-dimensional poverty counties better. However, there is a large discrepancy in the match with the traditional list of poor counties issued by the state from the perspective of absolute economic poverty. From the perspective of spatiotemporal evolution, it can be seen that the overall poverty level in Hebei Province has changed with time. Although there is aggregation among poverty areas, the aggregation is not deep. The poverty level of the traditional national-level poor counties has also been reduced, but the pattern of poverty aggregation remains unchanged. The "C-shaped" poverty belt around Beijing formed by Chengde, Zhangjiakou, Baoding and other surrounding counties in northern Hebei Province is still the focus of poverty alleviation work in the next stage.

1 INTRODUCTION

Poverty is a persistent and complex challenge that humanity has long faced and endeavored to address (Steele et al., 2017). At a global scale, the United Nations has identified the eradication of poverty as one of the Millennium Development Goals. China, as the first developing country to achieve the poverty reduction targets set by the United Nations for 2030, has made significant progress in poverty alleviation under its guiding poverty alleviation strategies. The number of rural impoverished population in China has decreased from 98.99 million in 2012 to 16.6 million by the end of 2018, and the poverty incidence has been reduced to 1.7%. On November 23, 2020, a total of 832 nationally designated poverty-stricken counties in China successfully lifted themselves out of poverty, accomplishing the goal of eliminating absolute poverty. This achievement has ensured that people have achieved a level of prosperity primarily in terms of food, healthcare, education, and housing. The State Council Leading Group Office of Poverty Alleviation and Development of China stated in 2021 that the next step in poverty alleviation work is to consolidate and expand the achievements made in poverty alleviation efforts. However, it should be noted that China's definition of poverty-stricken areas primarily relies on single indicators such as income or consumption statistics obtained through local government reporting or household surveys (Huang et al., 2015). The differing statistical methodologies employed and the considerable financial and time costs associated with conducting these surveys pose challenges (Barrón-Cedeño et al.,2014). Furthermore, the time-consuming nature of these surveys limits their ability to reflect the spatial distribution pattern of poverty at a macro-level. Therefore, this doesn't mean the end of rural poverty, but a new beginning and a new stage for consolidating the results of poverty alleviation, eliminating multi-dimensional poverty including income, education and medical care, and alleviating relative poverty in the "post-poverty alleviation period".

Since Amartya Sen first proposed the theory of "Multi-dimensional Poverty" in 1981, the shift from a singular income-based approach to a multi-dimensional measurement and identification of poverty has become a consensus in poverty research. The most widely used multidimensional poverty measurement model abroad is the A-F model. Chinese scholars have constructed multidimensional poverty measurement indicators from various dimensions such as economics, health, healthcare, education, and environment. They have employed methods like principal component analysis and analytic hierarchy process (AHP) to determine weights, although they still heavily rely on economic data. The Sustainable Livelihoods Approach (SLA) has gradually been applied to multidimensional poverty research. This approach selects financial, human, ecological, material, and social capital to construct a "livelihoods pentagon," and some studies also incorporate ecological vulnerability to measure poverty from multiple perspectives. However, these approaches also face challenges regarding data availability and completeness. How to make use of the massive data of spatiotemporal geographic information and advanced technology to carry out quantitative identification, monitoring and evaluation of poverty reduction and development, supporting the enhancement of sustainable development is an important issue nowadays.

With the development of nighttime light remote sensing technology, a study in 2009 utilized the ratio of nighttime light data to population data to construct a poverty index for global poverty measurement (Elvidge et al., 2009). The research verified a significant correlation between nighttime light data and poverty, demonstrating that the use of nighttime light imagery allows for the objective identification of poverty's spatial distribution using a unified standard nationwide. Therefore, constructing a multi-dimensional poverty framework based on nighttime light data provides timeliness, objectivity, and accuracy in identifying impoverished areas. However, there has been limited research on poverty identification and measurement using nighttime light data both domestically and internationally, with even fewer studies focusing on the developmental status of poverty-stricken areas and limited temporal coverage. The concept of using nighttime light remote sensing data to study poverty was proposed in 2005 (Ebener et al., 2005). In 2008, a study confirmed a strong correlation between average light intensity at the provincial level in African countries and poverty indices (Noor et al, 2008). In 2009, the use of DMSP-OLS nighttime light data in conjunction with population data to construct a poverty index for global poverty measurement yielded promising results. In China, research on poverty using nighttime light data emerged later than in foreign countries, primarily focusing on poverty-stricken regions within China. Studies have examined the correlation between light intensity indicators and poverty at different scales (Pan and Hu,2016), employing various nighttime light datasets for poverty identification. However, most of these studies have been limited to the identification of poverty at a single time point, lacking long-term monitoring of the developmental trajectory in the research areas.

In this context, this paper intends to carry out research on multi-dimensional poverty identification and evolution analysis based on nighttime lights remote sensing data in Hebei Province with the support of statistics and geographic information technology, so as to achieve rapid and efficient identification of multi-dimensional poverty counties and provide auxiliary decision-making support for consolidating and expanding the achievements of poverty alleviation and the next step of poverty alleviation work.

2 STUDY AREA AND DATA USED

2.1 Study area

Hebei Province is located in the northern part of the North China Plain, ranging from 36° 05′ N to 42° 40′ N and 113° 27′ E to 119° 50′ E. It surrounds the capital city, Beijing, and is adjacent to Tianjin in the east, with the Bohai Sea nearby. The southeastern and southern parts of the province are bordered by Shandong and Henan provinces, while the west is connected to the Taihang Mountains and Shanxi. The northwest and north regions share borders with Inner Mongolia, and the northeast is adjacent to Liaoning. With its diverse topography, Hebei is the only province in China that encompasses plateaus, mountains, hills, plains, lakes, and coastline.

Despite its proximity to the capital, Hebei Province is home to a concentrated and contiguous poverty-stricken area known as the "poverty belt surrounding the capital." This belt spans the Bashang Plateau, as well as the deep mountainous areas of the Taihang Mountains, Yanshan Mountains, and Hengshan Mountains. In 2010, the National Development Work Key County List included 39 counties from Hebei Province. In 2014, the National List of 832 Poverty-stricken Counties listed 45 counties from Hebei Province. Since 2016, poverty-stricken counties in China have been gradually lifted out of poverty. According to the "List of Historical Poverty-stricken Counties among the 832 National Poverty-stricken Counties," released annually, by 2018, Hebei Province had only 13 remaining poverty-stricken counties. The distribution of the research area is illustrated in Figure 1.

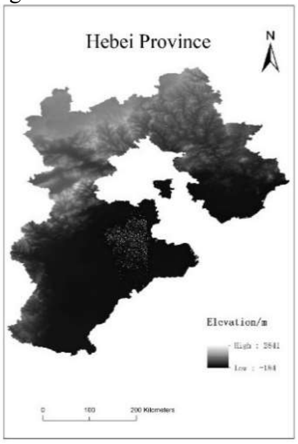


Figure 1 Study Area

2.2 DATA USED

The nighttime lights remote sensing data used in this study is sourced from the cross-sensor calibrated global 500-meter resolution "NPP-VIIRS-like" nighttime lights dataset for the years 2000 to 2018 (Chen et al, 2021). Due to variations in sensors, operational lifespans, and temporal scales of products, it is necessary to process and calibrate the data to ensure their compatibility. The "NPP-VIIRS-like" nighttime lights dataset not only converts the DMSP-OLS data prior to 2013 through saturation and temporal calibration into NPP-VIIRS-like annual composite data but also synthesizes the NPP-VIIRS monthly composite data from 2013 to 2018 into annual composite data. This provides a comprehensive and convenient long-term nighttime lights dataset for users of nighttime lights remote sensing data. As the nighttime lights data source covers the entire globe, the study area was clipped using the administrative planning data of Hebei Province as a mask through ArcGIS software, and the clipping result is shown in Figure 2.

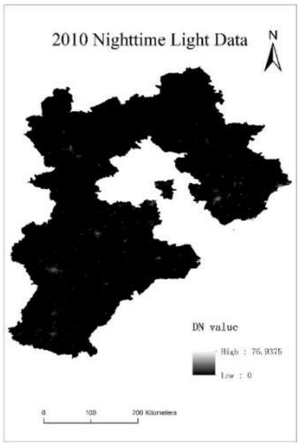


Figure 2 Pre-processed 2010 nighttime light data

The list of poverty-stricken counties was sourced from the official website of the National Rural Revitalization Bureau. Socio-economic statistical data was obtained from the "Hebei Rural Statistical Yearbook" as well as the statistical yearbooks and economic yearbooks of each city within the jurisdiction of Hebei Province. County-level administrative boundary data was acquired from GeoMap, and the Digital Elevation Model (DEM) data used was sourced from the 30-meter resolution ASTER

GDEM dataset provided by the Geographic Spatial Data Cloud. Prior to their utilization, the aforementioned datasets underwent preprocessing procedures such as georeferencing, clipping, and integration.

3 METHODOLOGIES

This study utilizes globally available 500-meter resolution "NPP-VIIRS-like" nighttime lights data, which has undergone cross-sensor calibration, in conjunction with socio-economic data. The analysis focuses on the years 2010, 2014, and 2018, examining various counties and county-level cities within Hebei Province. The multi-dimensional poverty measurement model is constructed using correlation coefficients, the Analytic Hierarchy Process (AHP), and the color correlation analysis method, aiming to identify areas of poverty. Furthermore, global Moran's I and Getis's G* statistics are employed to analyze the identified results, uncovering the spatiotemporal evolution patterns of poverty levels among Hebei Province's counties.

3.1 REGIONAL AVERAGE NIGHTTIME LIGHT INDEX(ANLI)

Research indicates that there is a stronger correlation between the regional ANLI and multidimensional poverty (Zhu et al., 2017). Therefore, a multidimensional poverty model is constructed based on the regional ANLI. The formula for calculating the regional ANLI is as follows:

$$\text{ANLI}=\sum_{i=1}^{n} DN_i/n \tag{1}$$

where DN_i = the brightness value of each pixel in the grid cell within the region
n = the total number of grid cells within that region

3.2 MULTI-DIMENSIONAL POVERTY INDEX(MPI)

Drawing from the AF method (Alkire and Foster, 2007) and previous research experience, we selected nine factors from the environmental, economic, and social dimensions as candidate indicators. These factors include average elevation, added value of the primary industry, general budgetary expenditure of local finance, regional gross domestic product, savings deposits of urban and rural residents, per capita disposable income of rural households, number of students in regular secondary schools, number of beds in hospitals and clinics, and number of beds in social welfare adoption units. To assess their correlation with the ANLI, we conducted a correlation analysis using Pearson's correlation coefficient. A threshold of 0.35 was used, and based on the analysis results, we eliminated the indicators of added value of the primary industry and the number of beds in social welfare adoption units.

The weights of the remaining seven indicators were calculated using the AHP method. AHP is a hierarchical analysis method that combines qualitative and quantitative aspects to simplify quantitative calculations when addressing problems. It generally involves the following four steps: (1) establishing a hierarchical structure model, (2) constructing pairwise comparison matrices, (3) performing hierarchical single ordering and consistency testing, and (4) conducting hierarchical total ordering and consistency testing.

In this study, the AHP method was applied to assign weights to the collected indicators of multidimensional poverty in order to construct the poverty identification model. Steps (3) and (4) were performed using SPSSAU software. During the experimental process, it is important to note that the values in the judgment matrices must be positive. In order to make the construction of the judgment matrices more scientific and objective, this study introduced the calculation of correlation coefficients.

When constructing the judgment matrices, the ratios of the correlation coefficients between each pair of indicators and the ANLI were used as the basis for judging the relative importance of the indicators. The judgment matrix based on the ratios is shown in Table 1. The correlation factor and weight distribution of each dimensional index are shown in Table 2.

Table 1 Judgment Matrix

	Rural and Urban Residents' Savings Deposit Balance / 10,000 RMB	**General Budget Expenditure of Local Finance / 10,000 RMB**	**Number of Students Enrolled in Regular Secondary Schools**	**Number of Hospital Beds and Clinic Beds**	**Gross Regional Product (GRP) / 10,000 RMB**	**Rural per capita disposable income / RMB**	**Average elevation / meters**
Savings Deposit Balance of Urban and Rural Residents / 10,000 RMB	1	1.370932755	1.821325648	1.373913043	0.98136646	0.905444126	1.736263736
General Budget Expenditure of Local Finance / 10,000 RMB	0.72943038	1	1.328530259	1.002173913	0.715838509	0.660458453	1.266483516
Number of Students Enrolled in Regular Secondary Schools / person	0.549050633	0.752711497	1	0.754347826	0.538819876	0.49713467	0.953296703
Number of Hospital Beds and Clinic Beds	0.727848101	0.997830803	1.325648415	1	0.714285714	0.659025788	1.263736264
Gross Regional Product (GRP) / 10,000 RMB	1.018987342	1.396963124	1.855907781	1.4	1	0.922636103	1.769230769
Rural per capita disposable income / RMB	1.10443038	1.514099783	2.011527378	1.517391304	1.083850932	1	1.917582418
Average elevation / meters	0.575949367	0.789587852	1.048991354	0.791304348	0.565217391	0.521489971	1

Table 2 Correlation factor and weight distribution of each dimensional index

Dimension	Index	Correlation factor	Weights
Environment	Average elevation / meters	-0.364	10.09%
Economy	Gross Regional Product / 10,000 RMB	0.644	17.86%
	General Budget Expenditure of Local Finance / 10,000RMB	0.461	12.78%
	Rural and Urban Residents' Savings Deposit Balance / 10,000 RMB	0.632	17.58%
	Rural per capita disposable income / RMB	0.698	19.36%
Society	Number of Students Enrolled in Regular Secondary Schools / person	0.347	9.62%
	Number of Hospital Beds and Clinic Beds	0.46	12.76%

Due to the subjectivity of the AHP, which is a subjective analysis method, and the fact that Grey Correlation Analysis reduces the subjective influence on results, it can provide a more accurate measurement of individual poverty levels (Ding, 2014). Grey Correlation Analysis is a method of multivariate statistical analysis that essentially measures the distance between two vectors and quantifies the correlation between them using mathematical methods. The basic idea is to normalize the original observed values of the evaluation indicators, calculate correlation coefficients and correlation degrees, and rank the evaluation indicators based on their correlation degrees.

Therefore, in this experiment, Grey Correlation Analysis is further employed to calculate the correlation coefficients between each multi-dimensional poverty indicator and the regional average light index, in order to determine the level of influence of each poverty indicator on the constructed multidimensional poverty model. The calculation formula is as follows:

$$\delta(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + e \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + e \max_i \max_k |x_0(k) - x_i(k)|} \quad (2)$$

where $x_0(\mathrm{k})$ = the characteristic sequence
$x_i(\mathrm{k})$ = the factor sequence
k = the sub-sequences
i = each individual indicator
e = the resolution, value= 0.5
$\delta(k)$ = the Grey Correlation coefficient

3.3 Coupled Regression Model of ANLI and MPI

The weights and Grey Correlation coefficients were determined using the AHP and Grey Correlation analysis, respectively, to establish the MPI as shown in equation (Wang and Fu, 2020):

$$MPI = \sum_{i=1}^{7} \delta(\mathrm{k}) * p_i \quad (3)$$

where p_i = the weight of the i indicator
i = the sequence of indicators

Due to the availability of comprehensive social-economic data for the counties and county-level cities within the study area in 2010, further investigation was conducted to explore the relationship between MPI and ANLI. The 2010 MPI values were selected to fit a regression model with the ANLI values. Linear, quadratic and cubic polynomial regressions were used to fit the regressions. As shown in Figure 3, the coefficient of determination R^2 reached 0.839, demonstrating that the constructed MPI correlates well with the regional ANLI. The fitting equation is as follows:

$$MPI = 0.921 + 0.157 * ANLI - 0.321 * ANLI^2 + 0.086 * ANLI^3 \quad (4)$$

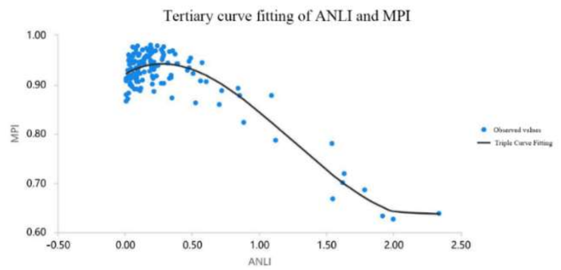


Figure 3 The regression results between MPI and ANLI for the year 2010

3.4 Spatial Autocorrelation Analysis

The introduction of global Moran's I and Getis's G* aims to explore the spatial evolution of poverty conditions in the research area based on the MPI identification results. Global Moran's I is an indicator that reflects the overall clustering pattern of the study objects. Its formula is as follows:

$$\mathrm{I} = \frac{\mathrm{n}}{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (5)$$

where n = the number of counties and county-level cities in Hebei Province
i, j = different counties
x_i, x_j = the MPI values of county i and county j, respectively
$\bar{x}$ = the average MPI value of all counties in Hebei Province
ω_{ij} = the spatial weight matrix that reflects the relationship between spatial units x_i and x_j. The spatial weight matrix is constructed using a first-order adjacency approach based on topological relationships. Specifically, if region i is adjacent to region j, ω_{ij} is set to 1; otherwise, it is set to 0 (Chen et al., 2011).

At a given significance level, if the Moran's I value is positive, a larger value indicates a stronger positive spatial correlation. Conversely, if the Moran's I value is negative, a smaller value indicates a stronger negative spatial correlation (Tang et al., 2012).

Getis's G*, also known as hotspot analysis, is used to identify types of clustering and utilizes the Z-score and p-value as statistical measures. When the p-value is relatively small, a high Z-score suggests a spatial cluster of high values, while a low Z-score suggests a spatial cluster of low values (Zhu et al., 2017).

4 RESULTS AND DISCUSSION

4.1 Multi-dimensional poverty identification results for each county in the study area

Using ArcGIS software, the geometric interval method was employed to classify the MPI values of each county in Hebei Province. Referring to existing literature (Pan and Hu, 2016), the counties in Hebei Province were classified into seven categories: extremely poor areas, deprived areas, disadvantaged areas, general areas, advantageous areas, affluent areas, and extremely affluent areas. The MPI values for the years 2010, 2014, and 2018 were visualized. Figure 4 presents the results obtained from the identification of the multi-dimensional poverty system in 2014. It can be observed that there were 9 identified extremely poor areas, 15 deprived areas, and 22 disadvantaged areas. In comparison with the national poverty line criteria, among these three categories, a total of 18 nationally designated poverty counties were identified. However, it should be noted that there were 45 national poverty counties in Hebei Province in 2014, indicating a relatively low accuracy of identification and a small number of national poverty counties included in the identified extremely poor areas. Nonetheless, the well-known poverty belt surrounding the capital region is clearly depicted in Figure 4.

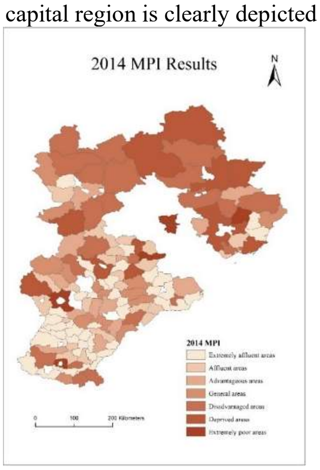


Figure 4 The results of multidimensional poverty identification for each county in Hebei Province in 2014

Table 3 Identification results of MPI

Identification results of MPI for the year 2010			
Extremely poor areas	Poverty Areas	Weak areas	Total number of identified poverty-stricken counties
10	28	31	24
Identification results of MPI for the year 2014			
Extremely poor areas	Poverty Areas	Weak areas	Total number of identified poverty-stricken counties
9	15	22	18
Identification results of MPI for the year 2018			
Extremely poor areas	Poverty Areas	Weak areas	Total number of identified poverty-stricken counties
6	6	25	6

The results of poverty-stricken county identification based on the ranking of MPI values using the geometric interval method in Table 3 indicate poor accuracy. Therefore, an investigation is conducted to establish the origin of MPI and the recognition of poverty-stricken counties using ANLI. Similarly, the ArcGIS software is employed to apply the geometric interval method for color classification of ANLI values in each county of Hebei Province. Referring to existing literature, the counties are classified into five categories: extremely low, relatively low, medium, high, and extremely high. The visualization of poverty-stricken county identification based on ANLI results is presented for the year 2014, as shown in Figure 5.

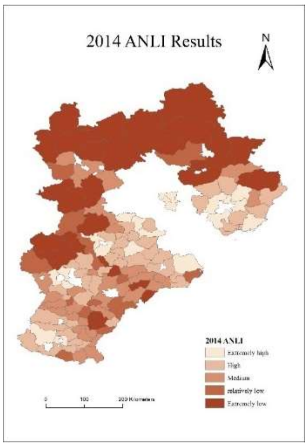


Figure 5 Identification results of poverty-stricken counties based on ANLI in each county of Hebei Province in 2014

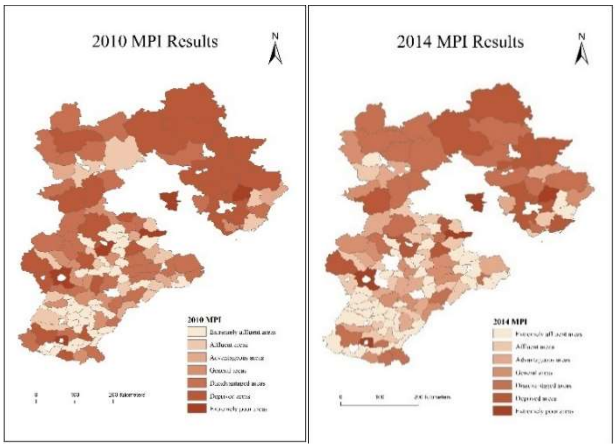
It can be observed from the graph that the poverty belt around the capital is clearly visible. However, based on the identification results, there are 44 poverty-stricken counties identified as "extremely low" based on ANLI values, which is only 1 less than the officially reported number of 45 national poverty-stricken counties. Among them, 32 national poverty-stricken counties were identified.

Table 4 ANLI recognition results

2010 ANLI Identification Results	
Very low number	Identification of poor counties
45	26
2014 ANLI Identification Results	
Very low number	Identification of poor counties
44	32
2018 ANLI Identification Results	
Very low number	Identification of poor counties
41	13

It can be observed in Table 4 that the ANLI can indeed accurately identify national poverty-stricken counties, but it also has the potential to misclassify non-national poverty-stricken counties as national poverty-stricken counties, and vice versa. The reason for this lack of accuracy may be due to the blind classification into 7 intervals based on previous experiences, which may not be suitable in practice. As a result, poverty identification based on ANLI values also has certain deviations.

4.2 Temporal evolutionary characteristics of multi-dimensional poverty by counties and districts in Hebei Province



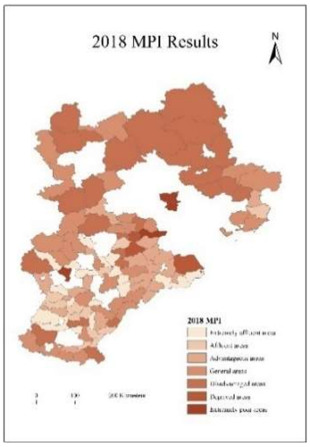


Figure 6(a)-6(c) 2010/2014/2018 MPI Identification Results

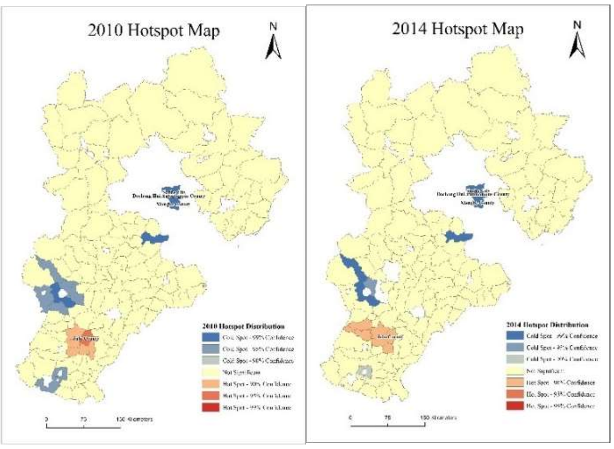
As shown in Figure6(a)-(c), from the overall analysis of the poverty distribution over the three time periods, it can be observed that there haven't been significant changes in the spatial distribution of poverty-stricken counties in the span of 8 years. The poverty-stricken areas are primarily concentrated in a belt-like pattern in the northern part of Hebei Province. However, when considering the temporal scale, there is a gradual improvement in the poverty situation over the years. It is evident that the northern belt region has transitioned from being extremely impoverished and impoverished areas in 2010 to weaker areas and general areas, highlighting the effectiveness of the poverty alleviation efforts over the 8-year period.

4.3 Spatial evolutionary characteristics of multidimensional poverty by county and district in Hebei Province

By utilizing global Moran's I and Getis's G* statistics, we explored the spatial evolution of poverty conditions in the study area based on the MPI identification results. According to the analysis results of Moran's I presented in Table 5, it can be observed that there is spatial clustering of poverty in Hebei Province. However, the degree of clustering is not substantial, indicating that the spatial distribution of poverty is not highly concentrated.

Table 5 Moran's I analysis results

Time	Moran's I	Standard Deviation (SD)	Normal value (z-value)	Space pattern
2010	0.243793	0.002812	4.735167	Gathering
2014	0.225295	0.003014	4.238901	Gathering
2018	0.298875	0.003863	4.931315	Gathering



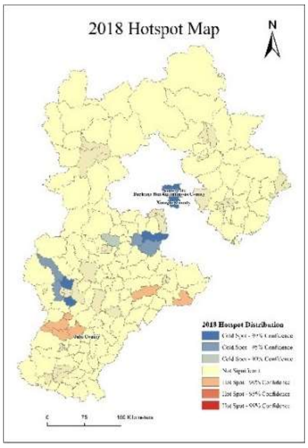


Figure 7(a)-7(c) 2010/2014/2018 Hotspot Distribution

As shown in Figure 7(a)-7(c), the hotspots identified in 2010 in Julu County and surrounding counties gradually transformed into sub-hotspots and expanded eastward and westward. The distribution of coldspots remained relatively stable. Three cities, namely Sanhe City, Xianghe County, and Dachang Hui Autonomous County, which are separated from the rest of Hebei Province, consistently remained coldspots. Other areas experienced a decrease in the extent of coldspots, but there was an increasing trend in sub-coldspots.

From the analysis results, it can be observed that the poverty level of traditionally designated national poverty counties has shown some alleviation over the 8-year period. However, the spatial clustering pattern of these areas has remained unchanged. Attention should be paid to the poverty status of the three counties and county-level cities—Sanhe City, Xianghe County, and Dachang Hui Autonomous County—which are geographically separated from most of Hebei Province. Additionally, the poverty belt formed in the northern region, known as the "poverty belt around the capital," has experienced a reduction in poverty levels over time and does not exhibit significant spatial clustering. Nevertheless, it remains a focal point for poverty alleviation efforts.

5. CONCLUSIONS

This paper carried out research on multi-dimensional poverty identification and evolution analysis based on night lights remote sensing data in Hebei Province with the support of statistics and geographic information technology. Based on the cross-sensor calibration global 500-meter resolution "NPP-VIIRS-Like" nighttime light data in 2010, 2014 and 2018, using correlation coefficients and hierarchical analysis to construct the Multi-dimensional Poverty Index (MPI), carried out county-level MPI calculations in Hebei Province as an example to verify the accuracy of the model. GIS technology is used to visualize the results of poverty counties identified by the model to explore the temporal evolution. The global Moran's I and Getis's G* are introduced to explore the spatial evolution.

From the experimental results, MPI established in this paper fits well with ANLI, and the discriminant coefficient R^2 reaches 0.839, which can be used for poverty identification and monitoring. The established multi-dimensional poverty model can identify multi-dimensional poverty counties better. However, there is a large discrepancy in the match with the traditional list of poor counties issued by the state from the perspective of absolute economic poverty. From the perspective of spatiotemporal evolution, it can be seen that the overall poverty level in Hebei Province has changed with time. Although there is aggregation among poverty areas, the aggregation is not deep. The poverty level of the traditional national-level poor counties has also been reduced, but the pattern of poverty aggregation remains unchanged. The "C-shaped" poverty belt around the capital (Beijing) formed by Chengde, Zhangjiakou, Baoding and other surrounding counties in northern Hebei Province is still the focus of poverty alleviation work in the next stage.

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