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Identification of Relative Poverty Based on 2012–2020 NPP/VIIRS Night Light Data: In the Area Surrounding Beijing and Tianjin in China

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Abstract: As absolute poverty in China, measured by the current standard, is being eliminated, the focus of future poverty reduction projects will necessarily shift to addressing relative poverty. Contiguous poverty areas have been identified in Hebei province around Beijing and Tianjin (HABT), and this is not conducive to the coordinated development of the Beijing-Tianjin-Hebei region. The dynamic identification of relative poverty at the county level within the region must be the basis for formulating scientific strategies for poverty reduction. Night light (NTL) data can reveal socio-economic information and reflect human activities, and has a wide range of other applications for evaluating and identifying poverty. For this reason, NPP/VIIRS (Visible Infrared Imaging Radiometer Suite equipped on the Suomi National Polar orbiting Partnership satellite) NTL data from 2012 to 2020 were corrected, and NTL data for HABT were obtained. A multidimensional relative poverty index (MRPI) that assesses being "free from worries over food and clothing and having access to compulsory education, basic medical services, and safe housing" using social statistical data was created with the analytic hierarchy process and entropy weight method. A panel regression model with fixed effects was established for MRPI and corrected NPP/VIIRS NTL data. The R^2 of fitting was 0.6578 and confirmed a strong correlation between MRPI and corrected NPP/VIIRS NTL data. Based on this, the MRPI estimation model was constructed based on the MRPI and corrected NPP/VIIRS NTL data, and passed the accuracy test. Finally, using the national list of poverty counties, it was verified that, at the county scale, the corrected NPP/VIIRS NTL data could effectively identify areas of relative poverty. This study lays the foundation for the use of NPP/VIIRS NTL data in the identification of areas of relative poverty. It provides a feasible method and data reference for analyzing relative poverty at a smaller scale. The dynamic identification of areas of relative poverty can also provide a basis for formulating scientific poverty reduction strategies.

Keywords: NPP/VIIRS NTL data; relative poverty; multidimensional relative poverty index; the county scale; Hebei province around Beijing and Tianjin

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1. Introduction

Poverty is a long-term dilemma that governments face worldwide in the 21st century, especially in developing countries [1]. The elimination of absolute poverty and reduction in relative poverty are the primary goals of the Sustainable Development Goals (SDGs) set forth by the United Nations [2,3]. China began to implement reforms and opening up more than 40 years ago and has achieved sustained development [4,5]. From 2012 to 2019, the number of people living in poverty in China decreased from 98.99 million to

5.51 million, and the incidence of poverty decreased from 10.2% to 0.6% [6]. In December 2020, China achieved its "poverty eradication" targets. In addition, 832 poverty-stricken counties in China have been lifted out of poverty, absolute poverty has been eliminated, and poverty reduction targets, set by the United Nations 2030 Agenda for Sustainable Development for eliminating extreme poverty, have been achieved, 10 years ahead of schedule [6]. These achievements laid the foundation for constructing a moderately prosperous society and achieving common prosperity for Chinese citizens [7]. The Chinese government [8] set the goal to "Resolutely win the battle against poverty, consolidate the achievements of poverty alleviation, and establish a long-term mechanism to address relative poverty". According to this orientation, China's poverty alleviation work is intended to shift from eliminating absolute poverty to alleviating relative poverty [6]. However, within China's overall rapid economic development, its regional economic development has become unbalanced [6,9]. A survey conducted by the Asian Development Bank found that, around the cities of Beijing and Tianjin, where the economy has always shown rapid economic development, poverty-stricken areas are concentrated in Hebei Province [10,11]. To implement the coordinated development of Beijing-Tianjin-Hebei in the new era, it is necessary to evaluate and identify the areas of relative poverty in Hebei province around Beijing and Tianjin (HABT). Evaluating and accurately identifying relative poverty is an important precondition for the Chinese government to formulate a reasonable policy of poverty alleviation.

Absolute and relative poverty differ from each other, but they are also interdependent [12]. As the economy and society have developed, scholars' focus on poverty has shifted from absolute to relative poverty [13]. Basic needs are at the center of the concept of absolute poverty. The World Bank defined absolute poverty in 1981 [14] and 1990 [15] as the inability to reach a minimum standard of living. Relative poverty measures the income imbalance of different groups in a society, which is related to the income of different groups, in addition to social equity and self-identity [16]. Fuchs (1967) [17] first proposed the concept of relative poverty, which stated that if a person or family's living conditions were lower than the average social level to a certain extent, they could be considered as being in a state of relative poverty. Absolute poverty can be eliminated through poverty alleviation, but relative poverty exists at any stage of social development [6,18,19]. Based on existing research, the conditions of absolute poverty and relative poverty can be summarized as follows: Absolute poverty refers to "subsistence poverty", that is, under certain circumstances, individuals or families cannot maintain their basic living needs by relying on their labor income and other legal income. Relative poverty does not mean the lack of the basic needs to maintain life, but refers to the state in which the resources related to the economy, life, education, medical care, social security, and other aspects owned by some members of society are obviously lower than the average level of resources controlled by other members of society. In the contemporary era, China's poverty alleviation work focuses on alleviating relative poverty, which reflects regional inequalities [4,6,7]. This requires the development of standards for evaluating relative poverty.

Previous studies have shown two main methods for measuring poverty. The first is to measure poverty based on one-dimensional indicators. The advantages of this approach are its simplicity and easy accessibility to data. One of the disadvantages of one-dimensional indicators is that they cannot truly reflect poverty [20]. In addition, it is difficult to fully reflect the complexity, persistence, and vulnerability of relative poverty by such means. The second set of measures are multidimensional assessments of poverty. Sen (1981) [21] first proposed the concept of multidimensional poverty in 1981. In 2010, the UNDP [22], together with the Oxford Poverty and Human Development Center (2010), constructed the Multidimensional Poverty index (MPI). The MPI is measured by ten specific indicators across the three dimensions of health, education, and living standards. MPI has also been recognized as a valuable tool by many scholars and has been widely used as a reference [23–25]. Multidimensional poverty is an important approach to measuring relative poverty. The results of the MPI are closely associated with relative poverty [26]. Studies by

Chinese scholars [4–8,27,28] show that, although the poverty alleviation departments of the Chinese government did not explicitly announce the adoption of multidimensional poverty standards, multidimensional poverty alleviation strategies and measurements have clearly been applied in the treatment of relative poverty [29–31]. Relative poverty is identified and assessed with multidimensional instruments based on statistical data, and this approach has achieved good results. Thus, this study used MPI to measure relative poverty.

However, studies using socio-economic statistical data have obvious shortcomings [28,32,33], such as the minimum statistical scale of statistical data is the county unit, and it is difficult to monitor relative poverty at the township level. Moreover, the acquisition of statistical data is difficult and takes a long time, and it is not convenient to monitor small-scale relative poverty in a timely manner. In turn, this is not conducive to the formulation of relative poverty alleviation strategies according to local conditions. Since NTL data can reflect comprehensive information, such as economic growth [34], human activities [35], urban development [36], energy consumption [37], and carbon emissions [38], it encompasses transportation, roads, economic development, population change, urban expansion, and other information closely related to human development. As a result of the development of NTL data and related analysis techniques, NTL data has been used prominently in the field of poverty monitoring [39].

Currently, three main types of NTL data are used in poverty research. These are the Program's Operational Linescan System (DMSP/OLS); the Visible Infrared Imaging Radiometer Suite equipped on the Suomi National Polar-orbiting Partnership satellite (NPP/VIIRS); and the LuoJia1-01 satellite launched in June 2018. However, DMSP/OLS NLT data have defects such as the lack of online calibration, insufficient spatial resolution, oversaturation of the signal (the NLT value in the urban center remains unchanged) [32], and having only a single band [40]. In addition, the spatial resolution of DMSP/OLS NLT data is only 1000 m, which means it cannot meet the needs of in-depth analysis. More importantly, DMSP/OLS NLT data have not been available since 2013 [33]. Although Luojia-1 has a finer spatial resolution (130 m) [33], the data provided by the satellite cannot provide the long-term sequence required for research before 2018. Unlike DMSP/OLS, NPP/VIIRS NLT data are a better choice due to their higher spatial resolution (500 m) [32,40]. In contrast to the Luojia-1 date, the NPP/VIIRS NLT data are available from 2012 to the present, which meets the long-term research requirements. Therefore, many scholars have used NPP/VIIRS NLT data to evaluate poverty.

Studies of poverty in China using NPP/VIIRS NTL data can be divided into two main categories. The first verifies the accuracy of poverty estimates using the NPP/VIIRS NTL data with statistical multidimensional assessments as a baseline. Previous work [5,28,32,40] identified multidimensional poverty at the county level using NPP/VIIRS NTL data for a single year. The authors [41,42] did so with NPP/VIIRS NTL data for consecutive years. Another group of studies combined NPP/VIIRS NTL data with other geographic or statistical indicators to enable the application of an MPI. The authors [2,43] used NPP/VIIRS NTL data from 2015 to establish an integrated MPI. Yin (2021) [44] combined NPP/VIIRS NTL data and geographic environment remote sensing data from 2012 to 2019 to identify counties with greater poverty.

Two main problems have arisen in the existing poverty research based on NPP/VIIRS NTL data. First, the NPP/VIIRS NTL data used by most research institutes covers a single year. This characteristic depends on the data provided by NPP/VIIRS, as 2015 and 2016 data are provided as annual data, and the data for other years are monthly data. This limits the spatiotemporal analysis of the poverty areas. Second, most existing long-sequence NPP/VIIRS NTL data on poverty studies are intended to support absolute poverty analysis. At present, China needs to formulate a countermeasure against relative poverty. This paper investigates whether NTL data can evaluate and provide spatial identification of relative poverty and whether the results are accurate.

The purpose of this study was to establish an MRPI calculation model from a multidimensional perspective in view of China's poverty alleviation goals in the new era. An MRPI estimation model was established using the corrected nighttime light data to verify the accuracy of this data in estimating relative poverty. Finally, for the monitoring of relative poverty at the township scale, where statistical data is lacking, feasible methods and data references are proposed. The results of this study broaden the scope of application of NTL data and provide a basis for the analysis of relative poverty of NTL data. The dynamic identification of relative poverty in the HABT is conducive to formulating scientific and effective poverty reduction strategies.

2. Study Area and Methodology

2.1. Study Area

In 2010, the Hebei provincial government published a map of HABT that included six regions, including Langfang city, Baoding city, Zhangjiakou city, Chengde city, Tangshan city, and Cangzhou city. This defines the geographical area of HABT.

The county is the basic unit of poverty assessment [32], and this study follows this by using the county as the unit scale of relative poverty to identify the areas of relative poverty. HABT contains 73 counties/cites (excluding municipal districts). The distribution of counties is as follows: 8 in the city of Langfang, 22 in the city of Baoding, 13 in the city of Zhangjiakou, 8 in the city of Chengde, 8 in the city of Tangshan, and 14 in the city of Cangzhou. The specific distribution is shown in Figure 1.

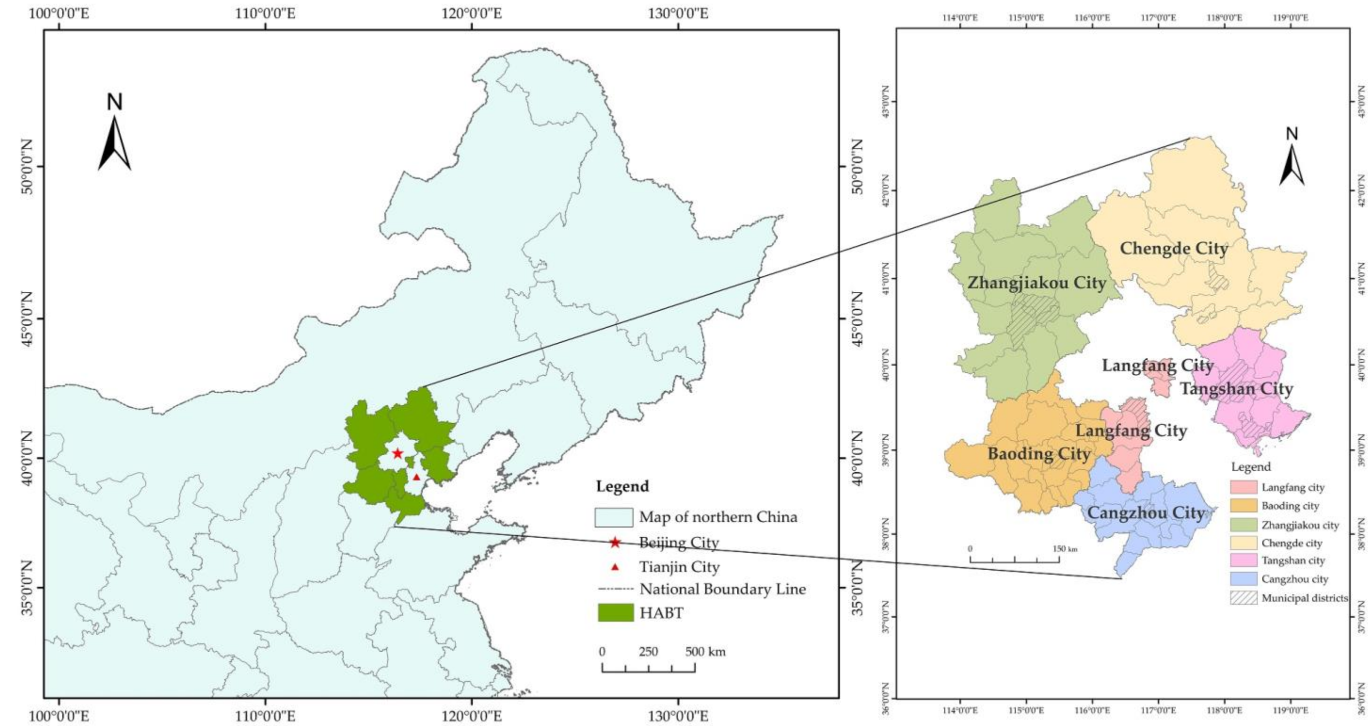

Figure 1. County distribution in HABT.

2.2. Index Selection of Relative Poverty

In the early stage of poverty governance, the measure of absolute poverty in China was based on per capita income [45]. At present, absolute poverty has been eliminated and the task of poverty alleviation has shifted to alleviating relative poverty; however, academia has not reached a unified consensus on relative poverty standards. In order to identify relative poverty, the establishment of a multidimensional relative poverty standard is urgently needed. Chinese scholars have attempted to construct relative poverty systems using different dimensions, and most studies referred to MPI [46], which was proposed by the United Nations Planning and Development Agency. This index measures the three dimensions of health, education, and life. The Chinese government's new poverty alleviation target is "By 2020, the poverty alleviation targets are free from worries over food and clothing and have access to compulsory education, basic medical services and safe housing [47]". In terms of quality of life, education, medical care, and social security, the index shows that China's current poverty alleviation goal is not just to solve the problem of survival, but to focus on the self-development of relative poverty groups. Based on this criterion, taking into account the availability of statistical data, 13 indicators were selected from the five dimensions of economy, living quality, education, health care, and social security to establish an MRPI for HABT. This study evaluated and identified the relative poverty of HABT from a multidimensional perspective. The specific index selection is shown in Table 1.

Table 1. Index selection of MRPI.

Dimension	Indicators	Indicators Explanation
Economy	Per capita GDP	County GDP/county population
	Per capita fiscal revenue	General public budget revenue/county population
	The employment rate	Employees/county population
Living quality	Per capita output of grain	Total grain output/county population
	Tap water benefit village rate	Villages benefiting from tap water/ number of villages
	Mobile Phone subscriber rate	Mobile phone subscribers/county population
	Density of road network	Road mileage/county area
Education	Teaching faculty	Total number of teachers/students
	Education level	Total number of students/county population
Health care	Number of beds in health facilities	Number of medical beds/10,000 citizens
	Proportion of medical technicians	Medical staff/county population
Social security	Basic medical insurance participation rate	Number of basic medical insurance participants/county population
	Basic endowment insurance participation rate	Number of basic endowment insurance participants/county population

2.3. Data Sources

2.3.1. NPP/VIIRS NTL Data

The NPP/VIIRS NTL data from 2012 to 2020 were obtained from the website https://eogdata.mines.edu/products/vnl/, accessed on 10 January 2022. Among these, 2015 and 2016 data were annually synthesized. The annual composites were only made using the vcm version, which excludes any data impacted by stray light. Monthly composite data are available for 2012, 2013, 2014, 2017, 2018, 2019, and 2020. Two versions of the monthly data [48] are provided, namely, vcm and vsmsl. The vcmsl version, which provides data corrected for stray light, has more data coverage toward the poles, but its data has reduced quality. Due to consideration of data consistency and continuity, the vcm version was used for both annual and monthly data.

2.3.2. Social Statistics

The MRPI was established based on social statistics, and specific indicators are shown in Table 1. All data were collected from 2012 to 2019, and were at the county scale. In addition, the county GDP information was derived from the China County Statistical Yearbook (https://data.cnki.net/area/Yearbook/Single/N2021050065?dcode=D26, accessed on 10 January 2022). The employment rate came from the statistical yearbooks for the six target cities. All other data were drawn from the Hebei Economic Yearbook and the Hebei Statistical Yearbook (http://tjj.hebei.gov.cn/res/nj2019/zk/indexch.htm, accessed on 10 January 2022). To ensure the integrity of data, data were collected from 71 counties/cites, for a total of 568 samples. In total, 14 gaps in the data were filled using the mean value.

2.4. Methodology

2.4.1. MRPI

According to the weights and standardized values of the above indexes, MRPI in counties in HABT was established. The specific calculation is shown in Formula (1):

$$MRPI = \sum_{i=1}^{n} w_i \times a_i \quad (1)$$

where, *MRPI* is the multidimensional relative poverty index. i is some index from 1 to n. w_i is the weight value of the ith index, obtained by the entropy weight method. a_i is the standardized value of each index.

2.4.2. Analytic Hierarchy Process

Analytic hierarchy process is a commonly used subjective weighting method, abbreviated as AHP. Analytic hierarchy process (AHP) decomposes the decision-making problem into different elements, and the elements are combined according to the correlation and affiliation to form a multi-level analysis structure from the overall objective to each level of the sub-objectives. Thus, the decision-making problem can be reduced to the determination of the relatively important weight from the lower level to the highest level.

In this study, a fuzzy consistent matrix was used as the judgment matrix of analytic hierarchy process, and the specific calculation steps are as follows.

Step 1: Build a hierarchy model. Using the top-down method, the multidimensional poverty indicators are divided into three layers. From top to bottom, they are the target layer, the criterion layer, and the indicator layer, and each layer of indicators belongs to its upper layer.

Step 2: Starting from the criterion layer, determine the weights of the indicators of each layer by pairwise comparison and construct the complementary judgment matrix. The general representation of the complementary judgment matrix is shown in Formula (2):

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \cdots & \cdots & \cdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, a_{ij} = 1 - a_{ji}. \quad (2)$$

The value description of a_{ij} in the formula is shown in Table 2.

Table 2. A scale of relative importance between peer indicators.

Scaling	Definition
0.5	equally important
0.6	slightly important
0.7	obviously important
0.8	much more important
0.9	extremely important

Step 3: Transform the complementary judgment matrix into a consistency matrix. The calculation method of the consistency matrix is shown in Formulas (3) and (4):

$$a_{ij} = \sum_{k=1}^{n} a_{ik}, i = 1, 2, \cdots, n \quad (3)$$

$$a_{ij} = \frac{a_i - a_j}{2n} + 0.5 \quad (4)$$

Step 4: According to the consistency matrix, the weight value of each level index relative to the previous level index is calculated using the comparative weight of the index. The specific calculation is shown in Formula (5).

$$g_i^k = \frac{1}{n} - \frac{1}{2c} + \frac{\sum_{j=1}^{n} a_{ij}}{nc}, (i = 1, 2, \cdots, n) \quad (5)$$

In the formula, $c = (n-1)/2$, and k is the number of index layers.

2.4.3. Entropy Weight Method

The entropy weight method is objective, and the index weight is determined by the data without interference from human factors [49].

Firstly, the selected indicators should be normalized. Since the selected indicators are all positive indicators, the standardized formula of the range method is shown in Formula (6):

$$a_{ij} = \left[x_{ij} - \min(x_{ij})\right] / \left[\max(x_{ij}) - \min(x_{ij})\right] \tag{6}$$

where, x_{ij} is the statistical value of each indicator.

Then, the entropy weight method is used to determine the weight of each index after standardization, and the specific steps are shown in Formulas (7)–(9):

$$p_{ij} = a_{ij} / \sum_{i=1}^{n} a_{ij} \tag{7}$$

$$e_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{8}$$

$$w_i = d_j / \sum_{j=1}^{m} d_j \tag{9}$$

where, j is the number of index items (j = 1, 2 ... ,m). i is the research object (i = 1, 2 ... ,n). a_{ij} is the standardized value of the jth index of the ith sample. p_{ij} is the proportion of the ith sample value of the jth index in the modified index. e_j is the entropy value of the jth index, $k = 1/\ln(n)$. w_i is the weight value of item i. d_j is the poverty measurement dimension of item j, which satisfies $e_j \geq 0$ and makes $d_j = 1 - e_j$.

2.4.4. Fixed Effect Models

The general form of the panel data model is shown in Formula (10):

$$y_{it} = \sum_{k=1}^{K} \beta_{ki} x_{kit} + u_{it} \tag{10}$$

where $i = 1,2,3,\ldots,N$, represent individual. $t = 1,2,3,\ldots,T$ represent time-points. y_{it} is the observed value of the explained variable to individual i at time-point t. x_{kit} is the observed value of the kth non-random explanatory variable for individual i at time-point t. β_{ki} is the parameter to be estimated. u_{it} is the random error term. This is expressed by the matrix, as shown in Formula (11):

$$Y_i = X_i \beta_i + U_i \ (i = 1,2,3,\ldots,N) \tag{11}$$

Fixed effect models are divided into three types [50]; The details are as follows.

The individual fixed effect model is a model with different intercept terms for different time series (individuals), as shown in Formula (12).

$$y_{it} = \lambda_i + \sum_{k=2}^{K} \beta_k x_{kit} + u_{it} \tag{12}$$

The time-point fixed effect model is a model with different intercepts for different sections (time-points) , as shown in Formula (13).

$$y_{it} = \gamma_t + \sum_{k=2}^{K} \beta_k x_{kit} + u_{it} \tag{13}$$

The time-point individual fixed effect model is a model with different intercepts for different sections (time-points) and different time series (individuals), as shown in Formula (14).

$$y_{it} = \lambda_i + \gamma_t + \sum_{k=2}^{K} \beta_k x_{kit} + u_{it} \tag{14}$$

2.4.5. Error Test

The relative error (RE) and average relative error (ARE) are used to test the error of MRPI. The calculation formula of the error test is shown in Formulas (15) and (16):

$$RE = (MRPI_e - MRPI_d)/MRPI_d \times 100\% \quad (15)$$

$$ARE = \sum_{i=1}^{n} |(RE)_i|/n \quad (16)$$

where RE is the relative error and ARE is the average relative error. $MRPI_e$ is the MRPI estimated using NTL data at the county level. $MRPI_d$ is the MRPI calculated by statistical data of the county. n is the number of counties.

3. Results

3.1. NPP/VIIRS NTL Data Correction

The NPP/VIIRS NTL data include annual and monthly data. The annual data are for 2015 and 2016. Monthly data are for 2012–2014 and 2017–2020. In order to maintain data consistency, the vcm version was selected. The correction of NPP/VIIRS data includes the following six steps [51].

(1) Annual synthesis of monthly NTL data

In order to maintain the consistency of data, monthly lighting data were averaged for fusion processing. The monthly data of NPP/VIIRS were imported from 2012–2014 and 2017–2020 into ArcGIS 10.4.1 software, the "cell statistics" in "Spatial Analyst Tools" were used to calculate the average value, and the annual data of the corresponding year were synthesized. Finally, NPP/VIIRS NTL data for 2012–2020 were obtained.

(2) Reprojection and resampling

The "projection transformation" function in ArcGIS software was used to convert the 2012–2020 VIIRS/NPP data into the "Albers Equal Area Conic" projection. The relevant parameters were set to: Central_Meridian: 105.0, Standard_Parallel_1: 25.0, Standard_Parallel_2: 48.0, Latitude_Of_Origin: 0.0. The resampling was 1 km × 1 km spatial resolution.

(3) Cutting

In order to observe whether the DN value of nighttime light data is consistent with the economic development of China, the nighttime light data were clipped for China. "Extraction—Extract by Mask" in ArcGIS software was used to cut the reprojection and resampling images to obtain the annual synthetic NTL data of Chinese administrative boundaries. The initial DN value is shown in Figure 2. Abnormal fluctuations are shown in the data, and further correction was thus required.

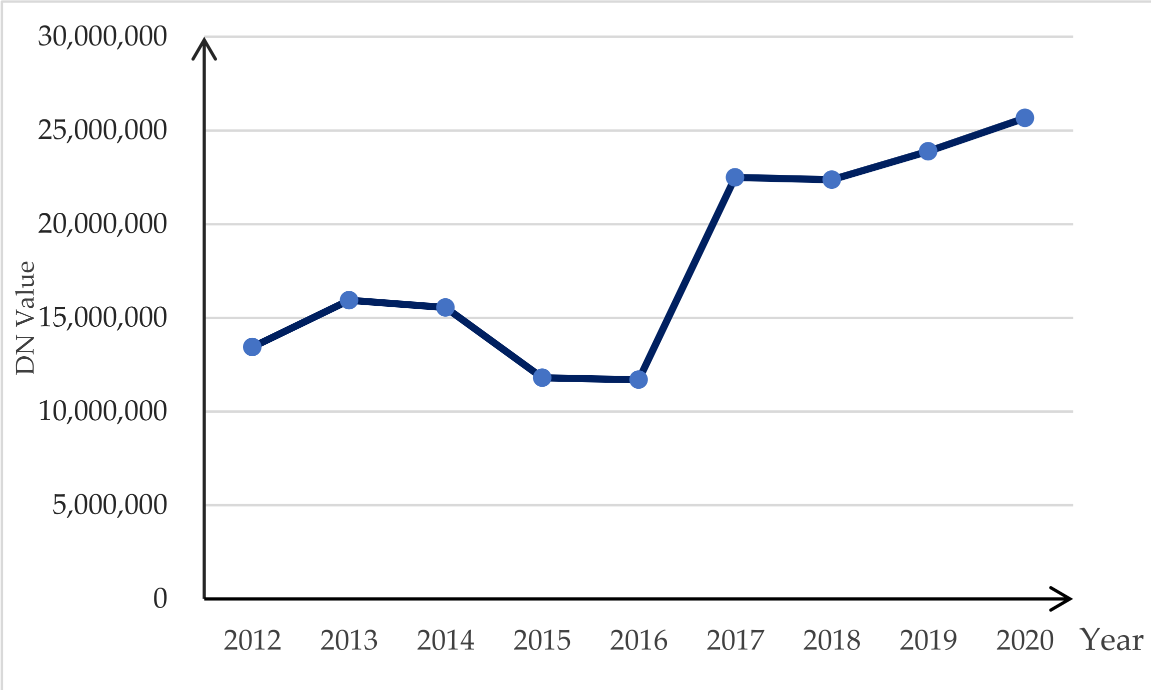

Figure 2. The DN value of the initial NPP/VIIRS.

(4) Stability correction

IIn order to reduce the influence of the background noise in the NPP/VIIRS NTL data, the NPP/VIIRS NTL data in 2016 were chosen as the constant area. The "con()" statement in the "raster calculator" in **ArcGIS** software was used to binarize the NPP/VIIRS NTL data in 2016 according to Formula (17).

$$\mathrm{DN}_{2016} = \begin{cases} 1, \mathrm{DN}_{2016} > 0 \\ 0, \mathrm{DN}_{2016} \leq 0 \end{cases} \tag{17}$$

The binarization result was multiplied with the data of other years to correct the stability of the data of other years. The correction formula is shown in Formula (18):

$$\mathrm{DN}_{(n,i*)} = \mathrm{DN}_{(2016,i>0)} \times \mathrm{DN}_{(n,i)} \tag{18}$$

where $n = 2012, 2013, 2014, 2015, 2017, 2018, 2019, 2020$, $\mathrm{DN}_{(n,i)}$ is the DN value of the ith pixel in the nth year. $\mathrm{DN}_{(n,i*)}$ is the DN value after stability correction in the nth year. $\mathrm{DN}_{(2016,i>0)}$ is the binarized value in 2016.

(5) Elimination of outliers

Observing the data after stability correction, the lowest value of some years was negative. According to Formula (19), negative values were normalized to 0 with the "raster calculator":

$$\mathrm{DN}_{(n,i*)} = 0, \text{when } \mathrm{DN}_{(n,i*)} < 0 \tag{19}$$

where n is the year in which the lowest value is negative. $\mathrm{DN}_{(n,i*)}$ is the DN value after stability correction in the nth year.

(6) Time series correction

The basic assumption of the time series correction is that the NPP/VIIRS NTL data are in a state of continuous diffusion and enhancement, which is consistent with China's rapid social and economic development. Therefore, it was necessary to ensure that the earlier DN values were not greater than the later DN values. For unstable pixels that were missing in some images, their DN value was replaced with 0. The calibration process is shown in Formula (20):

$$\begin{cases} \mathrm{DN}_{(n,i)} = 0, & DN_{(n+1,i)} = 0 \\ \mathrm{DN}_{(n,i)} = \mathrm{DN}_{(n-1,i)}, & \mathrm{DN}_{(n+1,i)} > 0 \text{ and } \mathrm{DN}_{(n-1,i)} > \mathrm{DN}_{(n,i)} \\ \mathrm{DN}_{(n,i)} = \mathrm{DN}_{(n,i)}, & \text{other} \end{cases} \quad (20)$$

$\mathrm{DN}_{(n-1,i)}$, $\mathrm{DN}_{(n,i)}$ and $\mathrm{DN}_{(n+1,i)}$ are, respectively, the DN value of pixel i after time series correction in the $(n-1)$th year, the nth year, and the $(n+1)$th year, respectively.

After the above data correction process, the corrected NPP/VIIRS NTL data of China from 2012 to 2020 were obtained. The DN values of the corrected NPP/VIIRS NTL data are shown in Figure 3. The corrected NPP/VIIRS NTL data rise steadily, which is consistent with China's social development reality.

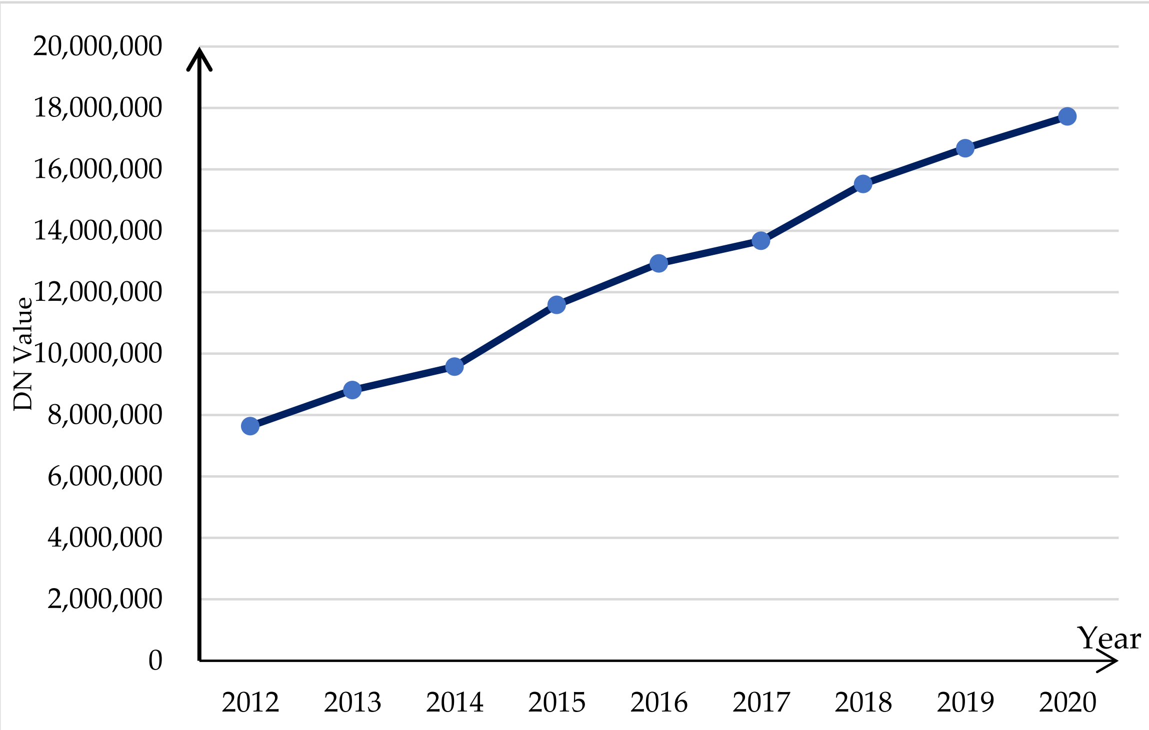

Figure 3. The DN value of the corrected NPP/VIIRS NTL data.

Target area clipping was performed on the corrected NPP/VIIRS NTL data and zoning statistics were derived for the average night light data (ANTL) (as shown in Table A1). The target area was HABT. The cropped NPP/VIIRS images from 2012 to 2020 are shown in Figure 4.

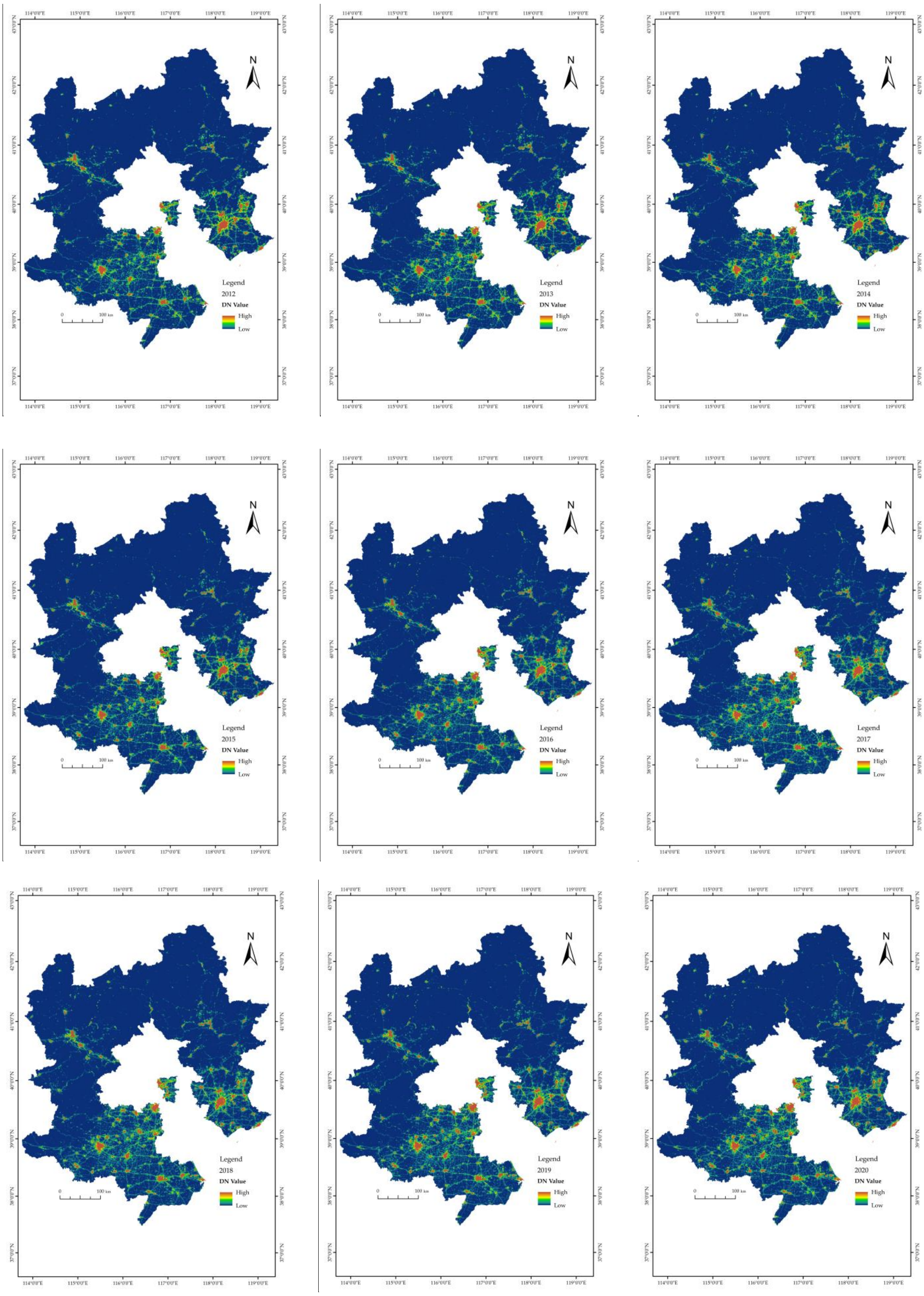

Figure 4. The corrected NPP/VIIRS images from 2012 to 2020.

3.2. Results of Multidimensional Relative Poverty Index

To distinguish the differences between various indicators, the AHP and entropy weight methods were used to assign weights to the MRPI, and the average weight was selected as the final weight. The result of weighting is shown in Table 3. After empowerment, MRPI is shown in Table A2.

Table 3. Weight summary from 2012 to 2019.

The Index Name	AHP	EWM	Average Weight
Per capital GDP	0.0533	0.1476	0.1425
Per capital fiscal revenue	0.0613	0.0038	0.0337
Employment rate	0.0454	0.2275	0.2417
Per capita output of grain	0.0394	0.0681	0.0616
Tap water benefit village rate	0.0461	0.0171	0.0371
Mobile Phone subscriber rate	0.0615	0.0609	0.0384
Density of road network	0.0580	0.0846	0.0822
Teaching faculty	0.1050	0.0478	0.0590
Education Level	0.0700	0.0299	0.0262
Number of beds in health facilities	0.1183	0.0979	0.1043
Proportion of medical technicians	0.0968	0.0871	0.1007
Basic medical insurance participation rate	0.1103	0.0543	0.0294
Basic endowment insurance participation rate	0.1348	0.0734	0.0431

3.3. Identification of Relative Poverty at County Level in HABT

This study refers to the relevant research experience of relative poverty in China [4,6,7,26,27] and the author's multidimensional relative poverty identification standard [52]. Firstly, the score of each dimension of the multidimensional relative poverty index was measured, and then 60% of the median of each dimension was selected as the relative poverty evaluation standard. Thus, the identification criteria of relative poverty from 2012 to 2019 are shown in Table 4.

Table 4. Multidimensional relative poverty criteria, 2012–2019.

Year	Economy	Living Quality	Education	Health Care	Social Security
2012	0.0330	0.0400	0.0261	0.0092	0.0141
2013	0.0346	0.0422	0.0262	0.0104	0.0171
2014	0.0348	0.0440	0.0267	0.0110	0.0170
2015	0.0354	0.0419	0.0273	0.0125	0.0167
2016	0.0363	0.0425	0.0261	0.0141	0.0162
2017	0.0358	0.0443	0.0270	0.0160	0.0186
2018	0.0369	0.0463	0.0289	0.0171	0.0176
2019	0.0382	0.0454	0.0298	0.0186	0.0260

The five dimension scores of the multidimensional relative poverty index of each county from 2012 to 2019 were compared with the dimension standard of the corresponding year. Counties with one of the dimensions below the standard were identified as having mild relative poverty. Counties with two dimensions below the standard were identified as having moderate relative poverty. Counties with three or more dimensions below the standard were identified as having severe relative poverty. The number of relative poverty counties from 2012 to 2019 is summarized in Table 5.

Table 5. Number of multidimensional counties experiencing relative poverty from 2012 to 2019.

Year	Number of Mild Relative Poverty Counties	Number of Moderate Relative Poverty Counties	Number of Severe Relative Poverty Counties	Number of Relative Poverty Counties	Relative Poverty Incidence
2012	21	7	0	28	39.44%
2013	21	8	0	29	40.85%
2014	20	5	0	25	35.21%
2015	19	4	0	23	32.39%
2016	13	4	1	18	25.35%
2017	19	4	0	23	32.39%
2018	14	5	1	20	28.17%
2019	9	11	1	21	29.58%

It can be seen from Table 5 that the maximum number of counties experiencing relative poverty was 29 in 2013, and the relative poverty incidence rate was 40.85%. The minimum number was 18 in 2016, and its relative poverty incidence was 25.35%. From 2012 to 2013, the number of relative poverty counties increased slowly. However, from 2013 to 2016, the number of relative poverty counties declined. From 2016 to 2019, the number of relative poverty counties experienced an unstable state of "increase-decrease-increase". From 2012 to 2019, mild relative poverty was the main type in HABT, and the number of counties experiencing severe relative poverty was the least.

The list of counties experiencing relative poverty in HABT from 2012 to 2019 is summarized in Table A3. As shown in Table A3, from 2012 to 2019, there were 13 counties in a state of long-term relative poverty for 8 years: Boye county, Chicheng county, Chongli county, Dachang county, Fuping county, Guyuan county, Huaian county, Kangbao county, Laishui county, Mengcun county, Shangyi county, Wei county, and Yangyuan county. There were five counties in a state of long-term relative poverty for 6 years: Haixing county, Laiyuan county, Wangdu county, Xinglong county, and Zhangbei county. There are four counties in a state of long-term relative poverty for 5 years: Fengning county, Wanquan county, Yongqing county, and Zhulu county. Anxin County, Gu'an county, Kuancheng county, and Weichang county were in a state of relative poverty for four years. Luanping county, Rongcheng county, and Xiong county were in a state of relative poverty for three years.

3.4. Establishment of Multidimensional Relative Poverty Index Estimation Model

MRPI (as shown in Table A2) and corrected NPP/VIIRS ANTL data from 71 counties in the HABT region from 2012 to 2019 were used as the dependent and independent variables to establish the panel regression model. The Hausman test was used to determine the choice of the fixed-effects model. The obtained results of the fixed-effects panel regression model are shown in Table 6.

Table 6. The results of the fixed-effects panel regression model.

Model	R^2	p-Value
Individual fixed effect	0.4309	0.0000
Time fixed effect	0.6198	0.0000
Individual–Time fixed effect	0.6578	0.0000

As shown in Table 6, the R^2 of the individual–time fixed-effects model is the best. The regression results of the individual–time fixed-effects model were used as the multidimensional relative poverty index estimation model. The fitting formula is as follows:

$$MRPI_{re} = 0.0523ANTL + 0.1907 \tag{21}$$

where $MRPI_{re}$ is MRPI at the county scale in HABT, and ANTL represents the NPP/VIIRS Average Night Light Index at the county scale.

3.5. Accuracy Test of MPRI Estimation Model

In order to verify the accuracy of the MRPI estimation model, RE and ARE were obtained for the estimated value and the real value of MRPI. The precision percentage of RE is shown in Table 7.

Table 7. Precision percentages for counties.

Year	Number of Counties			Precision Percentage (%)		
	RE < 25%	RE (25~50%)	RE > 50%	High	Middle	Low
2012	56	13	2	0.79	0.18	0.03
2013	53	17	1	0.75	0.24	0.01
2014	55	16	0	0.77	0.23	0.00
2015	54	14	3	0.76	0.20	0.04
2016	51	17	3	0.72	0.23	0.04
2017	51	19	1	0.72	0.27	0.01
2018	52	16	3	0.73	0.23	0.04
2019	42	23	6	0.59	0.32	0.09

From Table 7, in 2012–2019, more than 50% of counties over a period of 8 years had high accuracy, and the proportion of counties with low precision from 2012 to 2019 was less than 10%. From the analysis of the RE test, the MRPI estimation model based on the corrected NPP/VIIRS nighttime light data passed the error test.

The results in Table 8 show that the ARE of fifty-two counties was within 25%, the ARE of seventeen counties was between 25% and 50%, and the ARE of two counties was greater than 50%. From the analysis of the ARE, the MPRI estimation model based on the corrected NPP/VIIRS nighttime light data passed the error test. Combining RE and ARE, it was found that using the 2012–2019 NPP/VIIRS ANTL to estimate MRPI at the county scale passed the accuracy test. This lays a theoretical foundation for the subsequent study of the identification of relative poverty by night light data.

Table 8. Average relative estimation error (%).

County	ARE	County	ARE	County	ARE	County	ARE
Anguo City	0.0624	Gu’an County	0.0724	Mengcun County	0.1508	Wen’an County	0.2235
Anxin County	0.1373	Guyuan County	0.3340	Nanpi County	0.0144	Wuqiao County	0.2976
Bazhou County	0.1352	Haixing County	0.0949	Pingquan County	0.0392	Xian County	0.0955
Botou City	0.1201	Hejian City	0.1052	Qian’an City	0.2563	Xianghe County	0.4091
Boye County	0.1356	Huai’an County	0.1839	Qianxi County	0.3015	Xinglong County	0.2512
Cang County	0.1838	Huailai County	0.1538	Qing County	0.0920	Xiong County	0.1869
Chengde County	0.0821	Huanghua City	0.3133	Qingyuan County	0.0672	Xushui County	0.2413
Chicheng County	0.2637	Kangbao County	0.5223	Quyang County	0.0983	Yanshan County	0.0581
Chongli County	0.0769	Kuancheng County	0.2553	Renqiu City	0.1354	Yangyuan County	0.1701
Dachang County	0.4424	Laishui County	0.1188	Rongcheng County	0.0841	Yi County	0.1314
Dacheng County	0.6339	Laiyuan County	0.0512	Sanhe City	0.0875	Yongqing County	0.0820
Dingxing County	0.0303	Laoting County	0.3275	Shangyi County	0.2486	Yutian County	0.3190
Dingzhou City	0.2680	Li County	0.2552	Shunping County	0.0624	Yu County	0.4749
Dongguang County	0.0545	Longhua County	0.0732	Suning County	0.0364	Zhangbei County	0.0689
Fengning County	0.1055	Luannan County	0.3483	Tang County	0.1001	Zhuolu County	0.0600
Fuping County	0.1684	Luanping County	0.0957	Wanquan County	0.0277	Zhuozhou City	0.1248
Gaobeidian City	0.1663	Luan County	0.3651	Wangdu County	0.1253	Zuihua City	0.2256
Gaoyang County	0.0327	Mancheng County	0.1424	Weichang County	0.1338		

3.6. Identification of Relative Poverty at the Township Scale in the HABT

According to Table A3, there were 13 counties in a state of long-term relative poverty for 8 years: Boye county, Chicheng county, Chongli county, Dachang county, Fuping county, Guyuan county, Huaian county, Kangbao county, Laishui county, Mengcun county, Shangyi county, Wei county, and Yangyuan county. One of the counties was randomly selected, and Chongli county was taken as an example to identify relative poverty at the township level.

According to Formula (21), the grid calculator in ArcGIS software was used to calibrate the night light data in Chongli District at the county level. The estimated multidimensional relative poverty index of 11 villages and towns in Chongli District is shown in Table 9.

Table 9. The estimated MRPI of 11 villages and towns in Chongli District.

	2012	2013	2014	2015	2016	2017	2018	2019
Saiwanzi Street	0.28112	0.28112	0.28298	0.40960	0.43146	0.43097	0.45675	0.47235
Sitaizui Township	0.19407	0.19430	0.19498	0.19597	0.19724	0.19895	0.20267	0.20908
Saiwanzi Township	0.19398	0.19417	0.19460	0.19678	0.20150	0.20759	0.20970	0.21083
Gaojiaying Town	0.19382	0.19443	0.19485	0.19782	0.19888	0.19912	0.20011	0.20049
Baiqi Township	0.19116	0.19150	0.19153	0.19156	0.20018	0.20119	0.20127	0.20132
Shizuizi Township	0.19090	0.19096	0.19099	0.19130	0.19148	0.19161	0.19168	0.19175
Qingsanying Township	0.19089	0.19120	0.19152	0.19182	0.19264	0.19295	0.19316	0.19316
Shizigou Township	0.19078	0.19088	0.19088	0.19094	0.19113	0.19135	0.19135	0.19136
Hongqiying Township	0.19074	0.19075	0.19086	0.19094	0.19103	0.19105	0.19109	0.19111
Yimatu Township	0.19071	0.19072	0.19072	0.19073	0.19082	0.19090	0.19090	0.19090
Shiyaozi Township	0.19070	0.19070	0.19070	0.19070	0.19070	0.19070	0.19070	0.19070

Thus, the relative poverty index of Chongli district at the township scale was estimated. It provides a data reference and a indicates a feasible method for monitoring relative poverty on the township scale.

4. Discussion

Having eliminated absolute poverty, China will focus on alleviating relative poverty in the new era. The lack of identification standards of relative poverty leads to difficulties in the implementation of targeted poverty alleviation policies and is not conducive to the formulation of scientific policies for the alleviation of regional poverty. Taking HABT as an example, in order to facilitate the implementation of the Beijing-Tianjin-Hebei integration policy, MRPI was constructed at the county scale, to enable relevant research to be carried out.

The traditional evaluation of poverty is based on social statistical data, which are often untimely and difficult to collect. This leads to challenges in the realization of research on relative poverty at a smaller scale (such as the township scale) in the new era. NPP/VIIRS NTL data may contain more detailed human activity information, greater spatial resolution, and richer light signals. For this reason, NPP/VIIRS NTL data from 2012 to 2020 were obtained. After the annual fusion of monthly data, the DN values of China from 2012 to 2020 were produced. The original NPP/VIIRS NTL data exhibited abnormal fluctuations, for which stability correction and time series correction were carried out. Thus, the corrected 2012–2020 NPP/VIIRS NTL data for China were obtained. The 2012–2020 NPP/VIIRS NTL images of HABT were cut out, as shown in Figure 4. The corrected NPP/VIIRS ANTL data in HABT at the county scale are shown in Table A1. The images show the economic development of HABT at a grid scale, which is consistent with China's social reality.

The first step in studying relative poverty is to determine the evaluation criteria. Adopting the standard of "free from worries over food and clothing and have access to compulsory education, basic medical services and safe housing", combined with MPI, MRPI was established, as shown in Table 1. It contains five dimensions: economy, living quality, education, health care, and social security. Because the county is the basic unit of poverty assessment, 71 counties in HABT from 2012 to 2019 were selected as assessment objects. The AHP and entropy methods were used to assign weights, as shown in Table 3. The results of MRPI at the county scale in HABT are shown in Table A2.

In order to identify relative poverty at the county scale, 60% of the median of each dimension in the MRPI was selected as the relative poverty evaluation standard. The identification criteria for relative poverty from 2012 to 2019 are shown in Table 4. The recognition results were classified, and the classification results are shown in Table A3. As shown in Table A3, from 2012 to 2019, there were 13 counties in a state of long-term relative poverty for 8 years, five counties in a state of long-term relative poverty for 6 years, and four counties in a state of long-term relative poverty for 5 years. The number of counties experiencing relative poverty from 2012 to 2019 is summarized in Table 5. The maximum number of counties experiencing relative poverty was 29 in 2013, and the relative poverty incidence rate was 40.85%. The minimum number was 18 in 2016, and its relative poverty incidence was 25.35%. From 2012 to 2019, mild relative poverty was the main type in HABT, and the number of counties experiencing severe relative poverty was the least.

To confirm the correlation between the MRPI and the corrected NTL data, a panel fixed effect model was selected to perform regression fitting for the two variables. The R^2 of the individual-time fixed effect model was greater than 0.6. The results show that there is a strong correlation between MRPI and the corrected NTL data. Based on this, the MRPI estimation model was constructed using the individual–time fixed-effects model, as shown in Formula (21). As shown in Tables 7 and 8, the accuracy test of the relative poverty estimation model confirmed that both NPP/VIIRS NTL data estimation and MRPI showed good results.

Taking Chongli District as an example, according to Formula (21), the nighttime light data of Chongli District from 2012 to 2020 were corrected at the county level, and the nighttime light data of Chongli District from 2012 to 2020 were cut at the township scale. The estimated value of MRPI at the township scale in Chongli District from 2012 to 2020 was obtained, as shown in Table 9. This study provides a feasible method for the identification of relative poverty at the township scale, and provides a data reference for the monitoring of relative poverty.

The research results of this study can be used as a reference for other regions:

(1) This study selected HABT as the study area, and used "free from worries over food and clothing and have access to compulsory education, basic medical services, and safe housing" as the standard for establishing MRPI. In the study of relative poverty in other regions of China, researchers can refer to this choice of indicator.
(2) To conduct multidimensional relative poverty assessment based on social statistics, it may be necessary to wait for a long period until existing statistics are updated through economic censuses. Knowledge of the relative poverty in an area cannot be kept up to date over a short period of time, which limits targeted poverty alleviation work. The use of night light data can effectively identify the areas of relative poverty in a timely and effective manner. It also provides a convenient means of conducting poverty research in regions lacking social statistics.
(3) This study established an MRPI estimation model at the county scale based on MRPI and NTL data. The feasibility of using NTL data to evaluate the relative poverty of counties and identify areas of relative poverty was verified. This lays the foundation for the application of night light data in the identification of relative poverty at the county scale, and provides additional ideas for the identification of relative poverty in other regions on the county or smaller scales.

However, this study still features some limitations:

(1) When constructing MRPI, a five-dimension index system was constructed that takes into account the availability of statistical data. In the further study of relative poverty by government departments and scholars, more multidimensional indicators of relative poverty may be used to develop more reliable studies.
(2) Due to space limitations, after providing the estimates of the MRPI at the township scale, this paper does not further discuss and monitor the relative poverty at the township scale. In the future, further research on relative poverty at the township scale can be carried out, in order to provide a smaller-scale scope of reference for the policy formulation of relevant departments, and to provide a more refined spatial reference for the prevention of a large-scale return to poverty.
(3) As the scale of poverty research has been continuously narrowing and deepening, as a result of the future development of the work of the relevant departments, it will be feasible to obtain smaller-scale statistical data, which will provide an improved basis for the study of NTL data.

5. Conclusions

(1) The 71 counties of HABT from 2012 to 2019 were selected as the research scope, and MRPI was established in terms of the five dimensions of economy, quality of life, education, health care, and social security. Then, 60% of the median of each dimension was selected as the relative poverty evaluation standard, and 71 counties of HABT from 2012 to 2019 were identified. The identification results show that the maximum number of relative poverty counties was 29 in 2013, and the relative poverty incidence rate was 40.85%. From 2012 to 2019, mild relative poverty was the main type in HABT, and the number of severe relative poverty counties was the least.

(2) Analysis of the identified list of counties experiencing relative poverty from 2012 to 2019 shows that, from 2012 to 2019, there were 13 counties in a state of long-term relative poverty for 8 years: Boye county, Chicheng county, Chongli county, Dachang county, Fuping county, Guyuan county, Huaian county, Kangbao county, Laishui county, Mengcun county, Shangyi county, Wei county, and Yangyuan county. There were five counties in a state of long-term relative poverty for 6 years: Haixing county, Laiyuan county, Wangdu county, Xinglong county, and Zhangbei county. There are four counties in a state of long-term relative poverty for 5 years: Fengning county, Wanquan county, Yongqing county, and Zhulu county. Anxin Coun-ty, Gu'an county, Kuancheng county, and Weichang county were in a state of relative poverty for four years. Luanping county, Rongcheng county, and Xiong county were in a state of relative poverty for three years.

(3) A panel regression model was established using MRPI and adjusted NPP/VIIRS ANTL data of 71 counties in the HABT region from 2012 to 2019 as the dependent and independent variables. Hausman's test was used to determine the choice of fixed-effects model. Comparing the three fixed-effects models, it was found that the R2 of the individual–time fixed-effects model was best at 0.6573. Thus, an MRPI estimation model was obtained. From the results of the RE test, more than 50% of the counties had high accuracy for a period of 8 years, and the proportion of counties with low precision from 2012 to 2019 was less than 10%. The results of the ARE test showed that the ARE of fifty-two counties was within 25%, and the ARE of seventeen counties was between 25% and 50%. Combining the results of the RE and ARE tests, it was found that using the 2012–2019 NPP/VIIRS ANTL to estimate MRPI at the county scale passed the accuracy test. This lays a theoretical foundation for the subsequent study of the identification of relative poverty using night light data.

(4) This study constructed a multi-dimensional relative poverty index calculation model, and calculated the multi-dimensional relative poverty index from 2012 to 2019. A multidimensional relative poverty index estimation model was constructed using the corrected nighttime light data and the multidimensional relative poverty index. On this basis, county-level correction was performed on the nighttime light data in Chongli District, and the estimation of the multi-dimensional relative poverty index at the township level was realized. This provides a feasible method and data reference for the identification of relative poverty at the township scale. This study provides a theoretical reference for the identification of relative poverty and a practical basis for the application of NPP/VIIRS NTL data in the study of relative poverty. It provides a feasible method for the identification and monitoring of relative poverty at the township scale. Achieving the identification of small-scale relative poverty is helpful for formulating scientific and effective poverty reduction strategies, and is of great significance for preventing a large-scale return to poverty. This study provides a spatial reference for alleviating relative poverty in the future.

Author Contributions: J.W. and H.L. (Haibin Liu) conceived and designed the study. H.L. (Hao Liu) and J.W. processed the data and performed analysis, contributed to the interpretation of the results and wrote the study. H.L. (Hao Liu) and Y.C. provided assistance in software operation. X.L., Y.G. and H.H. participated in the revision of the article. All authors reviewed and edited the draft, approved the submitted manuscript, and agreed to be listed and accepted the version for publication. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: See the Appendix A for research data.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The corrected NPP/VIIRS ANTL of 71 counties in HABT from 2012 to 2020 were calculated using ArcGIS software.

Table A1. NPP/VIIRS ANTL at county level in HABT from 2012 to 2020.

County (City)	2012	2013	2014	2015	2016	2017	2018	2019	2020
Anguo City	0.1674	0.2182	0.2497	0.2998	0.4428	0.7807	1.0172	1.5205	1.8742
Anxin County	0.3921	0.4937	0.5140	0.6041	0.6980	0.8585	0.9321	1.0655	1.1509
Bazhou City	1.3672	1.9701	2.2171	3.0671	3.4518	3.5537	3.7595	3.9348	4.0658
Botou City	0.2368	0.3257	0.3573	0.4680	0.5623	0.6640	0.7431	0.8463	0.8978
Boye County	0.1494	0.1943	0.2264	0.2748	0.3462	0.4630	0.4823	0.5579	0.5840
Cang County	0.4310	0.5753	0.6581	0.8213	0.9165	1.0619	1.1349	1.2329	1.3829
Chengde County	0.0796	0.0951	0.1072	0.1538	0.1831	0.1923	0.2076	0.2304	0.2417
Chicheng County	0.0218	0.0240	0.0249	0.0288	0.0345	0.0381	0.0439	0.0466	0.0492
Chongli County	0.0363	0.0399	0.0446	0.0752	0.1056	0.1237	0.1449	0.1695	0.1811
Dachang County	1.3392	1.8691	2.4094	4.3303	5.0571	4.8889	5.3144	5.4682	5.5228
Dacheng County	0.3764	0.4855	0.5589	0.6673	0.7651	0.8349	0.8814	0.9258	0.9625
Dingxing County	0.2069	0.2961	0.3241	0.4064	0.5309	0.6098	0.6280	0.6995	0.7764
Dingzhou City	0.3730	0.4696	0.6384	0.9147	1.0941	1.1493	1.2578	1.3944	1.4782
Dongguang County	0.2200	0.2867	0.3086	0.3980	0.4648	0.5138	0.5373	0.6392	0.7048
Fengning County	0.0122	0.0174	0.0196	0.0242	0.0363	0.0487	0.0748	0.0895	0.0940
Fuping County	0.0564	0.0649	0.0697	0.0857	0.1072	0.1365	0.1546	0.1909	0.1949
Gaobeidian City	0.4602	0.6311	0.6974	0.9079	1.0510	1.5716	1.6020	1.7157	2.1909
Gaoyang County	0.5315	0.7095	0.7369	0.9284	1.0070	1.1590	1.2402	1.3908	1.4612
Gu'an County	0.6720	0.9814	1.1592	1.7491	1.8760	1.6357	2.1287	2.3000	2.4401
Guyuan County	0.0184	0.0221	0.0250	0.0398	0.0768	0.0881	0.0924	0.0979	0.1019
Haixing County	0.1936	0.2372	0.2519	0.2968	0.4125	0.5241	0.5461	0.5711	0.6014
Hejian City	0.4338	0.5421	0.5609	0.6583	0.7439	0.9395	0.9591	1.0639	1.1344
Huai'an County	0.1370	0.1545	0.1694	0.1929	0.2303	0.2372	0.2579	0.2807	0.2988
Huailai County	0.2297	0.2477	0.2629	0.3539	0.4694	0.5274	0.5632	0.6502	0.6695
Huanghua City	0.7422	0.9460	1.0565	1.4227	1.7471	1.9624	2.1021	2.2609	2.4212
Kangbao County	0.0098	0.0123	0.0145	0.0175	0.0236	0.0264	0.0300	0.0334	0.0372
Kuancheng County	0.2077	0.2499	0.3035	0.4520	0.4863	0.4794	0.5278	0.5528	0.5651
Laishui County	0.1401	0.1982	0.2406	0.2787	0.3288	0.3575	0.3860	0.4117	0.4152
Laiyuan County	0.1071	0.1399	0.1599	0.1994	0.2325	0.2284	0.2589	0.2785	0.2924
Laoting County	0.7485	0.9613	1.1972	1.6685	1.7655	1.6307	1.8349	1.8847	2.0133
Li County	0.3238	0.4391	0.5054	0.6183	0.7328	0.8368	0.8716	0.9965	1.0164
Longhua County	0.0372	0.0468	0.0515	0.0661	0.0762	0.0770	0.0914	0.0973	0.1033
Luannan County	0.5173	0.6705	0.8730	1.0476	1.1947	1.1619	1.3243	1.3730	1.4270
Luanping County	0.1064	0.1294	0.1456	0.1792	0.2070	0.2120	0.2436	0.2679	0.2819
Luan County	0.7970	0.9361	1.1186	1.4407	1.7710	1.7344	1.8645	1.9412	1.9886

Table A1. *Cont.*

County (City)	2012	2013	2014	2015	2016	2017	2018	2019	2020
Mancheng County	0.4285	0.5625	0.6537	0.8352	0.9580	1.0215	1.1078	1.3815	1.4080
Mengcun County	0.5272	0.6197	0.6384	0.7210	0.8134	0.9736	0.9923	1.0117	1.0708
Nanpi County	0.1962	0.2780	0.3163	0.4271	0.4921	0.5672	0.6107	0.6881	0.7890
Pingquan County	0.0763	0.0856	0.1023	0.2090	0.2454	0.2544	0.2692	0.2833	0.2974
Qian'an City	1.6468	1.7522	1.8390	2.3232	2.4110	2.1379	2.5231	2.6936	2.7425
Qianxi County	0.3206	0.3570	0.3742	0.4589	0.4993	0.4805	0.5530	0.6597	0.6988
Qing County	0.3224	0.4126	0.4366	0.5102	0.5782	0.6931	0.7096	0.7469	0.7950
Qingyuan County	0.3630	0.4725	0.5030	0.6429	0.7734	1.0300	1.0733	1.1628	1.1910
Quyang County	0.1504	0.1952	0.2195	0.2550	0.3686	0.4566	0.4751	0.5483	0.6113
Renqiu City	0.9509	1.2426	1.2980	1.8350	2.0062	2.2886	2.4693	2.6765	2.8404
Rongcheng County	0.4159	0.5868	0.6446	0.8058	0.9186	1.0334	1.2011	1.4784	3.2714
Sanhe City	1.7494	2.2241	2.4639	3.4282	3.7081	3.5692	3.8877	4.1110	4.2072
Shangyi County	0.0253	0.0263	0.0306	0.0453	0.0560	0.0592	0.0690	0.0847	0.0919
Shunping County	0.1310	0.1807	0.2096	0.2512	0.2982	0.3667	0.3910	0.4472	0.4576
Suning County	0.5118	0.6858	0.8100	1.1882	1.2578	1.1861	1.4226	1.6085	1.7791
Tang County	0.1145	0.1558	0.1811	0.2177	0.2676	0.3253	0.3449	0.3967	0.4041
Wangdu County	0.1813	0.2287	0.2639	0.3617	0.4358	0.4970	0.5307	0.6684	0.6829
Wanquan County	0.2334	0.2627	0.2760	0.3397	0.3764	0.3690	0.4179	0.4674	0.4881
Weichang County	0.0116	0.0144	0.0170	0.0234	0.0341	0.0396	0.0424	0.0470	0.0490
Wen'an County	0.5697	0.7874	0.8525	1.0383	1.1373	1.2163	1.2725	1.3472	1.4510
Wuqiao County	0.1421	0.1605	0.1814	0.2030	0.2350	0.2956	0.3078	0.3557	0.4100
Xianghe County	0.8936	1.2764	1.4544	2.5333	3.2387	3.3366	3.4399	3.6372	3.7330
Xian County	0.2202	0.2870	0.3084	0.3503	0.3924	0.4235	0.4637	0.5319	0.5656
Xinglong County	0.0487	0.0544	0.0597	0.0892	0.1027	0.1190	0.1330	0.1431	0.1496
Xiong County	0.5719	0.8206	0.9141	1.2111	1.4471	1.5141	1.5826	1.7841	2.3284
Xushui County	0.4586	0.6196	0.7585	0.9600	1.4613	1.7740	1.8890	2.2952	2.5431
Yangyuan County	0.0777	0.0889	0.0968	0.1215	0.1443	0.1479	0.1754	0.1849	0.1886
Yanshan County	0.2929	0.3764	0.4201	0.4895	0.5822	0.6371	0.6673	0.7103	0.7803
Yi County	0.0641	0.0965	0.1211	0.1398	0.1817	0.2195	0.2308	0.2523	0.2565
Yongqing County	0.4143	0.5378	0.5840	0.6822	0.8872	1.0940	1.1669	1.3244	1.4318
Yutian County	0.4681	0.5478	0.7487	1.1575	1.2908	1.3088	1.4088	1.5028	1.5477
Yu County	0.0785	0.0857	0.0945	0.1113	0.1382	0.1423	0.1562	0.1687	0.1740
Zhangbei County	0.0487	0.0513	0.0570	0.1026	0.1541	0.1630	0.1732	0.1859	0.1921
Zhuolu County	0.0833	0.1002	0.1150	0.1524	0.1727	0.1975	0.2095	0.2262	0.2345
Zhuozhou City	0.6021	0.8054	0.9169	1.1499	1.3278	1.4362	1.5309	1.6434	1.7157
Zuihua City	0.4142	0.4505	0.4654	0.5419	0.6215	0.6677	0.7254	0.8388	0.8685

Table A2. MRPI of relative poverty at county level in HABT from 2012 to 2019.

County (City)	2012	2013	2014	2015	2016	2017	2018	2019
Anguo City	0.2062	0.2130	0.2228	0.2306	0.2378	0.2479	0.2430	0.2562
Anxin County	0.1881	0.1942	0.1932	0.1962	0.2023	0.2047	0.1987	0.2196
Bazhou City	0.2686	0.2824	0.2819	0.2861	0.3000	0.3104	0.3257	0.3731
Botou City	0.2874	0.3084	0.2656	0.3009	0.2976	0.3020	0.2636	0.3021
Boye County	0.1959	0.1795	0.1805	0.1768	0.1917	0.1966	0.2067	0.2120
Cang County	0.2356	0.2361	0.2334	0.2525	0.2527	0.2621	0.2703	0.3090
Chengde County	0.1876	0.2146	0.2125	0.2103	0.2085	0.2290	0.2314	0.2606
Chicheng County	0.1421	0.1530	0.1570	0.1566	0.1437	0.1685	0.1630	0.1813
Chongli County	0.1692	0.1640	0.1917	0.1906	0.2085	0.2165	0.1964	0.2139
Dachang County	0.2586	0.2875	0.3285	0.3739	0.3778	0.3923	0.4197	0.4505
Dacheng County	0.2117	0.2205	0.2180	0.2239	0.2271	0.2543	0.2558	0.2936
Dingxing County	0.2104	0.2035	0.2115	0.2165	0.2260	0.2360	0.2323	0.2521
Dingzhou City	0.2245	0.2623	0.2441	0.2901	0.2962	0.3255	0.3300	0.4618
Dongguang County	0.2297	0.2329	0.2546	0.2433	0.2494	0.2704	0.2674	0.2681

Table A2. *Cont.*

County (City)	2012	2013	2014	2015	2016	2017	2018	2019
Fengning County	0.1628	0.1819	0.1942	0.2002	0.2013	0.2375	0.2397	0.2520
Fuping County	0.1457	0.1473	0.1622	0.1644	0.1675	0.1821	0.1792	0.2139
Gaobeidian City	0.2007	0.2139	0.2195	0.2163	0.2357	0.2529	0.2671	0.3087
Gaoyang County	0.2057	0.2162	0.2286	0.2261	0.2336	0.2598	0.2692	0.2809
Gu'an County	0.2074	0.2174	0.2474	0.2544	0.2720	0.2821	0.3271	0.3427
Guyuan County	0.1717	0.1730	0.1782	0.1723	0.1759	0.1986	0.2021	0.1763
Haixing County	0.1567	0.1693	0.1792	0.1921	0.1984	0.2208	0.2256	0.2084
Hejian City	0.2159	0.2235	0.2328	0.2192	0.2428	0.2303	0.2334	0.2971
Huai'an County	0.2279	0.1854	0.1828	0.1979	0.1762	0.1910	0.2126	0.2065
Huailai County	0.1941	0.2175	0.2486	0.2296	0.2368	0.2462	0.2603	0.2804
Huanghua City	0.2951	0.3060	0.3039	0.3015	0.3036	0.3151	0.3092	0.3400
Kangbao County	0.1399	0.1590	0.1890	0.1703	0.1812	0.2017	0.1908	0.1952
Kuancheng County	0.2317	0.2599	0.2594	0.2526	0.2624	0.2813	0.2603	0.2577
Laishui County	0.1676	0.1741	0.1804	0.1945	0.1917	0.1967	0.2010	0.2240
Laiyuan County	0.1748	0.1950	0.1911	0.1949	0.1997	0.2042	0.2159	0.2209
Laoting County	0.2549	0.2717	0.2658	0.2875	0.3003	0.3146	0.3542	0.3826
Li County	0.1878	0.1700	0.2024	0.2085	0.2158	0.2371	0.2355	0.2577
Longhua County	0.1885	0.1879	0.2099	0.2016	0.2068	0.2247	0.2300	0.2498
Luannan County	0.2657	0.2957	0.3021	0.2935	0.2875	0.2894	0.3120	0.3516
Luanping County	0.1882	0.2055	0.2184	0.2126	0.2232	0.2285	0.2675	0.2599
Luan County	0.2841	0.2924	0.3158	0.3125	0.3073	0.3210	0.3273	0.3799
Mancheng County	0.2062	0.2156	0.2239	0.2240	0.2313	0.2439	0.2503	0.2731
Mengcun County	0.1960	0.1999	0.2277	0.2215	0.2062	0.2069	0.2079	0.1873
Nanpi County	0.2137	0.2233	0.2228	0.2261	0.2307	0.2476	0.2512	0.2418
Pingquan County	0.1947	0.2094	0.2107	0.2097	0.2174	0.2420	0.2312	0.2515
Qian'an City	0.3801	0.3947	0.3886	0.2510	0.3871	0.4008	0.4235	0.4900
Qianxi County	0.2937	0.2917	0.2977	0.2904	0.3065	0.3083	0.3251	0.3547
Qing County	0.2188	0.2258	0.2332	0.2343	0.2495	0.2483	0.2538	0.2754
Qingyuan County	0.1919	0.1976	0.2039	0.2281	0.2397	0.2540	0.2562	0.3012
Quyang County	0.1765	0.1772	0.1953	0.1999	0.2144	0.2332	0.2472	0.2899
Renqiu City	0.2885	0.2918	0.3151	0.3304	0.3293	0.3382	0.3619	0.4033
Rongcheng County	0.2018	0.2126	0.2167	0.2241	0.2182	0.2286	0.2305	0.2163
Sanhe City	0.3512	0.3722	0.3776	0.3903	0.3901	0.3775	0.3884	0.4476
Shangyi County	0.1326	0.1570	0.1660	0.1664	0.1326	0.1821	0.1618	0.1533
Shunping County	0.1757	0.1793	0.2016	0.2064	0.2076	0.2229	0.2284	0.2394
Suning County	0.2302	0.2384	0.2553	0.2531	0.2521	0.2613	0.2747	0.2785
Tang County	0.1748	0.1754	0.1798	0.1908	0.2039	0.2164	0.2238	0.2849
Wangdu County	0.2208	0.2403	0.2361	0.2324	0.2437	0.2510	0.2527	0.2336
Wanquan County	0.1835	0.2098	0.2104	0.2134	0.2111	0.2155	0.2254	0.2250
Weichang County	0.1610	0.1747	0.1766	0.1784	0.1918	0.2277	0.2383	0.2677
Wen'an County	0.2325	0.2362	0.2569	0.2535	0.2510	0.2832	0.2907	0.3010
Wuqiao County	0.2419	0.2505	0.2527	0.2437	0.2499	0.2595	0.2655	0.2229
Xianghe County	0.2765	0.3026	0.3068	0.3382	0.3436	0.3477	0.3579	0.4043
Xian County	0.2096	0.2136	0.2226	0.2225	0.2352	0.2377	0.2467	0.2819
Xinglong County	0.1766	0.1894	0.1929	0.1932	0.1995	0.2078	0.2321	0.2441
Xiong County	0.1987	0.1989	0.2241	0.2285	0.2251	0.2204	0.2056	0.2337
Xushui County	0.2271	0.2369	0.2442	0.2454	0.2586	0.3060	0.2977	0.2878
Yangyuan County	0.1431	0.1527	0.1664	0.1628	0.1726	0.1882	0.1868	0.2045
Yanshan County	0.1942	0.2024	0.2066	0.2170	0.2012	0.2088	0.2028	0.2391
Yi County	0.1772	0.1844	0.1932	0.2021	0.1999	0.2286	0.2312	0.2711
Yongqing County	0.1925	0.2053	0.2069	0.2209	0.2296	0.2553	0.2611	0.2894
Yutian County	0.2804	0.2889	0.2854	0.2707	0.2784	0.2836	0.2974	0.3392
Yu County	0.1428	0.1567	0.1573	0.1556	0.1569	0.1781	0.1832	0.2043
Zhangbei County	0.1760	0.1791	0.1863	0.1979	0.1846	0.2027	0.2098	0.2453
Zhuolu County	0.1749	0.1874	0.1993	0.2028	0.1790	0.1959	0.1853	0.2144
Zhuozhou City	0.2459	0.2544	0.2627	0.2826	0.2951	0.3111	0.3174	0.3469
Zuihua City	0.2632	0.2748	0.2755	0.2687	0.2771	0.2766	0.2951	0.3803

Table A3. Relative poverty degree of each county in 2012–2019.

County	2012	2013	2014	2015	2016	2017	2018	2019
Anguo City	-	mild	mild	-	-	-	-	-
Anxin County	mild	mild	mild	-	-	-	mild	-
Boye County	mild	mild	mild	mild	mild	mild	mild	moderate
Chicheng County	moderate	moderate	moderate	moderate	moderate	moderate	moderate	mild
Chongli County	moderate	moderate	moderate	moderate	moderate	moderate	moderate	moderate
Dachang County	mild	mild	mild	mild	mild	mild	mild	moderate
Dongguang County	-	-	-	mild	-	-	-	-
Fengning County	mild	mild	mild	mild	mild	-	-	-
Fuping County	mild	mild	mild	mild	mild	mild	moderate	mild
Guyuan County	moderate	moderate	moderate	mild	moderate	mild	mild	moderate
Gu'an County	mild	mild	-	mild	-	mild	-	-
Haixing County	mild	mild	mild	mild	-	-	mild	moderate
Huai'an County	mild	mild	mild	mild	mild	mild	mild	moderate
Huailai County	-	mild	-	-	-	-	-	-
Kangbao County	moderate	moderate	mild	mild	mild	mild	mild	moderate
Kuancheng County	-	-	mild	-	-	mild	mild	mild
Laishui County	moderate	moderate	mild	mild	mild	mild	mild	moderate
Laiyuan County	mild	moderate	mild	-	-	mild	mild	mild
Li County	mild	mild	-	-	-	-	-	-
Luanping County	mild	mild	-	-	-	mild	-	-
Mengcun County	mild	mild	mild	mild	mild	mild	mild	moderate
Rongcheng County	-	-	-	mild	-	mild		mild
Shangyi County	moderate	moderate	moderate	moderate	severe	moderate	severe	severe
Suning County	-	-	-	-	-	mild	-	-
Wanquan County	mild	mild	mild	-	mild	-	-	mild
Wangdu County	mild	mild	mild	mild	-	-	mild	moderate
Weichang County	mild	mild	mild	mild	-	-	-	-
Xinglong County	mild	mild	mild	mild	mild	mild	-	-
Yu County	mild	mild	mild	mild	mild	mild	mild	mild

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