Poverty Evaluation Using NPP-VIIRS Nighttime Light Composite Data at the County Level in China

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***Abstract*—Poverty has appeared as one of the long-term predicaments facing development of human society during the 21st century. Estimation of regional poverty level is a key issue for making strategies to eliminate poverty. This paper aims to evaluate the ability of the nighttime light composite data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day–Night Band (DNB) carried by the Suomi National Polar-orbiting Partnership (NPP) Satellite in estimating poverty at the county level in China. Two major experiments are involved in this study, which include 1) 38 counties of Chongqing city and 2) 2856 counties of China. The first experiment takes Chongqing as an example and combines 10 socioeconomic variables into an integrated poverty index (IPI). IPI is then used as a reference to validate the accuracy of poverty evaluation using the average light index (ALI) derived from NPP-VIIRS data. Linear regression and comparison of the class ranks have been employed to verify the correlation between ALI and IPI. The results show a good correlation between IPI and ALI, with a coefficient of determination (R^2) of 0.8554, and the class ranks of IPI and API show relative closeness at the county level. The second experiment examines all counties in China and makes a comparison between ALI values and national poor counties (NPC). The comparison result shows a general agreement between the NPC and the counties with low ALI values. This study reveals that the NPP-VIIRS data can be a useful tool for evaluating poverty at the county level in China.**

***Index Terms*—China, county scale, integrated poverty index (IPI), nighttime light data, NPP-VIIRS, poverty.**

I. INTRODUCTION

POVERTY has appeared as one of the long-term predicaments facing development of human society during the 21st century [1]. Since the beginning of its economic reforms in the late 1970s, China has been undergoing a rapid process of economic development [2]. However, poverty is still an important issue for the development of China's modernization process [3]. A significant share of the areas in the western and middle China is still underdeveloped, and the gap of income between these areas and other areas in the eastern China has been widening [4]. Therefore, accurate and reliable information about poverty levels and spatial patterns of economic development is essential for the central and local government to make the policy and promote development.

Traditionally, gross domestic product (GDP) is the most popular index of socioeconomic status and has been widely used to assess poverty levels in China [5]–[7]. However, GDP has several shortcomings, including not differentiating costs from benefits, not distinguishing sustainable practices from unsustainable actions, and not identifying productive activities from destructive ones [8]. In other words, the presupposition of using GDP to measure economic development is that all monetary transactions would be equally good for social well-being. Some studies also exploited household survey data to evaluate poverty. For example, Labar and Bresson [9] adopted household survey data to analyze poverty in China from 1991 to 2006. Using large household survey data, Yao *et al.* [2] attempted to present a comprehensive picture and identify the main determinants of poverty in both the urban and rural districts of China. Although household survey data are detailed enough to assess poverty for different areas, the data collection and processing are very time-consuming plus labor and capital intensive. The multidimensional assessment of poverty using statistics has also been widely adopted. Such an approach considers the correlations between the different dimensions of poverty, and therefore are often more accurate than using GDP alone [9], [10]. However, this method requires a long time to update existing statistics through economic census, and the census can hardly be exhaustive.

In comparison with traditional methods, remote sensing techniques have an advantage of providing efficient and accurate spatial data for various social and physical science research purposes [11]–[13]. Nighttime light data are typical remotely sensed data for mapping population, GDP, electricity power consumption, and coal consumption based on the strong correlation between human activities and lights [14]–[17]. Consequently, nighttime light data carry the potential in regional poverty analysis. For example, Wang *et al.* [7] explored the relationship between nighttime average light index (ALI) and the poverty using regression analysis. Elvidge *et al.* [1] produced a global poverty map using nighttime light data. However, these works were committed to large-scale studies of poverty, such as provincial scale or national scale. In China, *county* is the basic unit for poverty assessment,

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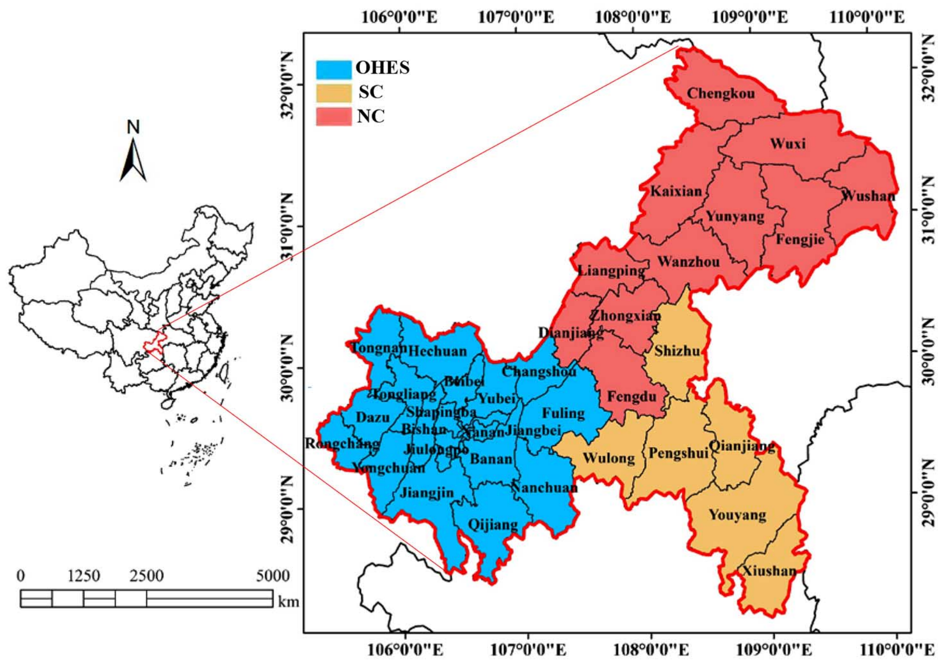


Fig. 1. Location of Chongqing in China and three economic regions of Chongqing.

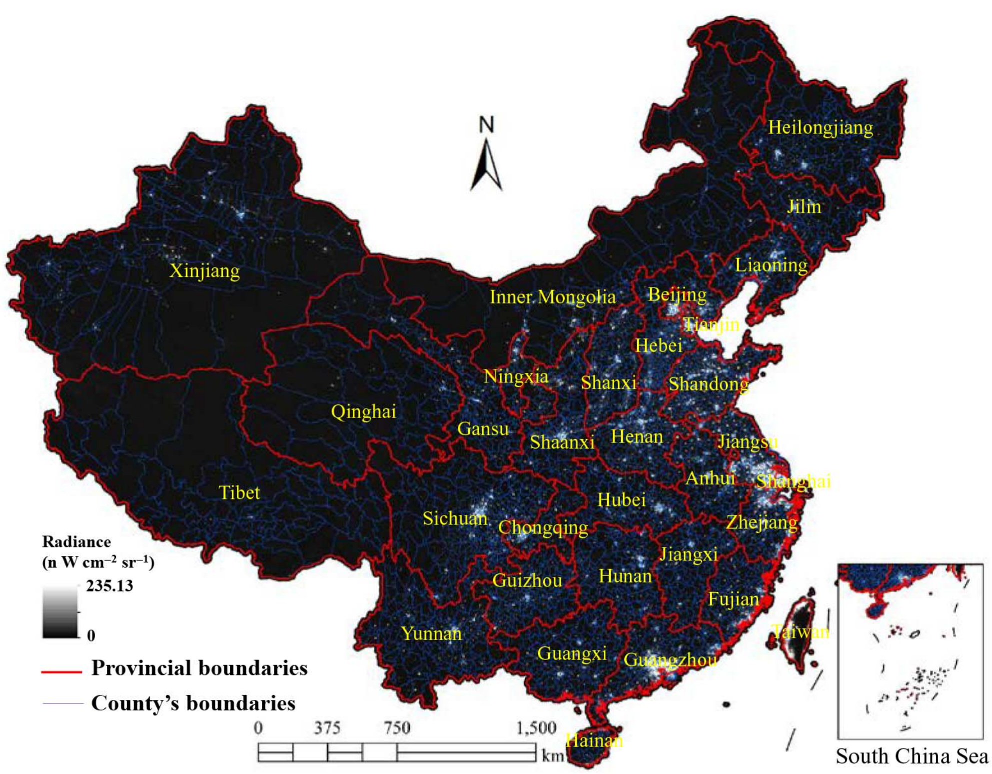


Fig. 2. A total of 2856 counties in 31 provinces for analysis in this study.

and poverty estimations from large-scale studies cannot be directly applied to decision situations which require results in a finer scale.

The nighttime light composite data acquired by the Defense Meteorological Satellite Program's Operational Line scan System (DMSP-OLS) archived by the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NOAA/NGDC) of the United States are the commonly used datasets for evaluating and mapping poverty at the spatial dimension. However, the DMSP-OLS data have a set of shortcomings, such as saturation on bright lights, six bit quantization, coarse spatial resolution, and so on [18],

TABLE I
EVALUATION INDEX SYSTEM AND WEIGHTS OF INDICES

ID	Index (X)	Weight (W)	Meaning
1	Per capita GDP	0.109	Representing the regional economic development level
2	Per capita revenue	0.292	Representing the financial strength of regional government
3	Per capita fiscal expenditure	0.083	Representing the ability of providing basic communal products and service
4	The net income per peasant	0.046	Representing the income level of peasants
5	Per capita living expenditure	0.028	Representing the consumption capacity of the residents
6	Urbanization rate	0.061	Representing the regional economic development level
7	Per student educational institutions	0.091	Representing the development level of education
8	Per student teachers	0.005	Representing the development level of education
9	Per capita beds in health	0.109	Representing the regional medical and health conditions
10	Per capita doctors	0.176	Representing the regional medical and health conditions

[19]. Such shortcomings often introduce inaccuracies into socioeconomic data modeling [20]–[22]. In the early 2013, the Earth Observation Group in NOAA/NGDC of the United States released a new generation of nighttime light composite data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day–Night Band (DNB) carried by the Suomi National Polar-orbiting Partnership (NPP) Satellite [23]–[25]. The NPP-VIIRS data were generated from VIIRS DNB data collected on nights with low moonlight during April 18–26 and October 11–23, 2012 [26]. Compared with the DMSP-OLS data, the NPP-VIIRS data have better qualities [27], [28]. The NPP-VIIRS data show a significant improvement over the products that can be derived from the DMSP-OLS data. For example, the NPP-VIIRS data have a wider radiometric detection range than the DMSP-OLS data. Secondary, the NPP-VIIRS data employ calibration, so mapping temporal change in lighting will be more reliable and easier than using the DMSP-OLS data [29]. Most importantly, the increase in spatial resolution of the NPP-VIIRS data (15 arc-second, about 500 m) as compared to the DMSP-OLS data (30 arc-second, about 1000 m) will allow us to expand the work to evaluate the poverty level in China. Detailed description on the comparison of DMSP-OLS and NPP-VIIRS data can be found in [30] and [18]. Some studies have modeled GDP and electric power consumption using the NPP-VIIRS data, and concluded that the NPP-VIIRS data are more reliable for evaluating the socioeconomic phenomena than the DMSP-OLS data [23], [27]. However, no related work has reported the ability of NPP-VIIRS data to evaluate poverty.

As aforementioned, *county* is the basic unit for poverty assessment in China. Therefore, this paper evaluates the ability of NPP-VIIRS data in estimating *county-level* poverty. The main objective of this study is to prove that the NPP-VIIRS data can be used as an alternative data source for poverty estimation at the county level in China. To fulfill the objective, two experiments have been conducted. The first experiment examines the counties in Chongqing, a municipality in southwestern China. This experiment uses the statistics-based multidimensional assessment as a benchmark to validate the accuracy of poverty estimated from the NPP-VIIRS data. A correlation analysis between the ALI, derived from the NPP-VIIRS data, and integrated poverty index (IPI), derived by combining multidimensional statistics, have been conducted. The second experiment investigates the applicability of NPP-VIIRS data to all counties in Mainland China. However, we cannot use statistics-based multidimensional assessment again in this nationwide experiment, due to the availability of statistical data. Although generic statistical data are available for many provinces and counties in China, these data are not comprehensive enough for evaluating poverty at the county level. This situation is especially severe in western China, where statistical data are not explicitly presented. Alternatively, we employ the records of national poor counties (NPC) as the reference data, and a comparison between the NPC data and the derived ALI values has been made in this paper. It is worth to note that although the second experiment utilizes data from the entire nation, we still focus on county-level poverty estimation.

TABLE II
IPI AT THE COUNTY LEVEL IN CHONGQING

County	IPI	Rank	County	IPI	Rank
Yuzhong	0.0892	1	Tongliang	0.0202	20
Jiangbei	0.0667	2	Wulong	0.0201	21
Jiulongpo	0.0523	3	Dazu	0.0192	22
Nanan	0.0488	4	Chengkou	0.0181	23
Yubei	0.0470	5	Hechuan	0.0178	24
Shapingba	0.0414	6	Xiushan	0.0176	25
Beibei	0.0384	7	Wuxi	0.0171	26
Dadukou	0.0365	8	Tongnan	0.0167	27
Banan	0.0292	9	Zhongxian	0.0161	28
Bishan	0.0289	10	Wushan	0.0159	29
Fuling	0.0275	11	Shizhu	0.0159	30
Yongchuan	0.0258	12	Fengjie	0.0155	31
Wanzhou	0.0251	13	Liangping	0.0152	32
Changshou	0.0229	14	Fengdu	0.0152	33
Jiangjin	0.0228	15	Kaixian	0.0149	34
Qianjiang	0.0225	16	Dianjiang	0.0146	35
Qijiang	0.0224	17	Pengshui	0.0140	36
Rongchang	0.0210	18	Youyang	0.0136	37
Nanchuan	0.0205	19	Yunyang	0.0135	38

The rest of this paper is organized as follows. Section II describes the case study area and data sources. Section III provides the introduction of ALI and IPI. The results and discussion are presented in Section IV. Finally, we summarize this work and draw some conclusions in Section V.

II. Case Study Area and Data

A. Case Study Area

Chongqing $(105°11'-110°11'\mathrm{E}, 28°10'-32°13'\mathrm{N})$ is one of the four national central cities in China. It is located in the southwestern part of the country and consists of 38 districts and counties (19 districts and 19 counties) with a total area of 82 402 km^2 (Fig. 1). A district has a higher administrative rank than a county, but their administrative areas are similar. Thus, each district is treated as statistically equal to the counties in this study. Since 1997, when Chongqing was designated as the fourth municipality under the direct administration of the central government of China, it has been undergoing rapid economic development and population growth. However, the uneven socioeconomic development has caused apparent socioeconomic inequality between One Hour Economic Sphere of Chongqing (OHES) and other regions, i.e., Northeast of Chongqing (NC) and Southeast of Chongqing (SC) (see Fig. 1). The socioeconomic development level of Chongqing city can be regarded as a miniature of China. The gap between OHES and other districts is already evident. For instance, by the end

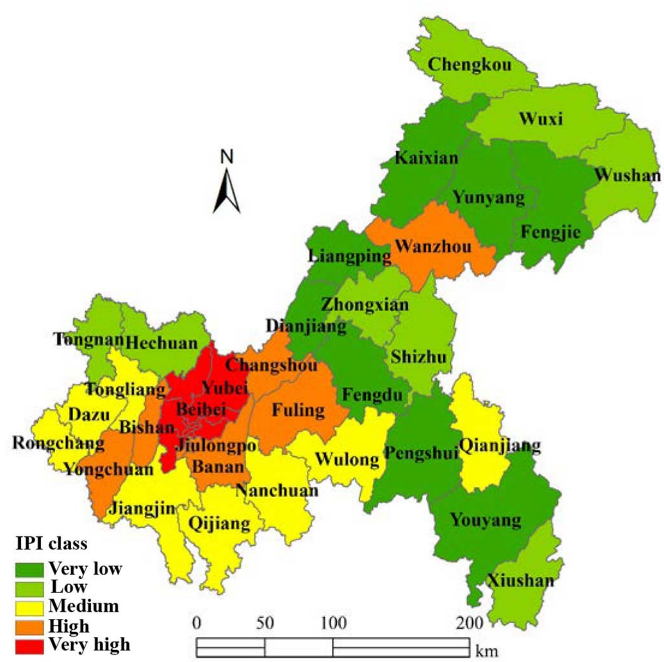


Fig. 3. Poverty classification map based on IPI values for 38 counties in Chongqing.

of 2012, the per capita GDP of NC and SC was 2676 Chinese yuan (CNY), whereas that of OHES was 47 069 CNY [31]. The OHES is the political, educational, finance, and commerce

TABLE III
IPI CLASS RANK VERSUS GDP CLASS RANK

County	IPI	IPI class rank	GDP (billion yuan)	GDP class rank	Difference
Yuzhong	0.0892	5	76.603	5	0
Jiangbei	0.0667	5	52.776	5	0
Jiulongpo	0.0523	5	77.630	5	0
Nanan	0.0488	5	46.556	4	1
Yubei	0.0470	5	87.932	5	0
Shapingba	0.0414	5	65.814	5	0
Beibei	0.0384	5	33.476	4	1
Dadukou	0.0365	4	12.708	2	2
Banan	0.0292	4	42.085	4	0
Bishan	0.0289	4	25.288	3	1
Fuling	0.0275	4	63.053	5	-1
Yongchuan	0.0258	4	40.268	4	0
Wanzhou	0.0251	4	66.286	5	-1
Changshou	0.0229	4	33.641	4	0
Jiangjin	0.0228	3	42.601	4	-1
Qianjiang	0.0225	3	14.795	2	1
Qijiang	0.0224	3	28.667	3	0
Rongchang	0.0210	3	22.981	3	0
Nanchuan	0.0205	3	17.618	3	0
Tongliang	0.0202	3	22.615	3	0
Wulong	0.0201	3	9.840	1	2
Dazu	0.0192	3	24.671	3	0
Chengkou	0.0181	2	4.075	1	1
Hechuan	0.0178	2	34.754	4	-2
Xiushan	0.0176	2	10.608	1	1
Wuxi	0.0171	2	5.311	1	1
Tongnan	0.0167	2	16.275	2	0
Zhongxian	0.0161	2	15.680	2	0
Wushan	0.0159	2	7.035	1	1
Shizhu	0.0159	2	9.310	1	1
Fengjie	0.0155	1	14.457	2	-1
Liangping	0.0152	1	15.665	2	-1
Fengdu	0.0152	1	11.108	2	-1
Kaixian	0.0149	1	22.955	3	-2
Dianjiang	0.0146	1	16.883	3	-2
Pengshui	0.0140	1	8.578	1	0
Youyang	0.0136	1	8.929	1	0
Yunyang	0.0135	1	12.663	2	-1

Note: 1 represents very low IPI (or GDP) class; 2 represents low IPI (or GDP) class; 3 represents medium IPI (or GDP) class; 4 represents high IPI (or GDP) class; 5 represents very high IPI (or GDP) class.

center of Chongqing city. On the contrary, the NC and SC have a lot of NPC, such as Fengjie, Yunyang, Wushan, and so on, where regional economy is mainly based on agriculture with harsh physical environment and poor industry. The regional inequality and poverty have now been recognized as a great barrier for the sustainable socioeconomic development in Chongqing. Therefore, Chongqing is the most representative region for evaluating the poverty at the county level in China.

While Chongqing has been used in the first experiment, the second experiment looks into all 2856 counties from 31 provinces in Mainland China (Fig. 2). Hong Kong, Macao, and Taiwan are not included in this study due to the lack of relevant statistical data.

B. Data Collections

Four types of data are used in this study: 1) the 2012 NPP-VIIRS nighttime light composite data; 2) socioeconomic statistics; 3) the NPC data; and 4) administrative boundary data. The 2012 NPP-VIIRS data (2 months composite) were obtained directly from the NOAA/NGDC website (http://ngdc.noaa.gov/eog/viirs/download_viirs_ntl.html). Since the original NPP-VIIRS data have not been filtered to remove bright albedo surfaces [27], it cannot reflect the true socioeconomic activities of humanity. An approach for correcting the NPP-VIIRS data, proposed by Shi *et al.* [27], has been employed in this research to remove the outliers. The details of this approach are as follows: 1) the lit areas in the 2012 NPP-VIIRS data and the 2012 DMSP-OLS data were assumed to be the same. 2) Then, a mask was emerged by extracting the pixels whose DN values are positive from the DMSP-OLS data. 3) The parts of 2012 NPP-VIIRS data corresponding to the extent of the mask were extracted to generate the primary corrected NPP-VIIRS data. 4) At last, the final corrected NPP-VIIRS data were generated by setting the optimal threshold value which depended upon economic development of three megacities (Beijing, Shanghai, and Guangzhou) in China. The corrected NPP-VIIRS data is shown in Fig. 2. A series of socioeconomic statistics were obtained from 2013 Chongqing Statistical Yearbook. The NPC data of year 2011 are obtained from the State Council Leading Group Office of Poverty Alleviation and Development (http://www.cpad.gov.cn/). Finally, the administrative boundaries for China and Chongqing of the year 2008 were obtained from the National Geomatics Center of China (NGCC).

III. Methods

A. Construction of Average Nighttime Light Index

Poverty can be caused by many aspects of the socioeconomic situations. As a high light density of nighttime light can only represent an intuitive impression of socioeconomic activities at night in a region [7], an ALI was built in order to better represent the average level of different areas in this paper. ALI is calculated as follows:

$$A = \frac{T}{N} \tag{1}$$

where A represents ALI and T donates the total nighttime light (TNL), which is measured by the sum value of all pixels in the corresponding administrative region. N is the sum of the number of all the pixels with positive radiance value.

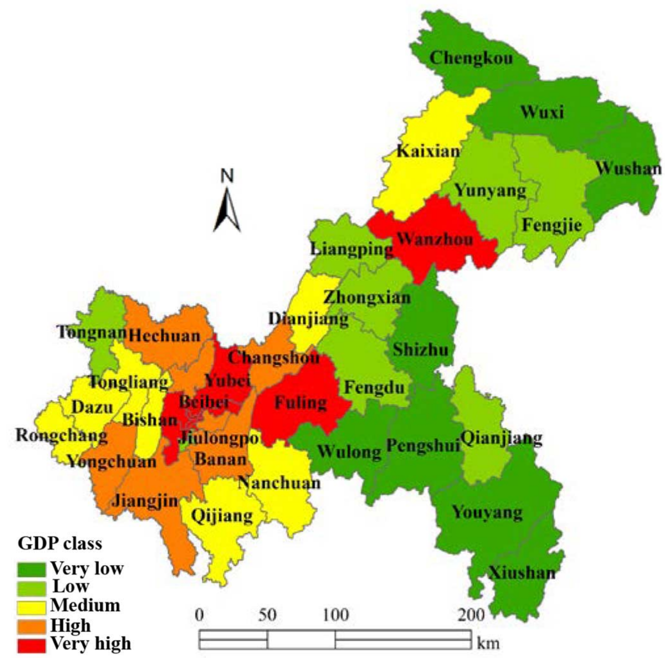


Fig. 4. Poverty classification map based on GDP values for 38 counties in Chongqing.

B. Establishment of IPI

The multidimensional evaluation of poverty using statistics has been widely accepted by researchers and practitioners [9], [32], [33]. Therefore, the multidimensional poverty index is employed to validate the accuracy of poverty evaluation using ALI in this paper. Usually, poverty is a general term describing living conditions that are involved multiple dimensions, such as economic development, health, and education [34]. Based on existing research and the socioeconomic status of Chongqing [7], [31], 10 socioeconomic variables, which are recognized as well-established indicators for reflecting poverty [7], [35], [36], have been used to build an IPI. The IPI could be used as a multidimensional community-level poverty indicator, as listed in Table I.

The weights of indices are essential to multidimensional poverty assessment. Therefore, the quality of the evaluation results is directly related to the methods of weight determination. There are several distinct techniques to calculate weights of indices, including Analytic Hierarchy Process (AHP) [37], Delphi method [34], entropy method [38], and so on. Among them, entropy method has been used in many fields of society and economy and achieved decent results [7], [38], [39].

TABLE IV
ALI AT THE COUNTY SCALE IN CHONGQING

County	ALI	Rank	County	ALI	Rank
Yuzhong	105.738	1	Qianjiang	4.215	20
Jiangbei	48.517	2	Tongnan	4.181	21
Nanan	31.094	3	Tongliang	4.141	22
Shapingba	29.527	4	Qijiang	4.087	23
Dadukou	29.032	5	Fengdu	3.589	24
Yubei	28.467	6	Kaixian	3.435	25
Jiulongpo	19.473	7	Shizhu	3.416	26
Changshou	11.127	8	Dianjiang	3.359	27
Beibei	9.584	9	Youyang	3.295	28
Bishan	7.975	10	Yunyang	3.273	29
Yongchuan	6.813	11	Fengjie	3.265	30
Rongchang	6.581	12	Xiushan	3.087	31
Banan	6.522	13	Pengshui	3.024	32
Hechuan	6.014	14	Liangping	2.768	33
Jiangjin	5.750	15	Wulong	2.657	34
Wanzhou	5.600	16	Zhongixan	2.604	35
Dazu	4.583	17	Wuxi	2.152	36
Fuling	4.333	18	Wushan	2.059	37
Nanchuan	4.331	19	Chengkou	1.824	38

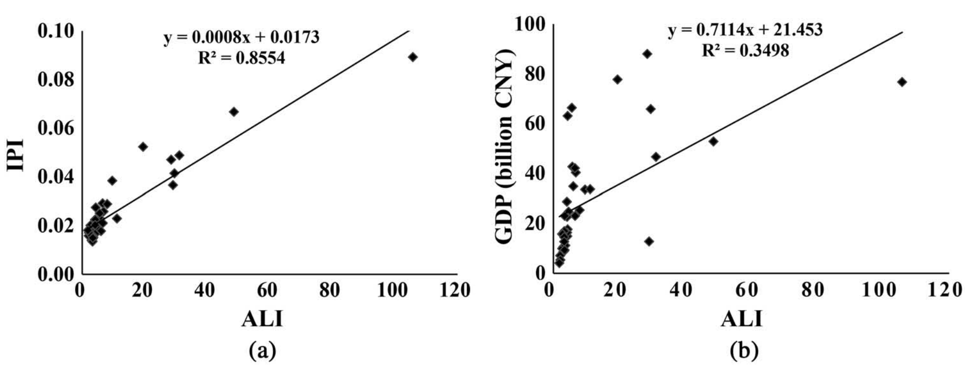


Fig. 5. Scatter diagram of linear regression analysis on relationship between ALI and IPI.

Therefore, it is employed in this study for weight determination. According to entropy theory, the lower the systemic disorder degree is, the smaller the entropy value is. Based on the amount of information, entropy method could be able to determine the index's weights. The process of entropy method is as follows: First, the standardization of each evaluation indicator was conducted. Then, according to the definition of entropy, the index's entropy was determined to continuously calculate variation coefficient. Finally, each index's weight was received with a mixed model. For the specific calculation process of entropy method, refer to Li *et al.* [39] and Shi *et al.* [38]. Then, the weights of each index were calculated using entropy method and listed in Table I.

In order to eliminate the different units which could result in incomparability, the standardization of each evaluation indicator was conducted in [40] as shown in the following equation:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}} \tag{2}$$

where P_{ij} is standardized value of index, X_{ij} is original value of index, i represents the ith county, and j represents the jth index.

The regional IPI is then calculated using the following equation:

$$\mathrm{IPI}_i = \sum_{j=1}^{n} W_j \times P_{ij} \tag{3}$$

where indicates IPI_i of the ith county, W_j indicates weight of the jth index, and P_{ij} denotes standard value of the jth index in ith county.

IV. Results and Discussion

A. IPI Values of 38 Counties in Chongqing

The IPI values of 38 counties in Chongqing are shown in Table II. The lower the IPI value is, the poorer the county is. All richer counties with larger IPI values are located in One Hour Economic Sphere of Chongqing (OHES). The poorest seven counties with IPI values less than 0.0155 are all located in NC and SC, where the regional economy is mainly relied on agriculture with poor transportation, less the secondary industry and tertiary industry.

To better represent the spatial distribution of poverty, the IPI values of the 38 counties were arbitrarily grouped into five classes in order of increasing size, as described in Fig. 3: 1) very low IPI (0.0135–0.0155, eight counties); 2) low IPI (0.0159–0.0181, eight counties); 3) medium IPI (0.0192–0.0228, eight counties); 4) high IPI (0.0229–0.0365, seven counties); and 5) very high IPI (0.0384–0.0892, seven counties). The main urban areas, including Yuzhong, Jiangbei, Jiulongpo, Nanan, Yubei, Shapingba, and Beibei, are the richest counties in Chongqing. Wanzhou with high IPI value is a cultural and economic center in NC. Besides, Qianjiang with medium IPI value is also an economic, cultural center, and transportation hub in SC. Other counties with high and medium IPI values are almost all located in OHES. The counties with lower IPI are mainly located in NC and SC. The results demonstrated that IPI was more reliable for representing poverty at the county level in Chongqing.

In order to assess accuracy of multidimensional assessment of poverty, a comparison between IPI and GDP was conducted in this study. GDP values of 38 counties were also arbitrarily grouped into five classes with the same number of counties inside each corresponding classes as the above classification. From Table III and Figs. 3 and 4, obvious differences were shown between IPI and GDP class ranks in majority of the counties because of different evaluation criterions. Large class rank differences (smaller than -1 or larger than 1) between IPI and GDP were identified in Dadukou, Wulong, Hechuan, Dianjiang, and Kaixian. Although the GDP class rank of Dadukou was low due to its small administrative areas, its good socioeconomic level and better social welfare generated the high-class rank of IPI. Conversely, Wulong, Hechuan, Dianjiang, and Kaixian had a good performance of GDP because of their larger administrative areas, but they could not provide a solid basis to improve people's living standard. This reveals that the level of poverty cannot be defined based on GDP. GDP is a total economic indicator, and is not capable of illustrating inequalities in well-being. As described in

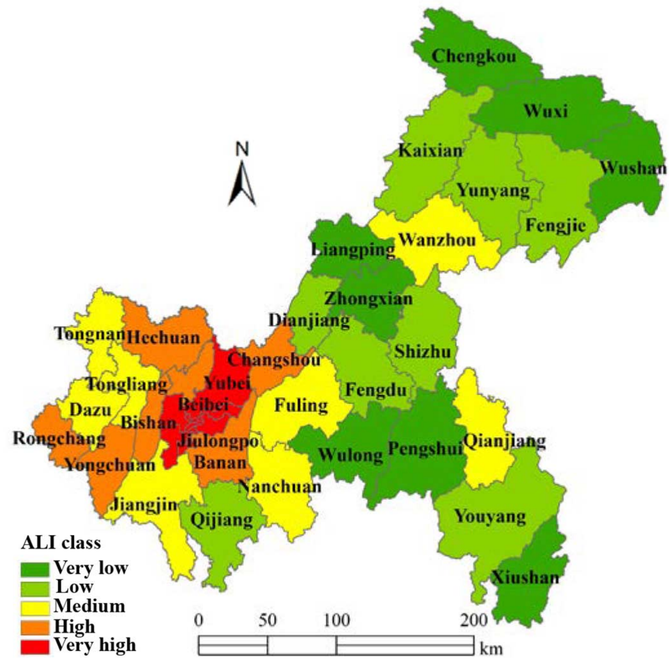


Fig. 6. Poverty classification map based on ALI values for 38 counties in Chongqing.

Section III, the IPI was defined using a comprehensive assessment approach that included many aspects associated with society, economy, education, and health that reflected true people's living standards. Compared with traditional census-based GDP data, it is believed that poverty could be well reflected by IPI at the county level in Chongqing.

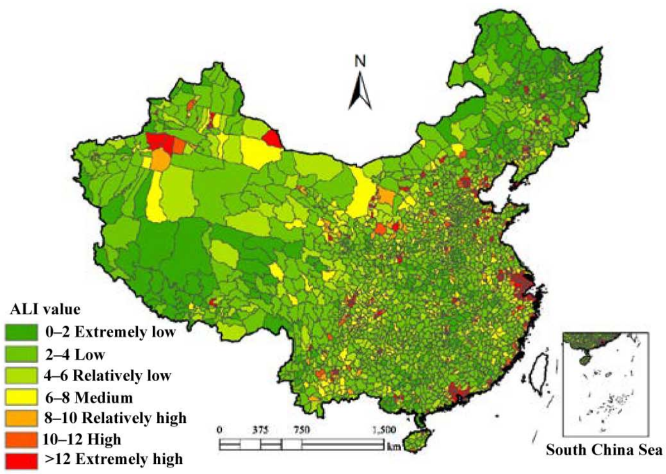
B. Relationship Between ALI and IPI

The ALI values of 38 counties in Chongqing, as listed in Table IV, were calculated using (1). Since most of socioeconomic activities have been found in developed areas with plentiful light at night, a higher ALI value represented more prosperous socioeconomic vitality in a region. From the comparison between Tables IV and II, we found that the ALI values displayed relative closeness as IPI values. The main urban areas, including Yuzhong, Jiangbei, Nanan, Shapingba, Dadukou, Yubei, and Jiulongpo, occupying the top ranks of the table, showed the highest ALI values. On the contrary, Wuxi, Wushan and Chengkou, Zhongxian, Wulong, Liangping, Pengshui, Xiushan, Fengjie, Youyang, and Yunyang holding the minimum ranks, were all located in NC and SC. For example, Youyang and Yunyang counties are two typical national poverty counties (NPC), with ALI = 3.295 and 3.273, respectively. Based on the ground truth data, we found that the important factors of poverty were abominable natural conditions and poor infrastructures. Youyang was one of the most serious areas of rocky desertification, accounting for 86.81% of the total area. In addition, with severe soil erosion, there was about half wasteland in Yunyang. Since there was a lot of wasteland in these counties, they have a relative dim light, i.e., a low ALI value at night. Moreover, a linear regression model was used to explore the relationship between ALI values and IPI values in this study.

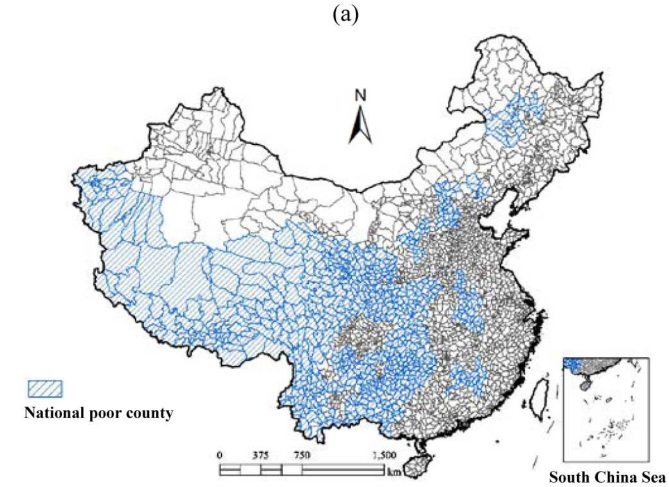
TABLE V
IPI CLASS RANK VERSUS ALI CLASS RANK

County	IPI class rank	ALI class rank	Difference
Yuzhong	5	5	0
Jiangbei	5	5	0
Jiulongpo	5	5	0
Nanan	5	5	0
Yubei	5	5	0
Shapingba	5	5	0
Beibei	5	4	1
Dadukou	4	5	-1
Banan	4	4	0
Bishan	4	4	0
Fuling	4	3	1
Yongchuan	4	4	0
Wanzhou	4	3	1
Changshou	4	4	0
Jiangjin	3	3	0
Qianjiang	3	3	0
Qijiang	3	2	1
Rongchang	3	4	-1
Nanchuan	3	3	0
Tongliang	3	3	0
Wulong	3	1	2
Dazu	3	3	0
Chengkou	2	1	1
Hechuan	2	4	-2
Xiushan	2	1	1
Wuxi	2	1	1
Tongnan	2	3	-1
Zhongxian	2	1	1
Wushan	2	1	1
Shizhu	2	2	0
Fengjie	1	2	-1
Liangping	1	1	0
Fengdu	1	2	-1
Kaixian	1	2	-1
Dianjiang	1	2	-1
Pengshui	1	1	0
Youyang	1	2	-1
Yunyang	1	2	-1

Note: 1 represents very low IPI (or ALI) class; 2 represents low IPI (or ALI) class; 3 represents medium IPI (or ALI) class; 4 represents high IPI (or ALI) class; 5 represents very high IPI (or ALI) class.



(a)



(b)

Fig. 7. (a) Distribution of ALI value in China. (b) Distribution of NPC in China. Note: the high ALI value represents rich and the low ALI value represents poor.

A positive linear relationship was established and the R^2 of the ALI and IPI values was 0.8554 (Fig. 5). In contrast, the R^2 value of GDP values with ALI values was 0.3498, which was lower than that value from ALI values with IPI values (Fig. 5). Therefore, the above correlation indicated that ALI could be accurate for poverty estimation in Chongqing.

Similarly, the ALI values of 38 counties have also been arbitrarily separated into five classes (with each class having the same number of counties as the IPI classification) to make the spatial distribution of poverty intuitively (Fig. 6). The classification criterion were 1) very low ALI (1.824–3.087, 8 counties); 2) low ALI (3.265–4.087, 8 counties); 3) medium ALI (4.141–5.750, 8 counties); 4) high ALI (6.014–11.127, 7 counties); and 5) very high ALI (19.473–105.738, 7 counties), indicating different levels of poverty. Comparing Fig. 3 with Fig. 6, a comparable spatial pattern of poverty could be identified. Most of the poor counties are centered in NC and SC, whereas rich counties are all located in OHES.

To further analyze the rationality of ALI, a comparison between IPI values and ALI values has been conducted in this paper, as described in Table V. The class ranks of the two indexes showed relative closeness in Chongqing. Eighteen counties had ALI class rank in accordance with IPI class rank. For example, Yuzhong is the political, cultural, and financial center of Chongqing with very high IPI and ALI. Jiangbei, Jiulongpo, Shapingba, and Yubei are the most prosperous areas in Chongqing. Their strong economy provided a solid basis to improve socioeconomic environment and produced adequate employment service. Therefore, their ALI class ranks are as high as their IPI class ranks. Pengshui, Liangping, and Yunyang are all underdeveloped areas. As a result, their public infrastructures are not facilitative and their backward secondary and tertiary industries fail to establish a good foundation for solving various poverty problems.

Only two counties, Wulong and Hechuan, displayed large differences in class ranks (equal to 2 or equal to -2). Since Wulong is the most important tourism zone and ecological agriculture base of Chongqing, it has a relative good foundation for solving various poverty problems. However, its tertiary industry (except tourism) is not prosperous, which lead to relatively low ALI class rank. Hechuan is an agricultural county with an agricultural population of 1056.9 thousand accounting for 67.74% of the total population. A large number of surplus labor forces have to go to the developed areas for work. Since the tertiary industry of Hechuan had a rapid development in the last 10 years, its IPI class rank was lower than that of ALI. Eighteen counties presented minor class rank differences (equal to -1 or 1) between ALI and IPI (Table V). Amongst these regions, Beibei, Fuling, Qijiang, and Wanzhou are all relatively developed counties with advanced industry, convenient transportation, and the perfect public facilities. Their secondary industry accounted for 66.56%, 61.35%, 50.54%, and 54.05%. However, the inadequate development of their tertiary industry only endowed them a rather lower ALI class rank. On the contrary, Fengjie, Tongnan, Kaixian, Fengdu, Kaixian, Dianjiang, Youyang, and Yunyang have achieved a great development of tertiary industry, but the poverty situation of those counties has not changed obviously. Overall, the comparative analysis had confirmed that the NPP-VIIRS data were reliable and efficient in evaluating poverty at the county level in Chongqing.

C. Relationship Between ALI and NPC

The previous analysis demonstrates that the NPP-VIIRS data can be a useful source for evaluating poverty at the county level in Chongqing. To evaluate the ability of NPP-VIIRS data in assessing poverty for a large number of counties, we conduct a poverty assessment for all counties in mainland China. ALI values of 2856 counties in China were grouped into seven classes. The seven classes are as follows: extremely low (EL, 0–2), low (L, 2–4), relatively low (RL, 4–6), medium (M, 6–8), relatively high (RH, 8–10), high (H, 10–12), and extremely high (EH, >12). Fig. 7(a) shows the ALI spatial distribution of China at the county level. Most counties, which are located in western and northeast China, are distributed in areas with mountains, deserts, and forests or had EL-to-RL values of ALI. In contrast, the counties with M-to-EH ALI values were mainly concentrated in some inland metropolitan areas and cities (Fig. 7).

TABLE VI
NUMBERS OF COUNTIES AND PROPORTION OF COUNTIES ON NPC AND NON-NPC

Classes	NPC		Non-NPC	
	Numbers of counties	Proportion of counties (%)	Numbers of counties	Proportion of counties (%)
EL	116	17.19	165	7.52
L	423	62.67	742	33.80
RL	103	15.26	296	13.49
M	20	2.96	182	8.29
RH	8	1.19	116	5.28
H	1	0.15	84	3.83
EH	4	0.58	610	27.79

Next, we perform a comparison between ALI values and NPC defined in 2011 by the Chinese central government. To evaluate the feasibility of ALI values for poverty evaluation comprehensively, we calculate the percentages of different levels of ALI values between NPC and non-NPC in China. As listed in Table VI, we found that the ALI values had a concentrated distribution trend in NPC, but a relatively dispersed distribution trend in non-NPC. The EL of EPC includes 116 counties, accounting 17.19% of the total NPC (675 counties). For EL of non-EPC, there are 165 counties with 7.5% of all 2195 counties. Moreover, the L of EPC includes 423 counties, accounting 62.67% of the total NPC, but there are 742 counties with 33.80% for EL in non-EPC. Most of all, the proportion of counties of the EH from EPC is 0.58%, whereas that of the EH from non-EPC is 27.79%. In general, NPC with level of EL to RL account to as much as 95.11%. On the contrary, the accumulated percentage of non-NPC with level EL to RL is 54.81% (Fig. 8). Overall, the ALI values of NPC are mostly at EL to RL levels. The results reveal a general agreement between the NPC and the counties with low ALI values.

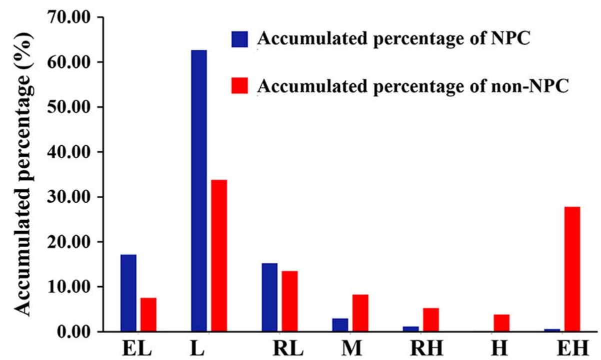


Fig. 8. Comparison of percentages of different level between NPC and non-NPC in China.

However, some NPC in western China had a surprisingly high ALI value. That is because there were many dry riverbeds, snowy mountains, and deserts in those regions. This might be ascribed to the negative effects caused by the background noises of NPP-VIIRS data [27]. Although the corrected data had removed a certain number of outliers, the residual noises still affect the results. Furthermore, we find that the Greater Khingan Range has rich resources and good infrastructures with few NPC in China. However, the forest percentage of Greater Khingan Range is about 80%, so the Greater Khingan Range has a relative dim light, i.e., a low ALI value at night. Consequently, there is an inaccurate poverty estimation. Nevertheless, the proportion of those areas is relatively small, thus the NPP-VIIRS data still have a strong ability in estimating poverty at the county level of China.

V. CONCLUSION AND FUTURE WORK

Estimation of regional poverty level is precondition for the government and policy makers to reduce poverty in China. Traditionally, poverty assessment is based on statistical data collected by local government and the relevant researchers. GDP as an indicator on its own is not capable of evaluating regional poverty level. Although household surveys contain detailed information for poverty assessment, it is time-consuming and requires huge capital investment. Similarly, the multidimensional assessment of poverty using statistics requires a long time period to update existing statistics through economic census and the census can hardly be exhaustive. In comparison with traditional methods, the NPP-VIIRS nighttime light composite data have been proven in this study as an effective and efficient data source for examining poverty issues at the county level.

Two experiments have been performed to evaluate the ability of NPP-VIIRS data in estimating poverty. The first experiment is based on a case study of Chongqing. The multidimensional assessment using statistics was employed as a reference to validate the poverty estimations from the NPP-VIIRS data. The results revealed a good correlation between IPI and ALI with a coefficient of determination (R^2) of 0.8554. The class ranks of IPI and ALI also showed relative closeness in Chongqing, and more than one-half of counties had ALI class rank in accordance with IPI class rank. The second experiment testified the viability and efficiency of the NPP-VIIRS data in assessing poverty in the whole of China, and a comparison between the ALI values and NPC was described. It was clear from the results that NPC were in general agreement with the counties with low ALI values.

Although the NPP-VIIRS data have demonstrated its efficiency and accuracy for poverty evaluation at the county level in China, the proposed measures still contain some uncertainty, caused by the following factor. 1) First, the IPI is a key factor affecting the evaluating accuracy since such data are the basis for the linear regression and poverty classification. 2) Second, the NPP-VIIRS data released by NOAA/NGDC are raw data which still have a lot of noises. Hence, there is still room for improving the data quality, and more measures should be applied to the data correction process. 3) Finally, even though some studies have proved the nighttime light data could be used to evaluate poverty [7], it has to be noted that the relationship between the ALI and poverty is an empirical relationship which cannot be regarded as an absolute law. However, the NPP-VIIRS data are still worthwhile to modeling poverty. This paper provides a new way for evaluating poverty in China at the county level, at which poverty information has often been difficult to quantify due to the lack of specific spatial data and a unified standard.

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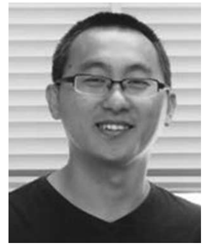

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