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Coupling Coordination Analysis of County Tourism Development and Multidimensional Poverty Based on Nighttime Light Data

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Abstract: In China, tourism development is a crucial approach to poverty alleviation. With the consolidation of poverty alleviation achievements and the promotion of rural revitalization, it is of great significance to explore the relationship between tourism development and poverty alleviation from the perspective of multidimensional poverty. Therefore, this study took 28 key assistance counties for rural revitalization in the Sichuan–Chongqing region (hereinafter referred to as "key counties") as the research objects, introduced NPP-VIIRS nighttime light (NTL) data, and a coupling coordination degree (CCD) model to explore the coordination relationship and mechanism between them. The results showed that from 2015 to 2020, the tourism development index (TDI) and estimated comprehensive development index (ECDI) of the key counties increased by 112.57% and 115.12%, respectively. In addition, the spatial differences in tourism development and multidimensional poverty both showed a narrowing trend. According to the results of the CCD model, the key counties basically faced coordination obstacles in the early stage, which were mainly transformed into reluctant coordination and moderate coordination in the later stage. This indicated that tourism poverty alleviation showed a coordinated development trend overall. However, the study also found that there may not be synchronicity between tourism development and poverty alleviation and analyzed the mechanism of their interaction. Overall, the study confirmed the positive impact of tourism development on alleviating multidimensional poverty. In addition, the study found that measuring multidimensional poverty based on NTL data has a high accuracy and can provide support for poverty research. These research results have an important reference value for China to carry out sustainable tourism poverty alleviation and comprehensively promote rural revitalization.

Keywords: multidimensional poverty; tourism poverty reduction; nighttime light; coupling coordination; Sichuan–Chongqing region

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1. Introduction

Poverty has been a long-term global issue, and its eradication is a common challenge for humanity and the primary goal of the United Nations for sustainable development by 2030 [1]. Many countries are facing the crucial task of poverty reduction [2]. China has carried out a great deal of poverty alleviation work and achieved remarkable results. By the end of 2020, 832 impoverished counties were lifted out of poverty, and overall regional poverty was eliminated. However, this did not signify the end of poverty eradication efforts. The elimination of poverty is a long and arduous process due to the developmental imbalance and the large scale of the impoverished population [3]. Past practical experience has shown that tourism poverty reduction has significant potential value in consolidating poverty alleviation achievements and curbing poverty return [4]. Currently, it is a critical period to consolidate and expand the results of poverty eradication and rural revitalization [5]. In order to improve the overall development level of poverty-stricken areas, the Chinese government has identified 160 key assistance counties for rural revitalization (https://www.people.cn/, accessed on 4 April 2023). Therefore, it is crucial to investigate the effect of county tourism development on multidimensional poverty and its mechanism to promote the overall revitalization of the countryside and the balanced development of the region.

As the study of poverty continues, personal income is no longer seen as the sole indicator of poverty because it ignores many factors related to individual and social well-being [6]. The definition of poverty has broadened from a purely economic dimension to a multidimensional one that includes natural, human, and other dimensions [7]. Many studies have conducted a multidimensional poverty evaluation based on the Multidimensional Poverty Index (MPI) proposed by Alkire et al. [8], considering the specific situation of the study area. Most of these studies were conducted based on multidimensional statistics and have confirmed their rationality and validity [9,10]. However, traditional statistics have a certain time lag and rely on economic and population censuses for updates [11]. In addition, more dimensions imply higher data completeness, which is a challenge for counties in poor areas. In China, the county serves as the basic unit of poverty assessment, and there is a need to study multidimensional poverty on this scale. Compared with traditional statistical or survey data, remote sensing data offers significant advantages in terms of long time series and multiple spatial scales. In particular, NTL data provides a timely and objective way to directly observe socio-economic dynamics [12], which can well solve the problem of missing statistics at the county level. Yu et al. [13] explored the spatial overlap between NTL data and national poverty-stricken counties, confirming that the NTL data were useful for assessing poverty in China. Yong et al. [14] combined different types of NTL data to assess county-level poverty in southwest China from 2000 to 2019. These studies have confirmed the rationality of this method and expanded its application range in related fields.

Tourism development is an essential tool for poverty eradication. Pro-poor tourism (PPT) and sustainable tourism for poverty eradication (ST-EP) have been introduced [15] to help eradicate poverty. "Tourism for Poverty Alleviation" is a concept that emerges from the intersection of China's tourism industry and its poverty alleviation strategy [16], which can increase employment opportunities, enhance living standards, and stimulate the growth of related industries. It plays an important role in promoting endogenous development in poor areas as a catalyst for poverty eradication. Studies have primarily focused on the patterns [1,17], effects [18,19], and countermeasures [20,21] of poverty reduction in tourism, most of which were based on statistical methods. As an objective assessment indicator, tourism poverty reduction efficiency has been studied extensively at various spatial scales [22,23]. However, there has been no consensus among scholars on the relationship between tourism development and poverty reduction, although tourism can boost local economies [24]. Some studies have argued that tourism tends to benefit poor households by providing them with diverse sources of livelihood [25]. Tourism development can bring external resources to villages, attract poor individuals to participate in construction, and enhance the regenerative capacity within rural communities, thereby promoting rural economic growth. Considering the pluralistic and relative nature of poverty and well-being, Winter et al. [26] found that opportunities associated with tourism resources contribute to the realization of different aspects of well-being for participants. However, some studies have argued that tourism development does not necessarily reduce poverty [27]. Phenomena such as unequal distribution of benefits and low subject participation [28] often contribute to the widening between rich and poor populations.

With the development of the concept of poverty, it has become a hotspot to research tourism poverty reduction from the perspective of multidimensions. Llorca-Rodríguez et al. [29] applied the fixed effects model to assess the impact of tourism on poverty reduction in Peru. The study found that tourism reduced multidimensional poverty, but its potential was not fully utilized. Scheyvens et al. [30] explored how tourism can achieve SDG1 using Fiji as an example, which showed that tourism could easily reduce economic poverty but was more complex in addressing other dimensions of poverty given the multidimensional nature of poverty. Ridderstaat et al. [19] constructed a framework for tourism development and poverty in Honduras, with the mediating roles of economic growth and human development. The results indicated that tourism was not very effective in reducing local poverty directly or indirectly. In empirical studies in China, scholars mostly identified and analyzed the dynamic relationship between tourism development and multidimensional poverty based on poverty-stricken areas. The results showed that tourism development had improved the local poverty situation to a certain extent, and there were differences in the development status of tourism poverty reduction in different poverty dimensions [31,32]. The coupled coordination degree (CCD) model was widely used to describe the degree of synergy between two or more subsystems. Ge et al. [33] assessed the coordination relationship between social economy and environment in poverty-stricken areas of China and proposed a sustainable poverty reduction model. Wang et al. [34] conducted a coupling analysis on the superiority of tourism resources and poverty alleviation in poverty-alleviated counties. In view of the complex mechanism between tourism and poverty reduction, the CCD model was applied to explore the relationship between tourism and poverty reduction, which could reflect the coordination level of tourism development and multidimensional poverty and promote the balance of tourism poverty reduction.

The proportion of tourism income to GDP in poor areas of southwest China has been rising year by year, exceeding 40% in 2019, making a more significant contribution to comprehensive poverty alleviation in 2020. Among them, the Sichuan–Chongqing region is rich in tourism resources, and tourism poverty reduction plays a crucial role in the process of regional development [31]. During the "13th Five-Year Plan" period, the average annual growth rate of total tourism income in Sichuan was as high as 16.89%, and 1 million poor people were driven out of poverty, cumulatively. New forms of rural tourism were vigorously developed in Chongqing, and more than 2000 villages hosted rural tourism, lifting 330,000 poor people out of poverty and increasing their income. Meanwhile, a total of 29 counties in the Sichuan–Chongqing region belong to the key counties, which still have a greater risk of returning to poverty. Studying tourism-based poverty reduction in key counties to grasp the link between tourism and multidimensional poverty could boost sustainable rural revitalization.

Therefore, this study proposes the following objectives: (1) introduce NPP-VIIRS data and construct a county-scale multidimensional poverty measurement model to achieve multidimensional poverty measurement in key counties in the Sichuan–Chongqing region; (2) analyze the spatio-temporal characteristics and regional differences of tourism development and multidimensional poverty in the key counties from 2015 to 2020; (3) explore the coupling and coordination between tourism development and multidimensional poverty relationship and the mechanism of action in the same period. Based on the above objectives, this study aimed to provide new ideas and methods for tourism poverty reduction research, guide the key counties to carry out sustainable tourism poverty reduction work, and provide the decision-making basis for policy formulation. In addition, the study provides references and scientific suggestions for other regions to consolidate the results of poverty alleviation and promote rural revitalization.

2. Materials and Methods

2.1. Study Area

The Sichuan–Chongqing region is located in the southwest of China, with a total of 221 county-level administrative districts. This region lies in the transitional zone between the Tibetan Plateau and the plains of the middle and lower reaches of the Yangtze River. The topographic conditions are highly complex, with plateaus, mountains, and hills dominating the landscape. The region's fragile ecological environment and frequent natural disasters, such as droughts, floods, and hailstorms, have resulted in low economic development, a large number of impoverished individuals, and high poverty rates. As of the end of 2022, the resident population of Sichuan and Chongqing was approximately 116 million, with the rural population accounting for around 450 million. The per capita disposable income in rural areas was below the national average, at less than CNY 20,000. However, the region is rich in tourism resources and has favorable conditions for tourism development. Therefore, poverty reduction through tourism has become an effective way to promote regional development.

This study took key counties in the Sichuan–Chongqing region as case sites to explore the impact of tourism development on multidimensional poverty. To ensure the completeness of the tourism data, we excluded Yuexi County and selected 28 key counties with relatively complete tourism data from 2015 to 2020 for analysis (Figure 1). These key counties are distributed in the Aba, Ganzi, and Liangshan prefectures in Sichuan, and excludes Chongqing. Tourism has been an effective means of promoting local socio-economic development and reducing poverty. In the key transition period from poverty eradication to rural revitalization, it is typical to study the impact of tourism development on multidimensional poverty in key counties in the Sichuan–Chongqing region.

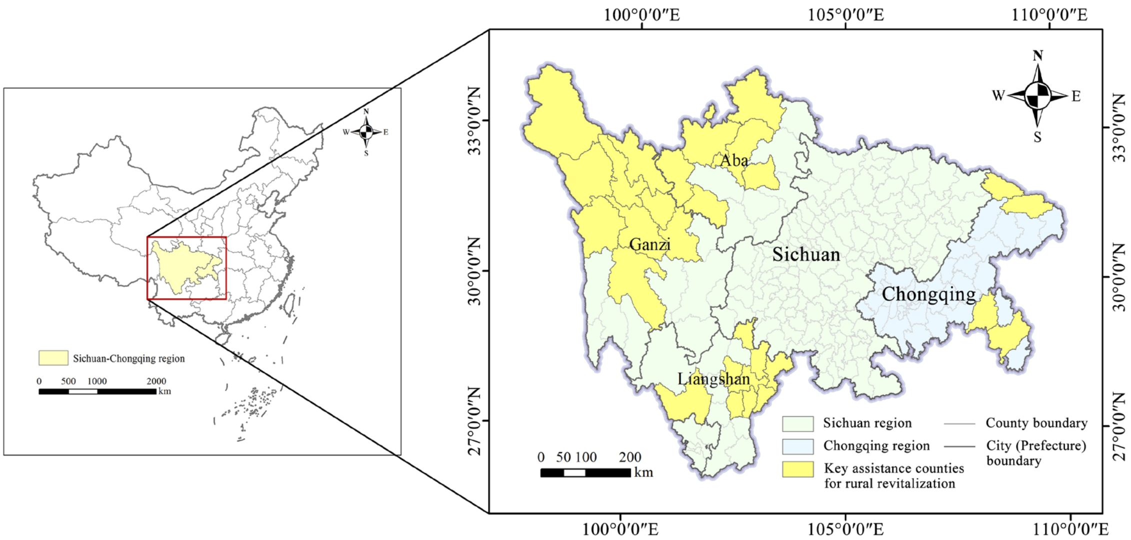


Figure 1. Spatial distribution of the 28 key counties in the Sichuan–Chongqing region.

2.2. Data Sources and Processing

This study used two main types of data: nighttime lighting (NTL) data and statistical data. Currently, the two most commonly used NTL products are DMSP-OLS and NPP-VIIRS. However, due to its higher spatial resolution, lack of brightness saturation issues, and greater time sensitivity, we selected NPP-VIIRS data. The NPP-VIIRS data used in this study were from the Earth Observation Group (EOG) of the Colorado School of Mines and cover the period from 2012 onwards. The study selected the annual VNL V2 date, which was converted into the Lambert projection coordinate system using ArcGIS 10.5, with the spatial resolution set to 500 m and cropped. A cell pixel radiance threshold of 472.86 was applied, and cells with negative pixel values were removed to deal with negative values and extreme anomalies [35].

The statistics include socio-economic data on the economy, education, health, and social security, apart from tourism data. The tourism data were from the national economic and social development statistics bulletin and the government work report of the key counties. The socio-economic data were from the Chongqing Statistical Yearbook. The data were normalized using the polarization method to control the data within the range of [0, 1] and reduce the effect of magnitude. Additionally, the study used administrative boundary vector data and DEM data. The description of each data source is in Table 1.

Table 1. Description of each data source used in the study.

Data	Description	Year	Source
NPP-VIIRS	Annual VIIRS Nighttime Lights Version 2	2015–2020	https://eogdata.mines.edu/products/vnl/, accessed on 12 April 2023
Socio-economic data	Data on economy, education, medical care and social protection of districts and counties in Chongqing	2015–2020	https://tjj.cq.gov.cn/, accessed on 18 April 2023
Tourism data	Key counties tourism income and tourism reception	2015–2020	Statistical Communiqué on the National Economic and Social Development of key counties (2015–2020)
Boundaries	Shapefiles of county-level regions in Sichuan and Chongqing	2019	https://www.webmap.cn/, accessed on 12 April 2023
DEM	GDEMV2 30M raster	/	https://www.gscloud.cn/, accessed on 20 April 2023

2.3. Research Methods

This study consisted of four key steps (Figure 2): (1) constructing a multidimensional poverty and tourism development index system, collecting data to calculate ACDI and TDI, and calculating ANLI by using NPP-VIIRS data; (2) taking each district and county in Chongqing as a sample area, establishing a regression model of ACDI and ANLI and testing precision, and applying it to key counties to obtain ECDI; (3) analyzing spatio-temporal changes of tourism development and multidimensional poverty in key counties, and measuring regional differences by the coefficient of variation; (4) based on the CCD model, CCD was calculated and classified, and the coupling and coordination relationship between tourism development and multidimensional poverty in key counties was studied to explore their mechanism.

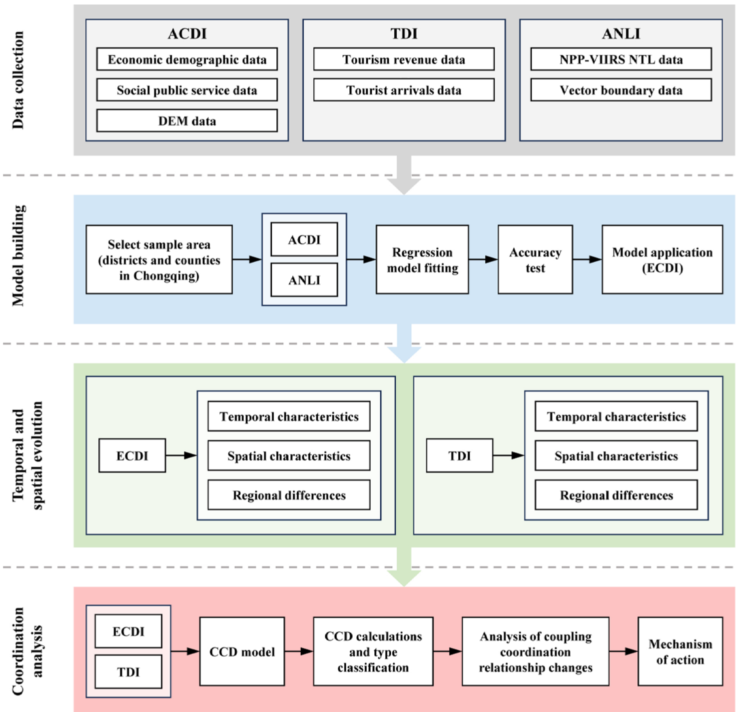


Figure 2. The process of applying methodologies.

2.3.1. Area Light Index

The total amount of regional lights (total intensity), or average lights (light density), can reflect the lighting characteristics in the region [36]. In this study, the regional average nighttime light index (ANLI) was used to measure poverty, and the ANLI was extracted using processed NPP-VIIRS annual nighttime light images with the formulae:

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

$$ANLI = \frac{TNLI}{n} \tag{2}$$

where $TNLI$ is the regional total light index, DN_i is the radiation value of each pixel in the region, and n is the number of pixels.

2.3.2. Evaluation Index System

(1) The evaluation of multidimensional poverty was as follows: Scholars have widely adopted statistics-based multidimensional poverty assessment [9,37], and the MPI has become the basis for regional poverty measurement. Based on the theory of multidimensional poverty, and adhering to the principles of scientificity, comprehensiveness, and data availability, a multidimensional poverty indicator system (Table 2) was constructed in combination with the poverty alleviation standards of "having no worries about food and clothing, and three guarantees" and the rural revitalization strategy. The system consists of five dimensions: natural environment, economic infrastructure, transport, public services, and social structure, with a total of 10 indicators. The actual comprehensive development index (ACDI) was constructed to characterize the comprehensive development level of key counties based on index data. The weight of each index was calculated using the entropy method with a time variable [38], resulting in a more objective calculation.

Table 2. Evaluation Index and Weight Distribution of Multidimensional Poverty.

Dimension	Index	Attribute	Weight
Natural environment	Average altitude (m)	−	0.044
	Proportion of area with slope above 25° (%)	−	0.049
Economic base	GDP per capita (yuan)	+	0.121
	Per capita local fiscal income (yuan)	+	0.144
	Per capita disposable income of rural residents (yuan)	+	0.091
Transportation facilities	Road network density (km/km^2)	+	0.064
Public service	Number of students enrolled per capita (persons/10,000 persons)	+	0.066
	Number of beds in hospitals and health centers per capita (beds/10,000 persons)	+	0.167
	Number of beds per capita in socially adopted units (beds/10,000 persons)	+	0.200
Social structure	Proportion of population aged 60 and over (%)	−	0.054

Note: "+" denotes the positive attribution; "−" denotes the negative attribution.

ACDI is calculated from the index weights and normalized values as follows:

$$ACDI_i = \sum_{j=1}^{n} w_j \times x_{ij} \tag{3}$$

where $ACDI_i$ is the value of the county in a certain year, w_j is the weight of the index, x_{ij} is the standard value of the index of the county in the same year, and n is the number of supporting counties in the region.

(2) The evaluation of tourism development was as follows: Based on the entropy method and the research results of most scholars [23,39], two indicators, per capita tourism income and per capita tourist reception, were selected to construct a tourism development index system (Table 3), and the tourism development index (TDI) was calculated. Per capita tourism income directly reflects the development effect of tourism, while per capita tourist reception represents the radiation-driving effect of tourism on related industries. It reflects the comprehensive contribution of the real economic input of tourism to the entire key counties and effectively represents the advantages and disadvantages of the pro-poor impact of tourism.

Table 3. Evaluation index and weight distribution of tourism development.

Index	Attribute	Weight
Per capita tourism income (yuan)	+	0.585
Per capita tourist reception (person–times)	+	0.415

Note: "+" denotes the positive attribution.

2.3.3. Measurement Model Construction

(1) The regression model fitting was performed as follows: The study chose each district of Chongqing as a sample area and established the relationship model between ANLI and ACDI, namely the multidimensional poverty measurement model. The economic and social development level of each district and county in Chongqing was quite different, which conformed to the poverty spatial difference in the entire region [14]. In addition, compared with other key counties in Sichuan, Chongqing, as a municipality directly under the central government, has more complete statistical data on its districts and counties, which is conducive to the construction of a multidimensional poverty index system.

ANLI and ACDI were calculated for each district in Chongqing from 2015 to 2020. ANLI was used as the independent variable and ACDI as the dependent variable to construct the relationship model between them. Linear, exponential, logarithmic, and polynomial regression models were used to fit and compare the R^2 of different models. The regression model with the best fitting effect was selected as the multidimensional poverty measurement model and applied to key counties in Sichuan–Chongqing region to obtain the estimated comprehensive development index (ECDI).

(2) The model accuracy test was performed as follows: To ensure the reliability of OECD calculations based on ANLI, we compared it with the ACDI calculations based on statistical data, calculated relative error (RE), and mean relative error (MRE) as follows:

$$RE = \left(\frac{ECDI - ACDI}{ACDI}\right) \times 100\% \tag{4}$$

$$MRE = \frac{\sum_{i=1}^{n} |RE_i|}{n} \tag{5}$$

where RE is the relative error, MRE is the mean relative error, and n is the number of supporting counties in the region.

2.3.4. Coefficient of Variation

The coefficient of variation, a statistic used to measure the relative difference between measures, is usually used to compare the degree of dispersion of different groups of data [40]. The coefficient of variation was used to reveal the spatial difference and degree of tourism development and multidimensional poverty in key counties. The formula is as follows:

$$CV = \frac{1}{\overline{x}}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}} \tag{6}$$

where CV is the coefficient of variation, indicating the relative degree of difference, x_i is the correlation index value of key counties, $\overline{x}$ is the average value of x_i, and n is the number of key counties in the region. The larger the CV value, the greater the spatial differentiation of the correlation index in key counties, the smaller the CV value, the smaller the degree of differentiation, and the more balanced the spatial distribution of the correlation index in key counties.

2.3.5. Coupling Coordination Degree Model

The coupling degree is a physics concept that describes the degree to which two or more systems affect and interact with each other [41]. However, higher coupling may occur when different systems are at a lower level. The coupling coordination degree (CCD) is the deepening of the system coupling degree, reflecting the coordination status of both sides of the system [42]. To measure the degree of coordination between tourism development and multidimensional poverty, the CCD model was calculated by the following formula:

$$C = 2\sqrt{\frac{u_1 \times u_2}{(u_1 + u_2)^2}} \tag{7}$$

$$T = \alpha u_1 + \beta u_2 \tag{8}$$

$$D = \sqrt{C \times T} \tag{9}$$

where C is the coupling degree, u_1 presents ECDI, u_2 presents TDI, T is the comprehensive coordination index, and α and β are undetermined coefficients with $\alpha + \beta = 1$ and taking $\alpha = \beta = 0.5$ according to system importance [33]. D is the degree of coupling coordination. The higher the D is, the higher the degree of coordinated development of the two. D was divided into four grades based on the available studies [34,43] and calculations (Table 4).

Table 4. Classification criteria of the coupling coordination degree.

Coordination Level	Type
$0 \leq D \leq 0.4$	Obstacles to coordination
$0.4 < D \leq 0.5$	Reluctant coordination
$0.5 < D \leq 0.6$	Moderate coordination
$0.6 < D \leq 1$	High coordination

3. Results

3.1. Multidimensional Poverty Measurement Model

3.1.1. Measurement Model Selection

The ANLI (independent variable) and ACDI (dependent variable) from 2015 to 2020 in various districts and counties of Chongqing were used for constructing a regression model, comparing the coefficient of determination R^2 across different regression models, with the results presented in Table 5. The results indicated that the logarithmic regression model demonstrated the most optimal fitting effect, with R^2 ranging from 0.850 to 0.906. Therefore, a logarithmic regression model was chosen as the multidimensional poverty measurement model of key counties from 2015 to 2020 (Figure 3). Based on the ANLI data of the key counties, the ECDI was calculated. It could be found that R^2 showed an overall upward trend with the increase in years, which might be related to the increasing intensity of NTL in key counties. In certain years, such as 2019, the R^2 value was relatively small, which might be attributed to the influence of the quality of the original remote sensing imagery. Furthermore, when the ANLI value in the key counties was less than three, the fitting effect was generally good, with ECDI closely resembling ACDI. However, as the ANLI value continued to increase, ACDI showed greater fluctuations and deviations from the fitting curve, indicating instability in the model's fitting process. Given that the ANLI values in the key counties were generally low, the logarithmic regression model could effectively reflect the multidimensional poverty status of these counties overall.

Table 5. Comparison of regression model fitting results of ANLI and ACDI in various districts and counties in Chongqing from 2015 to 2020.

Year	R^2 of Different Regression Models				
	Linear	Quadratic Polynomial	Cubic Polynomial	Exponential	Logarithmic
2015	0.660	0.737	0.784	0.495	0.850
2016	0.669	0.770	0.819	0.512	0.851
2017	0.630	0.747	0.829	0.473	0.896
2018	0.698	0.812	0.865	0.548	0.881
2019	0.639	0.732	0.797	0.505	0.853
2020	0.638	0.714	0.812	0.489	0.895

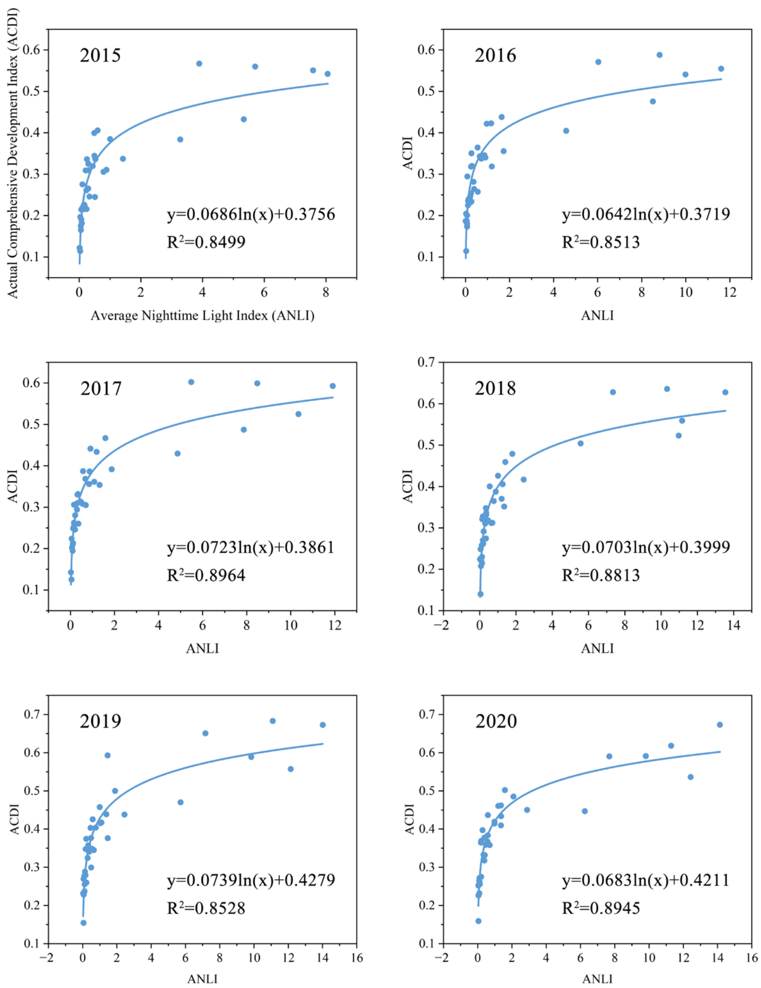


Figure 3. Logarithmic regression model fitting curve results from 2015 to 2020.

3.1.2. Accuracy Evaluation

A comparison was made between ECDI and ACDI to assess the accuracy of the logarithmic regression model by RE. Calculations of relative errors revealed that the MRE over six years was 11.11%, with the maximum annual MRE being 13.49% and the minimum being 8.60%. These results were similar to the study conducted by Pan et al. [44], indicating that NTL data could be effectively used for poverty measurement.

To comprehensively evaluate the prediction accuracy of the logarithmic regression model, the REs were categorized into three levels: 0~25% representing high accuracy, 25~50% representing medium accuracy, and above 50% indicating an error [45]. High accuracy suggested a low level of error and a high precision in predicting multidimensional poverty based on NTL data. Medium accuracy indicated a larger prediction error. An error signified that NTL data could not be used to measure multidimensional poverty. As indicated in Table 6, the accuracy of the test results of each year's regression models revealed that the proportion of high accuracy stood at the highest, averaging 92.79% over six years, significantly surpassing the 7.21% of medium accuracy. The proportion of errors was 0, indicating that predicting multidimensional poverty based on NPP-VIIRS data showed high precision. Therefore, in the absence of data from the key counties in Sichuan, NTL data could be used as a substitute for traditional socio-economic statistical data, enabling further research on the relationship between tourism development and multidimensional poverty.

Table 6. Accuracy test results of multidimensional poverty measurement model from 2015 to 2020.

Year	MRE	The Proportion of Mean Relative Error (MRE)		
		High Accuracy (0~25%)	Medium Accuracy (25~50%)	Error (50~100%)
2015	13.08%	89.19%	10.81%	0
2016	13.49%	86.49%	13.51%	0
2017	10.02%	97.30%	2.70%	0
2018	10.72%	94.59%	5.41%	0
2019	10.78%	91.89%	8.11%	0
2020	8.60%	97.30%	2.70%	0

3.2. Spatio-Temporal Characteristics of Multidimensional Poverty

Using NPP-VIIRS data, we obtained the ANLI for the key counties in the Sichuan–Chongqing region, calculated the ECDI, and measured the multidimensional poverty situation of these counties (Figure 4a). Overall, the level of multidimensional poverty in these counties gradually decreased, with the ECDI increasing from 0.082 in 2015 to 0.177 in 2020, an increase of 115.12%. Notably, the growth of ECDI was relatively slow before 2017, but accelerated between 2017 and 2020. This showed that regional development had been better supported, driven by poverty alleviation efforts and rural revitalization policies. Among them, the counties in Ganzi Prefecture experienced the fastest rate of multidimensional poverty reduction, with ECDI increasing by 225.86%. Chongqing, Aba Prefecture, and Liangshan Prefecture saw increases of 61.25%, 128.38%, and 92.33%, respectively. Although the Aba and Ganzi prefectures initially faced a high level of multidimensional poverty, they achieved remarkable progress in their comprehensive regional development through various poverty reduction efforts. In contrast, Chongqing and Liangshan Prefecture had a good economic foundation, so the comprehensive development level of key counties was relatively high, and the poverty alleviation rate was more moderate.

To further analyze the spatial distributions of multidimensional poverty in key counties in the Sichuan–Chongqing region, visualization results were conducted for the years 2015, 2017, and 2020. The ECDI values were categorized into three levels: high, medium, and low, using the natural breaks method (Figure 5). Key counties with low ECDI values were mainly distributed in Aba Prefecture and Ganzi Prefecture, accounting for 66.67% in both places in 2015. Geographical obstacles were the key factors hindering local development, often accompanied by problems such as inconvenient transportation, fragile ecology, and a single industrial structure, leading to a higher degree of multidimensional poverty. Key counties with medium ECDI values distribution were more scattered, with early distribution in four regions; later, spatial scope had been reduced, among which the distribution change in Liangshan Prefecture was more obvious. Key counties with high ECDI values were relatively concentrated in Chongqing and Liangshan Prefecture. As a municipality directly under the central government, Chongqing has advantages in policies, funding, and industries, resulting in significant multidimensional poverty reduction. Taking Youyang County as an example, its average ECDI was the highest at 0.204, which was closely related to the local promotion of rural cooperatives and industrial development in recent years. Compared to the Aba and Ganzi prefectures, Liangshan Prefecture had obvious geographical and transportation advantages, as well as abundant natural resources and industrial bases, providing strong support for economic growth. In 2020, the proportion of key counties with high ECDI values in Liangshan Prefecture reached 77.78%, much higher than that of the Aba and Ganzi prefectures. Additionally, key counties with high ECDI values tended to form local clusters, which matched regional development policies and actual conditions.

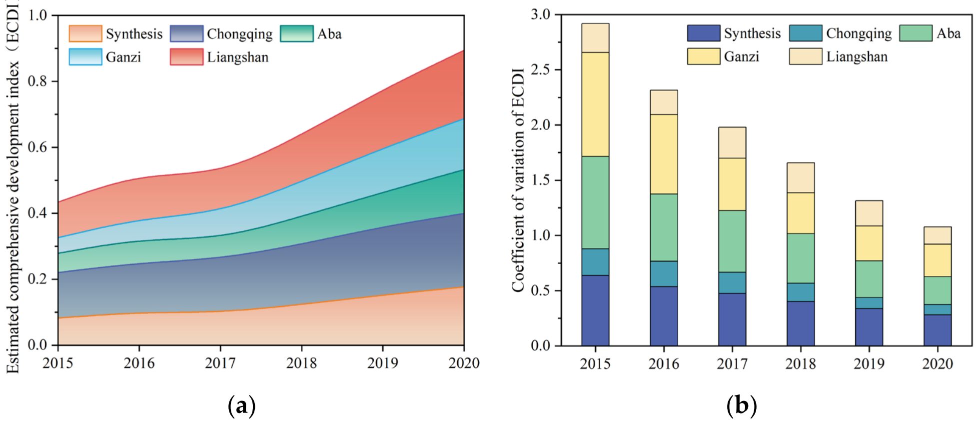


Figure 4. Temporal evolution of ECDI (**a**) and its coefficient of variation (**b**) in key counties as a whole and by region from 2015 to 2020.

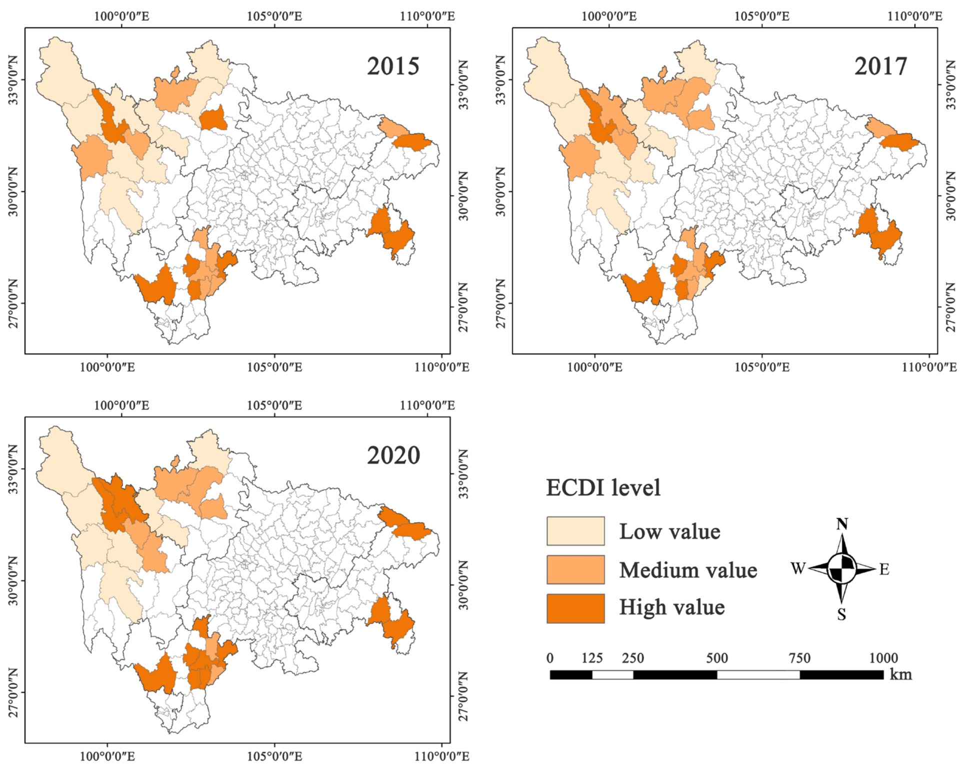
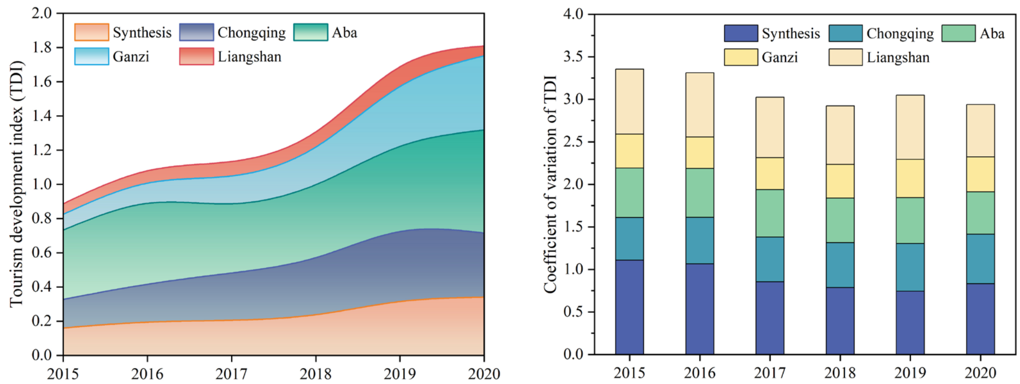


Figure 5. Spatial pattern evolution of multidimensional poverty in key counties from 2015 to 2020.

Using the coefficient of variation to analyze the regional differences in multidimensional poverty (Figure 4b), it was evident that the spatial differences in ECDI among key counties in the Sichuan–Chongqing region significantly decreased from 2015 to 2020. The coefficient of variation decreased from 0.637 to 0.282, a reduction of 55.76%. When analyzed regionally, the average coefficients of variation for Chongqing, Aba Prefecture, Ganzi Prefecture, and Liangshan Prefecture were 0.171, 0.506, 0.520, and 0.237, respectively. The data suggested that there was a relatively small spatial difference in multidimensional poverty among key counties in Chongqing and Liangshan Prefecture, which aligned with the concentrated distribution of high ECDI values. While the spatial distribution of multidimensional poverty in key counties in the Aba and Ganzi prefectures was uneven, the coefficients of variation decreased by 69.81% and 68.76%, respectively, indicating a gradual narrowing of spatial differences. Overall, the multidimensional poverty in key counties in the Sichuan–Chongqing region was tending towards equilibrium, and the regional differences in comprehensive development level were becoming increasingly smaller.

3.3. Spatio-Temporal Characteristics of Tourism Development

Based on the Tourism Development Evaluation System, TDI was calculated to analyze the tourism development level in key counties (Figure 6a). Overall, the tourism development level in key counties showed an upward trend from 2015 to 2020, with TDI increasing from 0.160 to 0.340, an increase of 112.57%. More specifically, the key counties in Chongqing showed relatively stable growth, with an increase ranging from 90.48% to 144.52%. Although the growth in Sichuan's key counties fluctuated more significantly, they still demonstrated an overall positive trend, with TDI increasing from 0.159 to 0.335. It was noteworthy that 20.83% of the key counties showed negative growth, while half of them achieved growth rates exceeding 100%. Among them, the growth rate of counties receiving assistance in Ganzi Prefecture reached up to 372.61%, while that of Liangshan Prefecture showed negative growth, at −7.90%.



(**a**) (**b**)

Figure 6. Temporal evolution of TDI (**a**) and its coefficient of variation (**b**) in key counties as a whole and by region from 2015 to 2020.

To better analyze the spatial pattern of tourism development, visualization results were conducted for the years 2015, 2017, and 2020. The TDI values were categorized into three levels: high, medium, and low, using the natural breaks method (Figure 7). Key counties with high TDI values were primarily distributed in Aba Prefecture, such as Heishui County, Ruoergai County, and Hongyuan County. Among them, Heishui County had a TDI of 0.932 in 2020, with a total tourism income of CNY 1.399 billion, indicating a leading position in terms of tourism competitiveness within the region. During the period from 2015 to 2020, the overall tourism development level of the counties receiving assistance in Ganzi Prefecture showed a significant improvement, with the proportion of key counties with medium TDI increasing from 11.11% to 88.89%. Thanks to Ganzi Prefecture's vigorous promotion of global tourism, the overall tourism development level in the region improved significantly. However, the overall development level of tourism resources in Liangshan Prefecture was relatively low, resulting in generally low tourism development level. In the later period, all counties in the region were key counties with low TDI values.

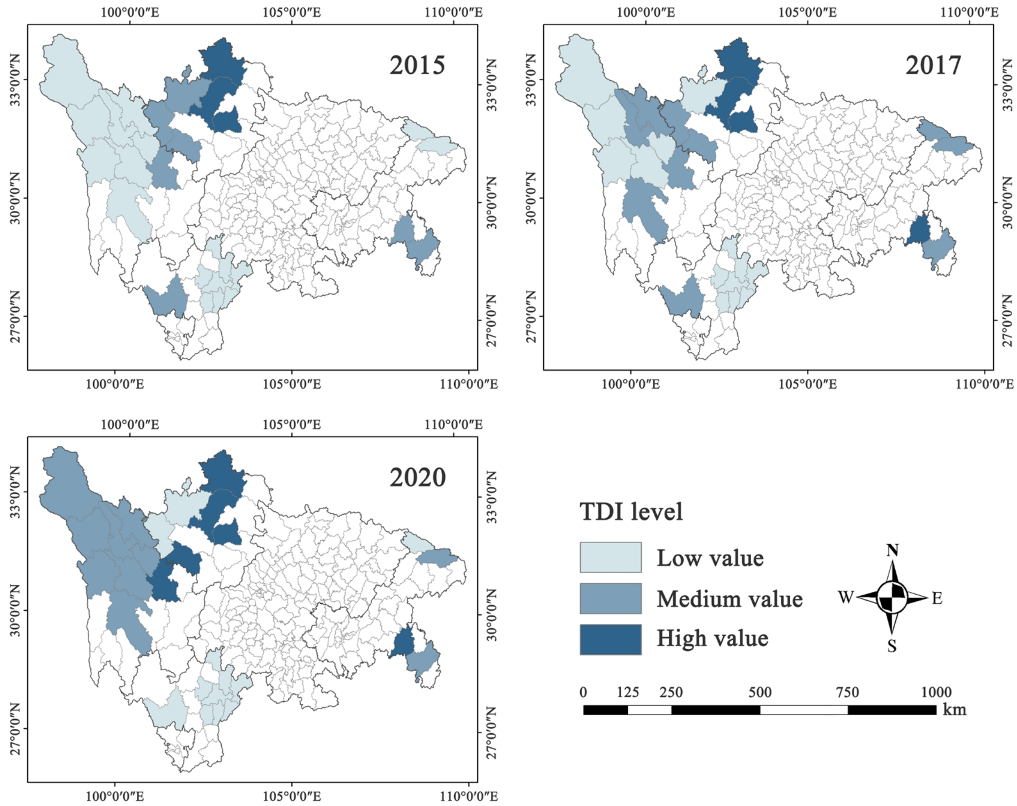


Figure 7. Spatial pattern evolution of tourism development in key counties from 2015 to 2020.

In terms of regional differences, the spatial differences in tourism development level among poverty-alleviated counties in the Sichuan–Chongqing region generally showed a narrowing trend from 2015 to 2020 (Figure 6b). The coefficient of variation decreased from 1.109 to 0.832, representing a decline of 25.00%. Among them, the coefficient of variation for key counties in Ganzi Prefecture was the smallest, with a mean value of 0.401, indicating a relatively balanced level of tourism development. The mean coefficients of variation for Chongqing and Aba Prefecture were 0.541 and 0.545, respectively. However, the differences in tourism development in Chongqing's key counties showed an expanding trend, which might be related to the differentiated development of internal tourism resources. The mean coefficient of variation for Liangshan Prefecture was 0.715, indicating significant spatial disparities in tourism development level. Nevertheless, the decline in this coefficient reached 19.36%, indicating a significant narrowing trend in disparities. This suggested that Liangshan Prefecture actively promoted the integration of tourism resources and facilitated coordinated regional tourism development.

3.4. Analysis of Coupled Coordination Relationship

3.4.1. Coupling Coordination Degree

Based on ECDI and TDI, the CCD was derived to analyze the changes in the coupling and coordination between tourism development and multidimensional poverty in key counties in the Sichuan–Chongqing region (Table 7). Overall, the CCD showed an upward trend, increasing from 0.288 to 0.444. Among different regions, Chongqing's key counties demonstrated the highest level of coupling and coordination, with an average CCD of 0.464 and a maximum value of 0.525. Compared to the western Sichuan plateau region, Chongqing boasts a superior location and economic environment, which facilitates the flow of tourism development elements and drives the comprehensive development of local key assistance counties for rural revitalization. However, the key counties in Liangshan Prefecture showed a relatively low level of coupling and coordination, with an average CCD of 0.302. This indicated that tourism development in Liangshan Prefecture had not formed a good synergistic relationship with the overall regional development. This may be attributed to the industrial structure of Liangshan Prefecture. Taking 2018 as an example, the proportion of total tourism income to GDP was 28.05%, significantly lower than that of Aba Prefecture and Ganzi Prefecture.

Table 7. CCD and its average value of key counties as a whole and by region from 2015 to 2020.

Region	Coupling Coordination Degree (CCD)						
	2015	**2016**	**2017**	**2018**	**2019**	**2020**	**Mean**
Synthesis	0.288	0.324	0.347	0.383	0.433	0.444	0.370
Chongqing	0.381	0.415	0.451	0.486	0.525	0.525	0.464
Aba	0.349	0.396	0.381	0.418	0.462	0.514	0.420
Ganzi	0.233	0.275	0.328	0.382	0.454	0.499	0.362
Liangshan	0.260	0.283	0.297	0.314	0.350	0.307	0.302

The color change in each key county reflects the variations in the CCD (Figure 8). Overall, from 2015 to 2020, it can be observed that the CCD in every key county, except Puge County, had increased. Counties in Ganzi Prefecture had seen the most significant growth, with five counties experiencing an increase of more than 100%. Notably, Shiqu County saw a remarkable growth of 195.64%. However, the trend of CCD change in the targeted counties of Liangshan Prefecture was not particularly significant, with an average increase of only 18.11%. The CCD of key counties in Chongqing and Aba Prefecture has grown more steadily, corresponding to relatively high CCD values. It is noteworthy that since 2019, there have been counties with a CCD exceeding 0.6, such as Pengshui County (2019–2020), Ganzi County (2019), and Heishui County (2020).

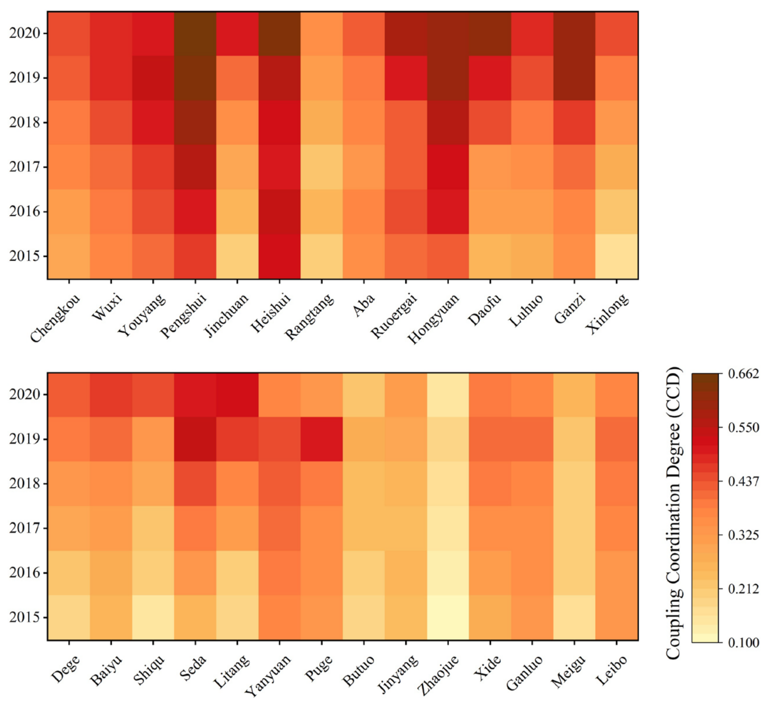


Figure 8. Temporal evolution of CCD in key counties from 2015 to 2020.

Furthermore, the coefficient of variation for CCD showed an overall trend of narrowing (Figure 9). Notably, from 2015 to 2019, it decreased from 0.355 to 0.255, indicating a gradual reduction in regional differences in poverty reduction through tourism. Among the key counties, Chongqing showed the smallest spatial variation in poverty reduction through tourism, with a mean coefficient of variation of 0.153. In contrast, Liangshan Prefecture had a mean coefficient of variation of 0.296, reflecting significant differences in poverty reduction through tourism among its counties and corresponding to a lower CCD. The coefficients of variation for CCD in Aba Prefecture and Ganzi Prefecture decreased significantly by 41.26% and 52.37%, respectively. This demonstrated that the effectiveness of poverty reduction through tourism had been enhanced, and the intensity of poverty reduction through tourism among the key counties within the region was tending towards spatial equilibrium.

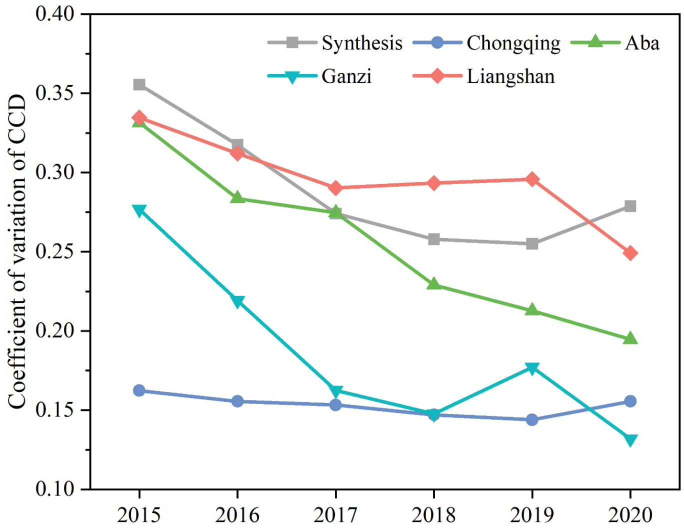


Figure 9. Temporal evolution of CCD variation coefficient of key counties as a whole and by region from 2015 to 2020.

3.4.2. Coupling Coordination Type

Based on the classification criteria in Table 4, the CCD between tourism development and multidimensional poverty in key counties in the Sichuan–Chongqing region was divided into four types. Considering the corresponding periods, we also chose 2015, 2017, and 2020 to visualize the types of coupling and coordination (Figure 10). It could be observed that in 2015, the key counties were basically in the stage of obstacles to coordination, with only one county achieving moderate coordination. By 2017, the number of key counties with obstacles to coordination decreased, mainly transforming into reluctant coordination. By 2020, three key counties had reached high coordination, and the proportion of the remaining three types of counties was relatively balanced. Among them, the proportion of key counties with obstacles to coordination decreased from 82.14% in 2015 to 35.71% in 2020. Over time, the number of regions with an imbalance between tourism development and multidimensional poverty decreased significantly, while the number of coordinated regions increased significantly, which was consistent with the changing characteristics of TDI and ECDI.

From the perspective of spatial distribution, the counties with obstacles to coordination from 2015 to 2017 were mainly distributed in Ganzi Prefecture and Liangshan Prefecture, and in 2020 they were concentrated in Liangshan Prefecture. The counties with reluctant coordination were relatively scattered, with a higher proportion in Ganzi Prefecture in 2020, reaching 55.56%. The counties that showed moderate coordination were mainly distributed in scattered locations in the early stage, but later formed a certain degree of local clustering in Aba Prefecture and Ganzi Prefecture. The counties that achieved high coordination in

2020 were located in Chongqing, Aba Prefecture, and Ganzi Prefecture, adjacent to or near the counties with moderate coordination. It was noteworthy that Daofu County, Ganzi County, Seda County, and Litang County in Ganzi Prefecture transformed from obstacles to coordination in 2015 to moderate and high coordination in later years. This indicated that the poverty reduction effect of tourism in these areas was significant, and the two were in a mutually promoting stage of coordinated development. Taking Daofu County as an example, it had numerous tourist attractions and a relatively high level of tourism development in 2015, but its overall development level was still at a low stage. With policy support, the local government promoted the construction of all-for-one tourism, increased the income of the poor population, and significantly reduced the poverty level in the region.

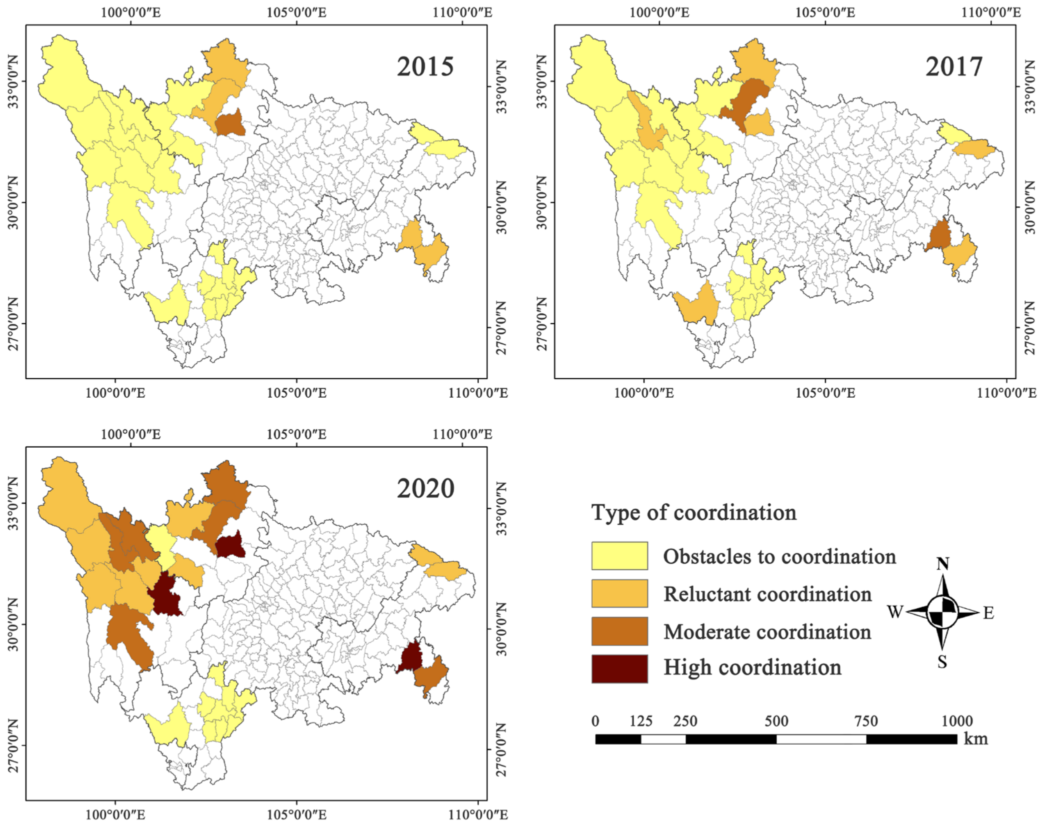


Figure 10. Spatial pattern evolution of coupling coordination types in key counties from 2015 to 2020.

In general, the key counties in the Sichuan–Chongqing region have gradually transitioned from the initial obstacles to coordination stage to the relatively higher coordination development stage. In addition, the coordinated key counties will further promote the quality and efficiency of economic development by redeveloping tourism resources and increasing investment in tourism elements. At the same time, better economic conditions can provide strong support for tourism. It plays a positive role in improving tourism infrastructure and absorbing the surplus rural labor force. The resulting mutual driving effect makes the regions with high coordination relationships form agglomeration in geographical space.

4. Discussion

4.1. Assessing Multidimensional Poverty by NTL Data

In this study, NTL data were used to measure the multidimensional poverty level in the key counties for rural revitalization. A logarithmic regression model was constructed for ANLI and ACDI, with an average R^2 of 0.871. The results of the accuracy test showed that the average annual RE was 11.11%. The above results show that NTL data can be used as an alternative data source to assess poverty, which is consistent with most studies. For example, Yu et al. [13] found a good correlation between the Integrated Poverty Index (IPI) and the Average Light Index (ALI), with an R^2 of 0.855. Pan et al. [36] tested the regression model of the average night light index and the Multidimensional Poverty Index (MPI), and the estimated MPI relative error was only 11.12%.

However, we also found that some studies had suggested that NTL data were not suitable for studying areas with low population density, including most rural areas [46]. Gibson et al. [47] took low-density areas in Africa, Asia, and the Pacific as an example, where up to 70% of the population was not detected by DMSP or VIIRS, even though more than half of the households used electric lights. One of the reasons is that the lights used in rural areas are usually not easy to detect, compared with the street lights and industrial facilities light sources concentrated in urban areas [48]. In addition, the overpass time of the earth observed by the Suomi satellite carrying VIIRS was about 1:30 a.m., and it is unlikely that the lights of rural households were on at that time, while the street lights of cities are often on all night [46]. This means that when the NTL data is used to estimate the low-level and low-density areas, it may only reveal the development of its center, ignoring the larger range of rural areas.

Throughout our study, this limitation of the NTL data was not obvious in the poor areas in southwest China. Many studies have chosen the districts and counties of Chongqing as samples when building evaluation models, and the models show good evaluation ability [13,36]. In addition, with the promotion of policies and economic development, the light signal in rural areas is gradually increasing, which may have a more robust relationship with economic activities.

4.2. Synchronization of Tourism Development and Poverty Reduction

In Section 3.4.2 Coupling and Coordination Types, we found that although the tourism development level of some counties was relatively high, it did not bring significant tourism poverty reduction effects. There was not necessarily synchronization between them. Taking the key counties in Aba Prefecture as an example, the difference between TDI and ECDI was calculated, and the annual difference was 0.383, much higher than that of other regions. Among them, Hongyuan County was close to the high coordination stage in 2019, but the difference value was as high as 0.810. Given this phenomenon, we need to explore the relationship between tourism development and multidimensional poverty in depth.

Existing studies have mentioned the threshold effect of tourism development on poverty alleviation. Wang et al. [49] believed that tourism development had a nonlinear positive impact on poverty alleviation in less developed areas, and the poverty alleviation effect was different in the poverty rate and the number of poor people. Zhao et al. [50] found that when the development level was low, tourism could significantly alleviate rural poverty. But when the tourism development level crossed the threshold value in turn, the poverty alleviation effect was no longer significant, and there was a potential tendency to aggravate poverty. The reason might be that with the improvement of tourism development level, rural tourism had shifted from extensive operation to intensive and large-scale operation. The transformation and upgrading led to an increase in the employment threshold, the number of employed people was relatively reduced, and the poverty alleviation effect of rural tourism might show a marginal decreasing trend [51]. Therefore, when the tourism development level of key counties was high and exceeded the threshold value, the tourism development and poverty alleviation might be in an asynchronous development relationship.

From the perspective of the mechanism of action, the poverty reduction effect of tourism in poor areas is complex [52]. On the one hand, tourism resources can provide jobs, drive the development of related industries and transportation, and increase the income of the poor. In addition, the “trickle-down effect” of tourism development will promote the improvement of education, medical care, and other aspects. Winter et al. [26] investigated tourism in northeastern Brazil and found that, in addition to providing employment and income, tourism also provided non-monetary resources that supported capacity expansion and fulfilment of functions. On the other hand, the "leakage effect" of tourism income and the unreasonable distribution mechanism may occur, leading to the widening gap between the rich and the poor. An empirical study by Alam et al. [53] of 49 developing economies worldwide between 1991 and 2012 showed that tourism increased income inequality. However, the results of squaring tourism income suggested that income inequality would be significantly reduced if tourism were to double its current level. Seetanah et al. [54] studied 83 countries over the period 1990–2019 and found that tourism had a role in reducing income inequality (although relatively small). Moreover, the impact of tourism on income inequality was greater in developing and tourist-dependent economies than in developed economies. Causality was difficult to establish because of the many potential endogenous sources.

In contrast, this study focused on the poverty reduction effect of tourism, and poverty reduction was not equal to income inequality. The relationship between tourism and income inequality further illustrated the complexity between tourism development and poverty reduction. This study reflected the asynchronous relationship of tourism poverty reduction to some extent, but it was certain that the promotion of tourism development level had a positive impact on poverty reduction in key counties. To further consolidate the poverty alleviation achievements, the poor should obtain more tourism income and improve the utilization efficiency of tourism poverty reduction factors.

4.3. Limitations and Future Research Directions

Inevitably, this study had certain limitations. First, in terms of the time series of data, the data from 2015 to 2020 were selected, which might ignore the cumulative poverty reduction effect of tourism development in the early stage. Secondly, long-term time series data were faced with problems such as inconsistent statistical channels and data missing, and the availability of data also affected the comprehensiveness of the indicator system and the model fitting results. In addition, the weight of each ACDI indicator was determined by information entropy, which might have a certain deviation from the actual situation. Finally, the CCD model might not fully reveal the complexity of the specific mechanism of tourism poverty reduction.

In future research, data acquisition efforts can be improved to explore a long-term scale for a more comprehensive study [14]. At the same time, when constructing a multidimensional poverty and tourism development indicator system, more effective and reliable indicators should be selected based on more regional empirical research to provide a more in-depth evaluation. Considering the complexity of the poverty reduction effect of tourism, a theoretical model of the mechanism of action can be constructed for pre-analysis [55] in combination with the requirements of consolidating poverty alleviation achievements and rural revitalization. On this basis, the robustness and reliability of the model can be further improved through the adjustment and optimization of time series, coverage area, and sample selection.

5. Conclusions

5.1. Main Findings

This study examined the method of measuring multidimensional poverty based on NPP-VIIRS data and analyzed the spatial-temporal characteristics and regional differences in tourism development and multidimensional poverty in key counties in the Sichuan–Chongqing region. Furthermore, the CCD model was used to investigate changes in the coupling and coordination relationship and the mechanism of action. It was found that NTL data had high precision in measuring multidimensional poverty at the county level, and ANLI and ACDI had a good fitting effect, making them useful for poverty-related research. The main findings were as follows:

(1) From 2015 to 2020, the level of tourism development in key counties in the Sichuan–Chongqing region had shown an upward trend. The counties receiving high-level tourism development assistance were mainly concentrated in Aba Prefecture, while

Liangshan Prefecture's tourism development level was generally low. The spatial difference in tourism development among each assisted county was narrowing. Of all, Chongqing's key counties exhibited the most balanced tourism development. While Liangshan Prefecture showed significant spatial differences, there was a noticeable trend towards narrowing the gap.

(2) During the same period, the multidimensional poverty level of key counties had continuously improved, especially since ECDI was in the accelerated growth stage from 2017 to 2020. The median and low ECDI values were mainly distributed in Aba Prefecture and Ganzi Prefecture, while the high ECDI values were relatively concentrated in Chongqing and Liangshan Prefecture. The spatial distribution of multidimensional poverty was consistent with the distribution of ECDI, with regions having a slight difference corresponding to high ECDI values, while regions with low ECDI showed an unbalanced spatial distribution of multidimensional poverty.

(3) Since 2015, most key counties' CCDs supporting county tourism development and multidimensional poverty had increased to varying degrees, indicating coordinated development, holistically. Among them, Chongqing's key counties' coordination level was the highest, while Liangshan Prefecture's coordination level was relatively low. In addition, regional differences in tourism poverty reduction were gradually narrowing, regional development was moving towards synergy and equilibrium, and the speed of narrowing differences was slowing down.

(4) In terms of coordination type, the key counties were obstacles to coordination in the early stage and mainly transformed into reluctant coordination and moderate coordination in the later stage. In 2019, high coordination began to appear. The obstacles to coordination were mainly distributed in Ganzi Prefecture and Liangshan Prefecture in the early stage and concentrated in Liangshan Prefecture later. The distribution of reluctant coordination and moderate coordination counties was relatively scattered, and local agglomeration was formed near high coordination counties in the later stage. Generally speaking, the overall transition from the initial obstacles to coordination stage to a relatively high coordination development stage. However, the threshold effect of tourism poverty reduction led to a certain degree of non-synchronization between tourism development and poverty reduction in Aba Prefecture.

5.2. Policy Implications

The results of this study can guide the sustainable development of tourism poverty reduction in the Sichuan–Chongqing region and other poverty-stricken areas. On the one hand, the results showed that the key counties with a higher level of coordination were more likely to experience localized agglomeration. This part of the county should make full use of its own tourism resources and transportation advantages, speed up the landing of funds, technology, and talents, cultivate tourism development growth poles, give full play to the radiation effect of tourism, and drive the key counties to alleviate poverty.

On the other hand, the coordination level of Liangshan Prefecture was relatively low, so it should increase the development of tourism resources, innovate the tourism development mode, and optimize local industrial structure. At the same time, it should improve regional transport conditions and tourism infrastructure to enhance the effectiveness of tourism in poverty reduction. In addition, the tourism level of Aba Prefecture was relatively high, but the poverty reduction effect of tourism was not significant. Governments should pay attention to the threshold effect of tourism in poverty reduction and the consequent marginal decline. With the continuous expansion of the tourism industry, the county should enhance the efficiency of its tourism elements and promote a shift in tourism development from external dependence to endogenous driving. At the same time, we should construct a reasonable tourism benefit distribution mechanism, reduce tourism leakage, and explore the secondary distribution inclined to poor households. To avoid the tourism "resource curse", it is crucial to strengthen the interaction between tourism-related economic activities and the local economic system. This will allow for the co-creation of tourism value.

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