Socioeconomic development evaluation for Chinese poverty-stricken counties using indices derived from remotely sensed data

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ABSTRACT
Comprehensively and objectively evaluating the development of poverty-stricken counties is important for poverty alleviation. In this study, we propose a relatively objective and efficient method that utilizes indicators derived from remote sensing images to assess the socioeconomic development of poverty-stricken counties. Four indicators representing the area of developed land, area of forest vegetation cover, area of cultivated land, and average nighttime light intensity were integrated via the entropy method and used to construct a model for evaluation of the socioeconomic development of poverty-stricken counties (ESDPC). Then, 42 impoverished counties in Henan Province and Liangshan Yi Autonomous Prefecture of Sichuan Province in China were selected, and their ESDPC values for 2013, 2015, and 2017 were estimated. The average ESDPC value of the selected poverty-stricken counties increased from 0.29 to 0.34 between 2013 and 2017. The accuracy of this estimate was verified through an assessment based on the comprehensive development index (CDI) model constructed using 10 socioeconomic indices. The correlation coefficient between the ESDPC values and the CDI values was 0.60, and the fitting relationships between the two models and the remotely sensed indicators showed good consistency, indicating the potential for use of these remotely sensed indicators to assess regional socioeconomic development.

Introduction
Poverty is a serious social problem plaguing developing countries (Elvidge et al., 2009). In recent years, China has invested considerable manpower and material resources in poverty alleviation. Accurate and efficient assessments of development in poverty-stricken counties for the purpose of understanding development trends and establishing new development schemes are an important component of poverty alleviation. Traditional studies involving regional development assessments were mainly based on socioeconomic statistics (Wang & Alkire, 2009; Xia et al., 2007; J. Zhang et al., 2018); although such methods are appropriate for summarizing and reviewing trends, they do not allow real-time monitoring and evaluation. In addition, the collection of traditional statistical data requires considerable manpower, material resources and time, and the results are influenced by subjective factors.

The fast, efficient and large-area data acquisition capabilities of remote sensing technology make remotely sensed data appropriate for use in poverty and regional development evaluations (Ding et al., 2019; Ge et al., 2019; Liao et al., 2018; Qiao et al., 2018). For example, using nighttime light data derived from remote sensing images obtained by the Defence Meteorological Satellite Program (DMSP), a global poverty map was constructed and used to estimate the total number of people living in poverty (Elvidge et al., 2009). Then, taking Chongqing as an example, data acquired by the Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP VIIRS) were effectively utilized in an assessment of county-level poverty in China (Yu et al., 2015). Based on the capability of nighttime light data to represent socioeconomic conditions, some researchers have established multidimensional socioeconomic indices that are highly correlated with stable nighttime light data obtained by the DMSP/Operational Linescan System (DMSP/OLS), and a method for estimating regional poverty based on these data was proposed (Wang et al., 2018). With the development of other fine-resolution remote sensors, the potential for application of remotely sensed data in related fields has increased. Surface reflectance data acquired by Landsat 8 were used to monitor changes in land use in poor areas from 2013 to 2018 and to construct an annual land use change map for these areas (Ge et al., 2019). Some scholars explored the relationships between regional social statistics and the environment using remotely sensed indicators and used the remotely sensed environmental indicators to estimate the poverty level of rural households in India (Wathom et al., 2013, 2016, 2019). The results of...
these studies indicate the potential for using remotely sensed data for poverty estimation. Some scholars have also constructed poverty evaluation models by estimating poverty evaluation indicators from remote sensing images, thereby providing a new approach to poverty study based on remote sensing (Ding et al., 2019).

Overall, poverty studies based on remote sensing have mainly focused on poverty measurements, and research on dynamic monitoring in poor areas is relatively limited. Moreover, most studies have focused on the monitoring and analysis of a single factor, such as land use or nighttime light data, in poverty-stricken counties (Andreano et al., 2020; Li et al., 2020), and comprehensive and quantitative research is lacking. This study proposes a method through which remotely sensed data acquired by Landsat 8 and the NPP VIIRS can be used to monitor and evaluate socioeconomic development in poverty-stricken counties. Forty-two impoverished counties in Henan Province and Liangshan Yi Autonomous Prefecture of Sichuan Province were selected for this study, and their socioeconomic development from 2013 to 2017 was analysed.

Materials and methods

Study area

Henan Province is one of the birthplaces of ancient Chinese civilization and is located in the middle and lower reaches of the Yellow River between 31°23′-36°22′ N and 110°21′-116°39′ E; it has a total area of 167,000 km². The terrain is high in the west and low in the east, with plains and basins, mountains and hills accounting for 55.7%, 26.6% and 17.7% of the total area, respectively. Laoyacha in Lingbao City, with an altitude of 2413.8 m, is the highest peak in the province; the lowest elevation, 23.2 m, occurs at the point at which the Huaihe River of Gushi County exits the province. As the province with the largest population in China, Henan’s permanent resident population reached more than 90 million in 2012. The soil is fertile, and the province is dominated by agricultural development. Therefore, the gross domestic product (GDP) is always high, but the per capita income is relatively low.

Liangshan Yi Autonomous Prefecture is located between 26°03′–29°18′ N and 100°03′–103°52′ E in the southwestern part of Sichuan Province in China. This area has the largest minority population in Sichuan Province and the largest Yi ethnic population in China. The complex and diverse terrain of the region includes mountains, deep valleys, basins, and hills, all of which are interlinked. The highest regional elevation, 5958 m, occurs at Chanadorje Peak in the Tibetan Autonomous County of Muli, and the lowest elevation, 305 m, occurs at the bottom of the Jinsha River valley in Leibo County; the difference in the elevations of these two points is 5653 m. Due to its distinct natural features and to social factors, Liangshan Prefecture has always been a key area for economic development and for the alleviation of poverty.

In this study, 42 national poverty-stricken counties located in the two typical poverty-stricken areas in China described above were selected, as shown in Figure 1, and the feasibility of using indicator information from remotely sensed data to evaluate the socioeconomic development level of poverty-stricken areas was explored.

Data and processing

Remotely sensed data

Landsat 8 is the eighth Earth observation satellite to be jointly developed by the National Aeronautics and Space Administration and the United States Geological Survey. It was launched on 11 February 2013 as a continuation of the Landsat program of Earth observation missions. Landsat 8 is equipped with the Operational Land Imager and the Thermal InfraRed Sensor, which together can collect image data at wavelengths of 0.433–12.51 µm across 11 spectral bands. The spatial resolutions of the monochromatic and panchromatic bands are 30 and 15 m, respectively, and colour images with spatial resolutions of 15 m can be obtained by combining these bands. In this study, Landsat 8 images of the selected research area taken from February to May were obtained from the Geospatial Data Cloud website www.gscloud.cn. After radiometric correction, atmospheric correction, image fusion, image mosaicking, and clipping, fine-quality images of the research area in 2013, 2015, and 2017 were obtained.

The information provided by the NPP VIIRS is widely used to derive nighttime light data, as are the data provided by DMSP/OLS. However, the day/night band of the VIIRS sensor can detect nighttime light intensities with finer spatial resolution and without the saturation issues that affect DMSP data. In recent years, various population (Li, Wang, et al., 2018), economy (Li & Li, 2015a; F. Li et al., 2016; Ma et al., 2014), ecological environment (Liao et al., 2018; Qiao et al., 2018), and urban development (Small et al., 2013; M. Yang et al., 2009) studies have been based on nighttime light data. In this study, the monthly composite data for the selected study area obtained by the NPP VIIRS for February and May of 2013, 2015, and 2017 were retrieved from the official website of the National
Oceanic and Atmospheric Administration. Using these data, the average nighttime light intensity values in the study area were calculated.

**Socioeconomic data**

The comprehensive development index (CDI) (National Statistical Society of China, 2011), which contains 44 indicators in five areas including economic development, improvement in people’s livelihood, social progress, ecological civilization and scientific and technological innovation, was proposed by the National Statistical Society of China in 2011 according to Chinese national conditions and corresponding scientific development requirements. The evaluation method used in the CDI is based on the measurement method used in the United Nations human development index (HDI); the basic idea is to deal with each indicator in a nondimensional way, to confirm the weight of each indicator based on scoring by experts, and finally to synthesize the CDI according to the weight of each indicator. The CDI is most commonly used to investigate and compare the historical process and the relative ranking in comprehensive development of Chinese administrative regions at all levels.

To verify the utility of the model for socioeconomic development evaluation constructed from remotely sensed indicators, 10 socioeconomic indices of the two aspects of economic development and improvement in people’s livelihood of the CDI model in 2013, 2015, and 2017, including GDP, per capita GDP, share of added value of services to the GDP, share of household consumption in the GDP, urbanization rate, productivity of social labour, proportions of urban and rural income in the GDP, income ratio of urban and rural residents, per capita disposable income of urban residents and per capita net income of rural residents, were obtained from the official websites of the statistical bureaus of Sichuan and Henan Provinces.

The selection of the study area was based on the List of Key Counties for Poverty Alleviation and Development Work (2012) obtained from the official website of the State Council Leading Group Office of Poverty Alleviation and Development. The vector maps of the relevant counties were obtained from the Geographical Information Monitoring Cloud Platform website (www.dsac.cn).

**Methods**

**Selection and construction of remotely sensed evaluation indicators**

The relationships between poverty and natural resources have been found to be complex and varied, and remote sensing is an efficient method of obtaining
real-time and multiscale natural indicators that can be used to explore or evaluate the socioeconomic development of poverty-stricken areas. In this study, according to the Outline for Development-Oriented Poverty Reduction for China’s Rural Areas (2011–2020) (the Central Committee of the Communist Party of China & the State Council, 2011) and the principles of rationality, scientific soundness and accessibility for indicator selection, four remotely sensed indicators that consider dynamic change and development were selected and used to construct a socioeconomic development evaluation model for poverty-stricken counties.

Developed land index (DLI)
To promote poverty alleviation, the state has made extensive efforts to develop infrastructure in poverty-stricken counties; such measures include road construction, construction related to irrigation and water conservation, housing renovation, relocation from other areas, and the construction of characteristic industries and cultural centres (the Central Committee of the Communist Party of China & the State Council, 2011). These changes have been accompanied by a sharp increase in developed land in poverty-stricken counties. Accordingly, the country also gave poverty-stricken counties larger quotas of usable area for land development under the condition that the area used for development was strictly controlled (Wu et al., 2019). Many studies related to land development and changes in poverty-stricken counties have shown that the development process in poverty-stricken counties is often accompanied by an increase in developed land (Guo et al., 2014; Li, Liu, et al., 2018). As mentioned above, the increase in developed land in poverty-stricken counties to some extent reflects the development of social infrastructure and improvements in social security capacity. Therefore, the DLI was selected in this study as one remotely sensed indicator for monitoring social development in poverty-stricken counties.

Cultivated land index (CLI)
Cultivated land, as the basic natural resource input of agricultural production, provides a food security guarantee and is a natural driver of sustainable development in poverty-stricken counties. There are two problems related to cultivated land in poverty-stricken counties: the massive loss of labour force in villages has led to the abandonment of large areas of cultivated land, and construction and development in poverty-stricken counties have led to a large reduction in the cultivated land area (Xiang, 2016). It is of great importance to rationally balance land use (Wang, 2019; S. Yang et al., 2019); to do this, the government needs to reclaim an appropriate area of cultivated land from previously cultivated land or from developed land that has been abandoned to offset the cultivated land that has been used for construction, thus ensuring a sufficient quantity and quality of cultivated land in poverty-stricken counties while developing the local infrastructure.

The relationship between cultivated land and poverty cannot be easily summarized. Too little cultivated land leads to weak food security; however, too much cultivated land in places with backward agricultural production conditions may increase poverty, as people in these areas will then devote a great deal of manpower and time to agricultural production instead of to other alternative production activities. Therefore, it is important to maintain a balance between cultivated and non-cultivated land within the region according to the conditions of the area. In this paper, the CLI was estimated from remote sensing images and used to monitor the conditions of agricultural production and the vitality of sustainable development in poverty-stricken counties.

Forest vegetation cover index (FVCI)
Ecological fragility and vulnerability to poverty are interrelated and interactive. In the process of promoting the development of poverty-stricken counties, the state is required to consider a scientific approach to balancing socioeconomic development and natural environmental protection (the Central Committee of the Communist Party of China & the State Council, 2011). As a core component of Earth and a link among the soil, the atmosphere and water (B. Zhang et al., 2020), forest vegetation is an important ecological indicator. Vegetation cover indices based on remote sensing are often used as important inputs in models used to estimate land surface temperature, rainfall, and net respiration productivity (X. Li et al., 2019; Tang et al., 2020). Thus, the FVCI was selected in this study as one of the remotely sensed indicators of healthy socioeconomic development in poverty-stricken counties.

The relationships between poverty and forest vegetation have been found to be complex in many regions (Lenz et al., 2017; W atmough et al., 2013), and the same is true in China. On the one hand, to ensure the healthy and green development of the society and the economy in poverty-stricken counties, the National Poverty Alleviation Program stipulated that the forest coverage in poverty-stricken counties should increase by 3.5% between 2010 and 2020 (the Central Committee of the Communist Party of China & the State Council, 2011). On the other hand, poverty occurs more often in mountainous areas with extensive forest cover, and this means that the effects of an increase in forest vegetation cover on poverty may differ in different areas. Likewise, forest vegetation cover indicators may also need to maintain a certain balance, especially under the coordination of the cultivated land indicator.
Average nighttime light intensity index (ANLI) has been shown to be strongly correlated with the intensity of light at night and regional population, energy consumption, and income levels; the economic development level is relatively high in regions with high nighttime light intensities. For example, Li (Li & Li, 2015a, 2015b) conducted a detailed review of the application of nighttime light data and evaluated the variations in the domestic population and economy caused by the outbreak of the Syrian Civil War. Furthermore, Yu (Yu et al., 2015) used NPP VIIRS data to study the correlation between the average nighttime light index and the poverty index in poor regions of China and found that nighttime light data can be used to effectively evaluate the degree of poverty in such counties. Based on these results, the ANLI was used in this study as one of the remotely sensed indicators of economic development in poverty-stricken counties.

Based on the information discussed above, four remotely sensed indicators – DLI, CLI, FVCI, and ANLI – were used to evaluate the socioeconomic development level of poverty-stricken counties. The remotely sensed indicators and the corresponding calculation methods are listed in Table 1.

**Estimation of remotely sensed indicators using random forests**

Random forests is a machine learning algorithm that was developed from decision trees by Breiman in 2001; it can be used for both regression and classification (Breiman, 2001). As indicated by its name, random forests uses forests that are established randomly and are composed of many irrelevant decision trees; in this method, classification results are obtained from the voting results of multiple decision trees. Therefore, the random forests algorithm has high classification accuracy and is a good method for classifying remote sensing images and estimating the remotely sensed indicators used in this study.

Images obtained by Landsat 8 were classified using the random forests algorithm in the Environment for Visualizing Images (ENVI 5.3.1) (Exelis Visual Information Solutions, Inc., 2015) to estimate values for the selected remotely sensed indicators DLI, CLI, and FVCI. Surface features were classified as water bodies, developed land, forest vegetation, cultivated land, and other land in a total of five categories. Prior to classification, image samples featuring a variety of surface features were collected from Landsat 8 images by combining fine-resolution images from Google Earth for the relevant timeframes based on visual inspection. The process for the estimation of the ANLI is relatively simple, and the mean radiation brightness of poverty-stricken counties can be calculated after denoising.

**Construction of the ESDPC model based on the entropy method**

A comprehensive evaluation method uses multiple indicators to evaluate various factors. The underlying objective of such a method is to transform multiple indicators into a single indicator that can be used to evaluate a given scenario. In the evaluation process, the weighted contribution of each indicator within the final comprehensive indicator must be determined. The entropy method (Han et al., 2019), which can be used to determine the weights of an indicator based on the degree of correlation or variation, is a relatively objective assessment method. Each assessment target will have a unique weight allocation result for the indicators due to its unique situation; therefore, the method exhibits good estimation ability when there is a potentially nonlinear relationship between the estimated results and the indicators.

The entropy method originates from information theory, in which the entropy value is a measure of uncertainty. According to the entropy method, if the difference among the annual values of a given indicator is relatively large, the information conveyed by that indicator will likewise be relatively extensive, and both the uncertainty and the corresponding entropy value will be small. In that case, the indicator is relatively stable, and the weight in the final comprehensive evaluation will be large. Conversely, when the entropy value is large, the weight of the indicator will be small (Han et al., 2019).

In this study, the entropy method was used to determine the weights of the remotely sensed indicators, and a model for the evaluation of the socioeconomic development of poverty-stricken counties (ESDPC) was established. First, the values of each indicator were standardized because the indicators use different units, as shown in Equation (1). In the equation, $X_{n,m,n}^s$ is the value of remotely sensed indicator $m$ in the $n$th year in poverty-stricken county $s$ after normalization, and $c$ and $r$ are the total numbers of poverty-stricken counties and years, respectively, evaluated.

| Remotely sensed indicator | Calculation method |
|---------------------------|--------------------|
| DLI                       | $DLI = \frac{S_{DL}}{S_{DL}}$ |
| CLI                       | $CLI = \frac{S_{DL}}{S_{DL}}$ |
| FVCI                      | $FVCI = \frac{S_{DL}}{S_{DL}}$ |
| ANLI                      | $ANLI = \frac{S_{DL}}{S_{DL}}$ |

Notes: Where $S_{DL}$ is the number of pixels that comprise the buildings, $S_{FD}$ is the number of pixels that comprise the cultivated land, $S_{NFL}$ is the number of pixels that comprise the forest vegetation, NTL is the sum of the nighttime light radiation values, and $N_s S_{sum}$ are both the total number of pixels.
\[ X_{s,m,n} = \frac{X_{1,m,n} - \min\{X_{1,m,1}, X_{1,m,2}, \ldots, X_{1,m,r}, \ldots, X_{c,m,r}\}}{\max\{X_{1,m,1}, X_{1,m,2}, \ldots, X_{1,m,r}, \ldots, X_{c,m,r}\} - \min\{X_{1,m,1}, X_{1,m,2}, \ldots, X_{1,m,r}, \ldots, X_{c,m,r}\}} \]

The entropy value of each remotely sensed indicator in every poverty-stricken county was then calculated. In this process, we calculated the proportional contribution of the annual value of each remotely sensed indicator for each poverty-stricken county to the total value, as shown in Equation (2). In the equation, \( P_{s,m,n} \) is the ratio of the data for remotely sensed indicator \( m \) in the \( r \)th year for poverty-stricken county \( s \) to the sum of the index data in year \( r \).

\[ P_{s,m,n} = \frac{x'_{s,m,n}}{\sum_{s=1}^{n} x'_{s,m,n}} \quad (s = 1, 2, \ldots, c; m = 1, 2, 3, 4) \]

Subsequently, the entropy value \( e_{s,m} \) and the difference coefficient \( d_{s,m} \) to represent the uncertainty and the degree of variation, respectively, of indicator \( m \) in poverty-stricken county \( s \) across selected years, can be calculated based on the \( P_{s,m,n} \), as shown in Equation (3) and Equation (4). In this case, where \( k > 0 \), and \( k = 1/\ln(4) \), 4 is the total number of remotely sensed indicators.

\[ e_{s,m} = -k \times \sum_{m=1}^{n} P_{s,m,n} \ln(P_{s,m,n}) \]

\[ d_{s,m} = 1 - e_{s,m} \]

Eventually, the weights of the remotely sensed indicators in the socioeconomic evaluation model are determined from the difference coefficients of the remotely sensed indicators, as shown in Equation (5), where \( W_{s,m} \) is the weight of indicator \( m \) for poverty-stricken county \( s \).

\[ W_{s,m} = \frac{d_{s,m}}{\sum_{m=1}^{n} d_{s,m}} \]

Combining the weights and the annual data for each remotely sensed indicator, the socioeconomic development of poverty-stricken counties is evaluated as follows:

\[ \text{ESDPC}_{s,n} = \sum_{m=1}^{n} (W_{s,m} \times x'_{s,m,n}) \]

where \( \text{ESDPC}_{s,n} \) is the assessment value that represents the socioeconomic development level of poverty-stricken county \( s \) in the \( r \)th year. Large ESDPC values are indicative of high levels of socioeconomic development.

**Model validation by piecewise linear regression**

Piecewise linear regression (E, 1989) is a regression estimation method that is applicable when regression of the dependent variable on the independent variable obeys a certain linear relation over some range of the independent variable and obeys a linear relation that has a different slope over another range. When it is difficult to explain the relationship between two variables by a single linear regression model, it is good practice to find a proper breakpoint according to the response state, divide the independent variables into finite intervals, and construct linear regression models for different intervals to describe the relationship between the two variables. To verify the relationships between remotely sensed indicators and socioeconomic conditions and the ability of the ESDPC model to capture these relationships, this paper analyses the regression relationships between remotely sensed indicators and ESDPC and CDI by piecewise linear regression analysis.

**Results and analyses**

**Evaluation process**

Based on image data acquired by Landsat 8 and the NPP VIIRS, the socioeconomic development of poverty-stricken counties was monitored and evaluated. The ANLI, DLI, CLI, and FVCI were combined using the entropy method and used to construct the ESDPC model. A flowchart illustrating this process is presented in Figure 2.

**Weight evaluation for remotely sensed indicators**

Based on the random forest classification method introduced in Section 2.3.2, the images of the study area acquired in 2013, 2015, and 2017 by Landsat 8 were classified and used to estimate the area occupied by water bodies, developed land, forest vegetation, cultivated land and other land in each county in the study area. The overall classification accuracy, which was estimated using a confusion matrix and independent random samples collected from within the images, was greater than 85%. Because VIIRS light data are greatly affected by noise, the minimum threshold method proposed by Ma (Ma et al., 2014) and Li (F. Li et al., 2016) was adopted to remove noise before estimating the ANLI. Eventually, the remotely sensed indicators for each year were estimated according to the calculation methods presented in Table 1; the results are shown in Table 2.

According to the method used to calculate indicator weights in the ESDPC model established in Section 2.3.3, the weight of each remotely sensed indicator was determined based on its degree of variation during the studied years. The uncertainty of the weight of each remotely sensed indicator for poverty-stricken counties was then analyzed statistically using a type-A uncertainty evaluation method (Bessel Formula), and
the distribution at a 99% confidence level was obtained. As shown in Table 3, the DLI and ANLI have relatively large effects on socioeconomic development evaluation in the studied poverty-stricken counties; although the average weight of the FVCI was the same as those of the DLI and ANLI, there was great uncertainty in the weight distribution of the FVCI, and the effects of it were unstable. The weight of the CLI was relatively small, and its effect was also relatively small.

Assessment and validation of the ESDPC model

Feasibility analysis of the ESDPC model

The socioeconomic development scores of 42 poverty-stricken counties in 2013, 2015, and 2017 were estimated by ESDPC using four remotely sensed indicators, as shown in Table 4. The paired-sample t-test and Pearson correlation analysis were employed to test the correlation between the CDI constructed using the socioeconomic indices and the ESDPC constructed using remotely sensed indicators. The correlation coefficient for the two models was 0.60 at a significance level of 0.01, reflecting a significant positive correlation. As shown in Figure 3, a generally consistent trend is observed overall, especially in areas in which there is deep poverty.

Piecewise linear regression analysis was used to analyse and compare the relationships between remotely sensed indicators and ESDPC and CDI, as shown in Figure 4. The points at which the relationships between the remotely sensed indicators and ESDPC and CDI changed were detected using breakpoint detection in the R Programming Language (R 3.6.3) (The R Core Team, 2020); the "segmented" package in R was then used to linearly fit the relationship of each segment between the breakpoints. Finally, the graphs of the relationships between the remotely sensed indicators and the two evaluation indices were obtained.

The t-test results and the regression determinant coefficient $R^2$ of indicators indicates that the ANLI and DLI both show significant correlation with the CDI at a significance level of 0.01 and that both indices have large explanatory power in the ESDPC evaluation model. The correlations between the FVCI (significantly correlated at the 0.05 significance level), CLI (not significantly correlated) and CDI were small, and the explanatory power in the ESDPC model was also relatively small.

From the relationships between the remotely sensed indicators and two evaluation indices, the ANLI and DLI also exhibited similar change tendencies. Over the average nighttime light intensity range of 0–0.31, there was a strong positive correlation
between the CDI and the ANLI; the CDI increased rapidly with the increase in ANLI. Over the average nighttime light intensity range of 0.31–0.60, there was a negative correlation trend between the CDI and the ANLI, and there was a positive correlation between these two indices again when the average nighttime light intensity exceeded 0.60. The CDI increased rapidly as the DLI increased over the range of
Table 4. Output values from the model for the evaluation of the socioeconomic development of poverty-stricken counties (ESDPC) and the corresponding comprehensive development index (CDI) constructed by socioeconomic indices for 2013, 2015, and 2017.

| County     | ESDPC 2013 | CDI 2013 | ESDPC 2015 | CDI 2015 | ESDPC 2017 | CDI 2017 |
|------------|------------|----------|------------|----------|------------|----------|
| Butuo      | 0.15       | 0.19     | 0.18       | 0.22     | 0.20       | 0.31     |
| Ganlou     | 0.17       | 0.16     | 0.19       | 0.28     | 0.20       | 0.38     |
| Jinyang    | 0.18       | 0.17     | 0.21       | 0.24     | 0.25       | 0.34     |
| Leibo      | 0.22       | 0.25     | 0.24       | 0.32     | 0.27       | 0.41     |
| Mabian     | 0.18       | 0.23     | 0.19       | 0.35     | 0.21       | 0.43     |
| Meigu      | 0.11       | 0.14     | 0.13       | 0.23     | 0.16       | 0.31     |
| Pingshan   | 0.20       | 0.29     | 0.23       | 0.42     | 0.25       | 0.50     |
| Puge       | 0.13       | 0.27     | 0.17       | 0.34     | 0.18       | 0.41     |
| Xide       | 0.21       | 0.24     | 0.23       | 0.30     | 0.21       | 0.40     |
| Yuxu       | 0.19       | 0.27     | 0.20       | 0.35     | 0.20       | 0.44     |
| Zhaojue    | 0.15       | 0.23     | 0.19       | 0.30     | 0.19       | 0.35     |
| Lankao     | 0.33       | 0.44     | 0.40       | 0.57     | 0.56       | 0.68     |
| Luanchuan  | 0.21       | 0.54     | 0.27       | 0.66     | 0.25       | 0.77     |
| Songxian   | 0.29       | 0.46     | 0.29       | 0.58     | 0.32       | 0.68     |
| Ruyang     | 0.33       | 0.42     | 0.34       | 0.54     | 0.38       | 0.64     |
| Yiyang     | 0.39       | 0.46     | 0.37       | 0.58     | 0.47       | 0.69     |
| Luoning    | 0.29       | 0.44     | 0.29       | 0.56     | 0.34       | 0.67     |
| Lushan     | 0.38       | 0.38     | 0.32       | 0.46     | 0.38       | 0.53     |
| Huaxian    | 0.37       | 0.35     | 0.42       | 0.47     | 0.42       | 0.57     |
| Fengqiu    | 0.37       | 0.34     | 0.41       | 0.43     | 0.43       | 0.52     |
| Fuxian     | 0.46       | 0.39     | 0.50       | 0.49     | 0.47       | 0.58     |
| Taiqian    | 0.39       | 0.37     | 0.43       | 0.46     | 0.42       | 0.53     |
| Lushi      | 0.28       | 0.42     | 0.29       | 0.50     | 0.31       | 0.60     |
| Nanzhao    | 0.28       | 0.46     | 0.31       | 0.58     | 0.34       | 0.65     |
| Xichuan    | 0.28       | 0.47     | 0.31       | 0.59     | 0.27       | 0.67     |
| Sheng      | 0.37       | 0.42     | 0.31       | 0.53     | 0.36       | 0.66     |
| Tongbo     | 0.35       | 0.49     | 0.34       | 0.61     | 0.37       | 0.73     |
| Minquan    | 0.36       | 0.41     | 0.38       | 0.50     | 0.42       | 0.59     |
| Juxian     | 0.34       | 0.39     | 0.36       | 0.48     | 0.36       | 0.56     |
| Ningling   | 0.36       | 0.37     | 0.39       | 0.46     | 0.44       | 0.54     |
| Yucheng    | 0.38       | 0.42     | 0.45       | 0.51     | 0.45       | 0.60     |
| Guangshan  | 0.32       | 0.46     | 0.33       | 0.56     | 0.35       | 0.63     |
| Xinxian    | 0.28       | 0.52     | 0.28       | 0.62     | 0.31       | 0.72     |
| Shangcheng | 0.29       | 0.45     | 0.28       | 0.55     | 0.31       | 0.64     |
| Guzhi      | 0.33       | 0.49     | 0.35       | 0.60     | 0.38       | 0.70     |
| Huabin     | 0.30       | 0.42     | 0.27       | 0.51     | 0.30       | 0.61     |
| Shenggu    | 0.39       | 0.40     | 0.45       | 0.50     | 0.44       | 0.58     |
| Huaiyang   | 0.41       | 0.38     | 0.43       | 0.47     | 0.41       | 0.57     |
| Shangcai   | 0.32       | 0.42     | 0.39       | 0.51     | 0.39       | 0.59     |
| Pingyu     | 0.33       | 0.43     | 0.37       | 0.53     | 0.44       | 0.63     |
| Queshan    | 0.34       | 0.46     | 0.42       | 0.56     | 0.39       | 0.66     |
| Xincai     | 0.27       | 0.37     | 0.33       | 0.48     | 0.38       | 0.57     |
| Average    | 0.29       | 0.37     | 0.32       | 0.47     | 0.34       | 0.56     |

Figure 3. Correlation relationships between the assessment results of the ESDPC model and the CDI model.

0–2.67%; when the proportion of developed land area was between 2.67% and 16.26%, the CDI showed a downward trend with the increase in DLI, and there was again a positive correlation between these two indices when the proportion of developed land area exceeded 16.26%. In the ESDPC model, both the ANLI and the DLI showed a positive relationship, but the increase in ESDPC gradually decreased as the values of the remotely sensed indicators increased. The change trends appear over three specific ranges in which the breakpoints of the ANLI are 0.23 and 0.55, and those of the DLI are 2.55% and 6.28%. In addition to the ranges of values that show a negative correlation between the remotely sensed indicators and the CDI but a weakened positive correlation trend in ESDPC, the relationships between the ANLI, DLI and ESDPC are similar to those for the CDI.

The trends of the CDI and ESDPC in relation to the FVCI exhibited good consistency. When the vegetation coverage was less than 40%, the CDI and the ESDPC decreased as the FVCI increased, but their overall values were relatively large, reflecting the development characteristics of plain areas. The CDI and the ESDPC showed increasing trends with the increase in the FVCI when the area of forest vegetation cover was greater than 40%, but their overall values were generally small, reflecting the development characteristics of plateau mountains. Compared with the FVCI, the relationships between the CDI and socioeconomic development appeared inconspicuous and complex. In plateau mountainous areas, the CDI and the ESDPC showed increasing trends with the increase in cultivated land area. However, when the proportion exceeded a certain limit (27% in the CDI regression relationship and 33% in the ESDPC regression relationship), a negative impact occurred. In hilly and plain areas, the increase in cultivated land area has a positive influence on socioeconomic development when the proportion of cultivated land ranges from 35% to 64%, but when the cultivated land area continues to increase, certain restrictions on social and economic development are observed, as shown in Figure 4(a). The relationship between cultivated land area and socioeconomic development in the two types of terrain areas was compared. Plain areas tend to have convenient transportation and a high degree of modernization of agricultural production, and people who live in these areas need to spend less time and energy on agricultural activities; thus, the limit on the proportion of cultivated land is much larger in plain areas than in mountainous areas.

Analysis of the development of poverty-stricken counties

To provide an intuitive analysis of the variations in development over the past five years, the ratio of the ESDPC assessment values in 2015 to those in 2013 and the ratio of ESDPC assessment values in 2017 to those in 2015 were used to create thematic maps of the
Figure 4. Piecewise linear regression analysis of the relationships between remotely sensed indicators and ESDPC and CDI.

Figure 5. Thematic maps depicting the relative growth rates based on the output values of the model for evaluating the socioeconomic development of poverty-stricken counties in the study area.
The geographical plains of Henan Province are notably large. Although this province is rich in fertile land, convenient transportation, and highly modernized production technology; development opportunities may be more easily gained in the plains than in the southwest. Similarly, due to the geographical conditions, the poverty-stricken counties in Henan Province may overall have more development opportunities and faster development than those in Liangshan Prefecture of Sichuan Province.

For an individual poverty-stricken county, the socioeconomic development process is usually accompanied by various changes. The remotely sensed indicator data presented in Section 3.2 indicate that many poverty-stricken counties in the process of development display increased DLI and ANLI. In addition, there is a balance between regional socioeconomic development and FVCI and CLI as long as the forest vegetation coverage and the cultivated land area are not too small or too large. Although the ESDPC model regards the growth of the two indicators as positive, the negative correlation between the two indicators will limit the positive effect, that is, a sharp increase in either the FVCI or the CLI will inevitably lead to a decrease in the other indicator; when the two indicators exceed their equilibrium points, there is a mutual offset effect on the results of the model. Therefore, the ESDPC will not increase indefinitely as FVCI or CLI increases; this also makes the ESDPC more consistent with the actual relationships between regional socioeconomic development and the FVCI and CLI.

Discussion

Significance of the ESDPC model in poverty development assessment

In this study, a socioeconomic development evaluation model of poverty-stricken counties based on remotely sensed indicators is proposed. First, the model is constructed from a mostly objective perspective. Compared with traditional methods based on social statistics, the ESDPC model employs more objective and conveniently accessed data sources. In addition, the ESDPC model evaluates regional socioeconomic development based on synthetic changes in the DLI, FVCI, CLI and ANLI and quantifies these changes. Therefore, different poverty-stricken counties have distinct indicator weight distributions based on the corresponding changes in remotely sensed indicators, as shown in Table 3. As a result, the assessment of ESDPC values is highly objective and reflects the actual situation in the study area. Moreover, the ESDPC model is an analysis model based on time series data. The socioeconomic development levels of poverty-stricken counties can be compared in different temporal dimensions.

In practical applications, ESDPC can provide decision-making support for development planning in poverty-stricken counties. By analysing the variation trends of remotely sensed indicators and ESDPC assessment values, the main factors that influence the development of poverty-stricken counties can be determined. A notable variation in an indicator can lead to an increase in the ESDPC output value, indicating a positive trend in development. A large variation in an indicator can also lead to a decrease in the ESDPC value, indicating that the variation disrupted the balance of overall development. Based on these changes, the government should adjust its development plan to promote balanced and rationalized indicators and achieve steady ESDPC growth.

Further trends in the ESDPC model

Poverty is often broadly defined, and the international community usually adopts Alkire’s theory of
multidimensional poverty and the Multidimensional Poverty Index (MPI) (Wang & Alkire, 2009), which includes 10 indicators in three dimensions: health, education and the standard of living. The ESDPC model proposed in this paper is constructed from the perspective of socioeconomic development. However, evaluation of the development of poverty-stricken areas requires additional input related to education, quality of life and other humanistic development perspectives. In addition, due to the limited capability to estimate information from remote sensing images, new semantic analysis and information estimation technologies can provide new directions for monitoring human development in the big data era (Niu et al., 2020; Yuan et al., 2018). On the basis of remotely sensed data, the ESDPC model could be improved in its evaluation scale and in its capabilities by including happiness level, educational level and other information from residents of poverty-stricken counties based on big data in the future.

Conclusions
In this study, a model (referred to as the ESDPC model) was created based on multiple remotely sensed indicators that were integrated via the entropy method. Four remotely sensed indicators (the DLI, CLI, FVCI, and ANLI) were used to evaluate the socioeconomic development levels of poverty-stricken counties. The model was then used to assess the socioeconomic development of poverty-stricken counties in Henan Province and Liangshan Yi Autonomous Prefecture of Sichuan Province, China. Objective development scores were obtained for 42 poverty-stricken counties in 2013, 2015, and 2017. The accuracy of the scores was verified using another assessment model, the CDI. The correlation coefficient of 0.60 between the two sets of results and the good consistency of fitting relationships between the two models and the remotely sensed indicators validated the effectiveness of the ESDPC model. Compared with traditional evaluation methods based on socioeconomic statistics, the ESDPC model proposed in this study offers more objective, real-time evaluations. To some extent, this approach can also provide guidance for development and decision-making in poverty-stricken counties.

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Data availability statement
The remotely sensed indicator data, socioeconomic index data and the assessment results of the ESDPC and the CDI that support the findings of this study are openly available in figshare at http://doi.org/10.6084/m9.figshare.14139521.

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