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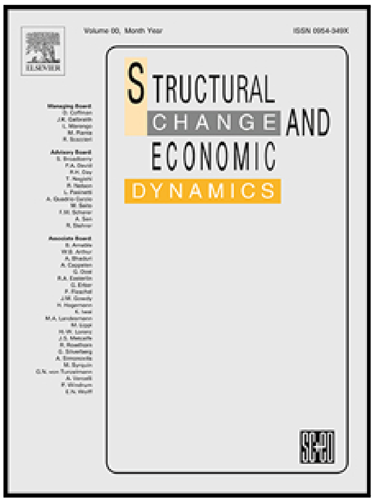

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Highlights

Quantify individual and interactive influences of factors on GDP density changes

Determine the optimal characteristics of key factors beneficial to GDP density growth

Detect the differentiation mechanism of GDP density in rural poverty

Guide targeted measures for poverty alleviation by category

Detecting influences of factors on GDP density differentiation of rural poverty changes

Guangjie Wang[1,2], Wenfu Peng[1,2*]

1. The Institute of Geography and Resources Science, Sichuan Normal University, Chengdu 610068, China;

2. Key Lab of Land Resources Evaluation and Monitoring in Southwest, Ministry of Education, Chengdu 610068, China

Abstract: We use geographical detectors to quantify the interactive influence of impact factors on gross domestic product (GDP) density changes on rural poverty, for identifying the differentiation mechanism in rural poverty. The optimal characteristics of the main factors that benefit GDP density growth were determined. We proposed poverty alleviation policies and measures for different types of poverty-stricken regions. Distance to main roads, the normalised differential vegetation index (NDVI), land use, average annual temperature, and elevation can satisfactorily account for GDP density changes in rural poverty. Impact factors have an interactive influence on GDP density. The synergistic effect of impact factors manifests itself as mutual enhancement and nonlinear enhancement, and the interaction of two impact factors strengthens the influence of each individual factor. We revealed the poverty differentiation mechanisms of economic development in poverty villages,and put forward targeted poverty alleviation measures with stratified guidance and key breakthroughs.

Keywords: GDP density; poor villages; dominant factors; Tibetan region; geographical detector

1.Introduction

Although the world has made remarkable progress in reducing extreme poverty, and some regions, such as East Asia and Southeast Asia, have met the target of halving their extreme poverty rates, other regions, such as sub-Saharan Africa and South Asia, still lag behind (United Nations, 2015). Poverty is still a major social problem and practical challenge worldwide. Eliminating poverty and narrowing the gap between urban and rural areas is one of the important goals for humanity to achieve sustainable development (Liu et al., 2016). In 2011, nearly 60% of the world’s one billion extremely poor people lived in just five countries: India, Nigeria, China, Bangladesh, and the Democratic Republic of the Congo (United Nations, 2015). The world’s most populous countries, China and India, play a central role in the global reduction of poverty. China, despite much progress in poverty reduction, ranked second and was home to about 13% of the global extreme poor. Its long-standing urban–rural duality and weak rural socioeconomic foundation have cemented China's status as the developing country with one of the largest populations of rural poor in the world (Liu et al., 2016). The anti-poverty efforts of the Chinese government have made significant contributions to the global reduction of poverty. According to the Millennium Development Goals Report 2015, the extreme poverty rate in East Asia has dropped from 61% in 1990 to only 4% in 2015, and the number of rural poor in China decreased from 250 million in 1978 to 55.75 million in 2015, with a corresponding drop in the incidence of poverty from 30.7% to 5.7%, as a result of progress in China (Liu et al., 2016). There is a strong regional distribution to present-day poverty in China (Qu et al., 2012), as poverty is mainly concentrated deep in the mountains, in plateau areas, and in areas of high prevalence for endemic diseases. Among them, mountainous areas, hilly areas, and restricted development zones are where poverty is most concentrated (Wang et al., 2015). Therefore, targeted poverty alleviation faces immense challenges: deep poverty remains acute; the remaining poor will be harder to lift out of poverty; infrastructure and basic public services are underdeveloped; overall carrying capacity is weak; and resource and environmental capacity is overloaded in some regions (Qiu et al., 2017).

The diversity of rural poverty in China, its complex causes, and difficulty in reducing poverty have attracted widespread attention from the government. In 2013, the Chinese government proposed an innovative strategy for reducing poverty (Liu et al., 2016; Li et al., 2016). In 2015, a third-party evaluation system for the effectiveness of targeted poverty alleviation was implemented to promote research on theories of rural poverty, strategies for targeted poverty alleviation, development models for poverty alleviation, and other issues (Liu et al., 2017). These have served as useful references for guiding the formulation of anti-poverty strategies and policies, thus effectively promoting China's efforts in poverty reduction. The National Third-Party Evaluation of targeted poverty alleviation in 2017 found that with the in-depth and thorough implementation of the central strategic plan for poverty alleviation, Mao County, which is located in the Tibetan region of the Northwest Sichuan Plateau in western China, has achieved significant preliminary results in its efforts to eliminate poverty. Nevertheless, the long-term effects of the natural environmental and economic constraints on the rural development of the Tibetan region of the Northwest Sichuan Plateau are still widespread (Li et al., 2016).

Poverty and its driving mechanism have become an issue of great concern. In recent years, studies have revealed a range of factors driving poverty changes. On the basis of a multinomial logistic regression model, Hua et al. (2017) quantitatively analysed the relationship between livelihood assets and livelihood strategies in the upper reaches of the Dadu River watershed in China's Eastern Tibetan Plateau. Liu et al. (2017) systematically examined the status quo and spatial distribution characteristics of poverty in rural China and its driving mechanism; their findings indicate that illness is the greatest contributor to transient poverty in rural China.

Applying a spatial approach to analyse program targeting and a spatial lag model, Liao et al. (2019) studied the determinants of the implementation of program targeting and found that major constraints to implementation include poor grid infrastructure, sparse population density, and low levels of economic activity in rural areas. On the basis of a multinomial logistic model, Wang et al. (2019) identified determinants of households' livelihood choice and indicated that drought has a significantly negative impact on farmers' choice of type. Somvang Phimmavong and Rodney J. Keenan (2019) used a top-down macro–microeconomic modelling framework to assess the impacts of plantation development policies on poverty and inequality in Laos. The results revealed an increase in welfare and inequality and a decrease in poverty incidence. Sewell et al. (2019) investigated and compared the perceptions of rural communities regarding the role of roads in poverty alleviation and explored the influence of rural roads on the socioeconomic conditions of rural communities in South Africa. Wang et al. (2019) revealed that degraded land consolidation provides an effective way to improve production and the living environment, promote industrial development, and activate endogenous motivation among poor households. On the basis of econometric models and spatial analysis techniques, Zhou et al. (2019) explored the geographical distribution pattern of rural poverty in China, identified the key factors affecting rural improvement, and revealed the relationship between regional eco-environmental degradation and improvement. Yadav et al. (2019) examined explanations for the slow adoption of solar home systems in rural areas from the perspective of a rural (Grameen) bank and revealed the subsidy scheme for current government energy policies, largely excluding those below the poverty line. Zhou et al. (2019) analysed the mechanism and path behind land consolidation boosting poverty alleviation and revealed that land consolidation has played an active role in increasing cultivated land area, improving rural production conditions and the living environment, alleviating ecological risk, and supporting rural development.

Although related studies have promoted the understanding of poverty, poverty reduction, and their driving mechanisms, most of the methods employed in the studies apply linear analysis, trend analysis, and correlation analysis (Peng et al., 2019). However, one crucial deficiency is the assumption that a significant linear relationship exists between changes in poverty and economic factors or natural factors, on the one hand, and a lack of quantitative research on the regional differentiation mechanism of targeted poverty alleviation and rural poverty in the Tibetan region of the Northwest Sichuan Plateau (Liu et al., 2017), on the other. The latter has led to problems such as poor guidance by research on poverty alleviation theories, lack of detailed research, and insufficient innovation in targeted poverty alleviation.

In fact, poverty alleviation and elimination in the Tibetan region of the Northwest Sichuan Plateau is more challenging than in other regions. Although hundreds of classification algorithms such as k-means and SOM have been used for classification or partitioning, statistical methods for spatial differentiation are still very limited (Wang et al., 2010; Wang et al., 2016). Therefore, how to proceed from the actual conditions of ethnic minority areas to truly and effectively carry out targeted poverty alleviation and elimination, thereby achieving the inclusive development of these areas, has become a social problem and practical challenge that urgently needs addressing (Lai et al., 2016).

With the development and popularisation of positioning and observation technologies, in the context of either more elaborate or larger research or spatial big data, the problem of spatial heterogeneity is highlighted. Identifying the causes of gross domestic product (GDP) density in poor villages is still challenging, yet this is important for helping us to understand the connections between the multi-factors in the plateau environment and the changes in GDP density in poor villages. However, studies rarely discuss the relationship between GDP density changes in poor villages and their multi-factors. GDP density in poor villages is one of the important indicators of social and economic development, regional planning, and resource and environmental protection. This metric replaces reliance on the traditional administrative statistical unit and brings great convenience to spatial statistical analysis in regional differentiation. Currently, the main methods include geographical detector models for spatial heterogeneity measurement and factor analysis (Wang et al., 2016). This study used Mao County, situated in the Tibetan region of the Northwest Sichuan Plateau, as a typical case and explores the main factors that resulted in GDP density differentiation of poor villages on the northwest Sichuan Plateau by means of geographical detector, GIS spatial analysis, and geographical statistics, based on the GDP density of poor villages. It reveals the differentiation mechanism of rural poverty and proposes poverty alleviation policies and measures for various poor regions.

The objectives of this study were to (1) identify the main impact factors and their role in GDP density change in poor villages; (2) distinguish whether the impact factors are independent or interdependent influences on GDP density change in poor villages; (3) determine the optimal characteristics of the factors most conducive to GDP density change in poor villages; and (4) detect the differentiation mechanism of GDP density in rural poverty. This paper consists of five parts: the first section is the introduction; the second section introduces the research area, data sources, and research methods; the third section reports the main results and findings of GDP density change and influences on factors of GDP density change in rural poverty; the fourth section discusses how impact factors within the optimal characteristics or value range serve to promote GDP density changes in rural poverty and detects the differentiation mechanism of GDP density in rural poverty; and the fifth section summarises the main results of quantifying the regional differentiation mechanism in rural poverty.

2. Materials and methods

2.1. Study area

The study was conducted in Mao County, located on the south-eastern edge of the Tibetan Plateau, in the arid valleys of the Min River and upper Fu River in the Northwest Sichuan Plateau, in western China. It is situated at 102°53′-104°7′E, 31°22′-32°42′N (Fig. 1), covering an area of approximately 3,903.28 km^2. It is bordered by Beichuan County, Anzhou District, and Mianzhu City to the east; Heishui County and Li County to the west; Songpan County to the north; and Wenchuan County, Pengzhou City, and Shifang City to the south. It is approximately 116.62 km from east to west and 93.73 km from north to south. Mao County has 6 towns, 15 townships, 149 administrative villages, and 3 neighbourhood committees. It has a total population of approximately 110,000. In 2015, its GDP was 3,191.91 million yuan; the disposable income per capita of urban residents was 25,170 yuan; and the disposable income per capita of rural residents was 9,830 yuan. According to the National Third-Party Evaluation in China, the income threshold for the definition of poverty is 2,300 yuan in this study.

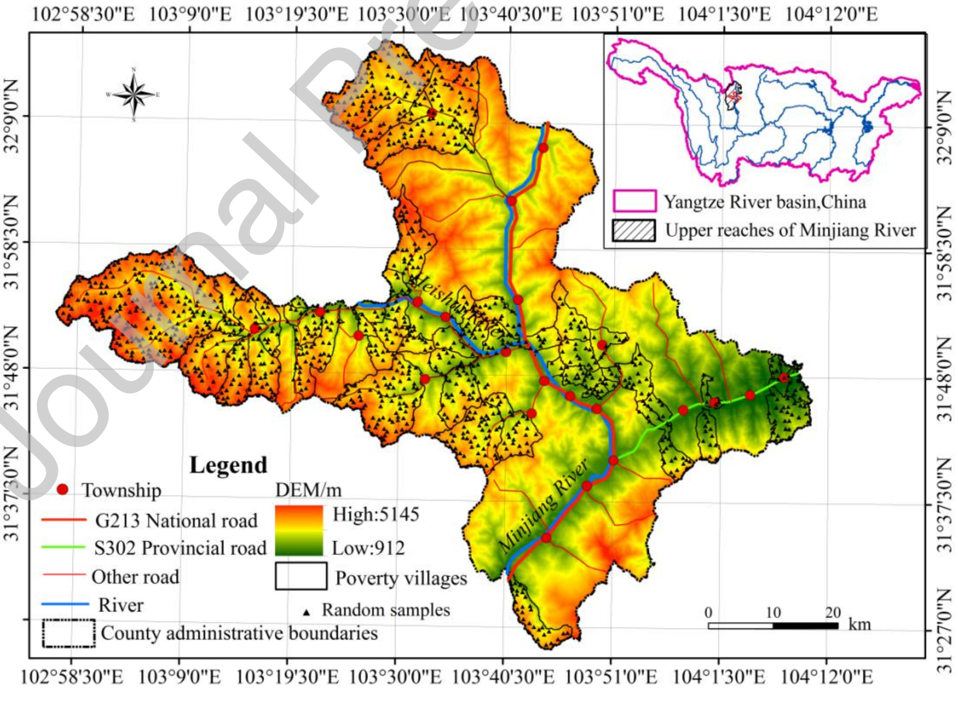

Fig.1 Location study area

Mao County is characterised by its ‘three-in-one’ combination of poverty-stricken areas, mountainous areas, and Tibetan plateau areas. (1) Mao County is a typical southwest inland underdeveloped region, with rural poverty that is most notably characterised by ‘scattered distribution, uneven development, and a large income gap’. Poverty and relapse into poverty caused by disasters, diseases, and disability features prominently in this region, and the intergenerational transmission of poverty is a significant problem, with the coexistence of poverty in concentrated, contiguous areas with a ‘floral arrangement’ pattern outside these areas. Hence, it has a pronounced poverty problem. As of late 2015, the county had 53 poor villages, 1,561 poor households, and a poor population of 5,316, while the incidence of poverty was 14.4%. (2) Alpine-canyon region in the transition zone between the Sichuan Basin and the Northwest Sichuan Plateau is composed of undulating mountain ranges and criss-crossing ravines with steep mountains. The terrain is high in the northwest and low in the southeast. Its topography is characterised by the deep cutting of medium-elevation mountains, and it belongs to the mountainous region on the western edge of the Sichuan Basin. The geological structure of this region is complex, with multiple arch-shaped folds and faults, and outcrops are mainly composed of metamorphic rock. Its geomorphology is that of a typical alpine-canyon region. Cultivated land, forest land, and grassland account for 2.61%, 67.5% and 21.6%, respectively, of the total county area. (3) The Tibetan region of the Northwest Sichuan Plateau has a Qiang population of about 103,200, accounting for 92.71% of the total county population and about 30% of the total Qiang population nationwide, which makes this region the largest Qiang-inhabited county in China. There are also 17 other ethnicities in this region, including Han, Tibetan, and Hui.

In the 2011 ‘Outline of Development-Oriented Poverty Alleviation for Rural China (2011–2010)’, Mao County was listed as one of the country’s contiguous poverty-stricken areas and a Tibetan plateau region with the clear implementation of special policies, serving as a major battleground for development-oriented poverty alleviation in the new era. Winning the battle against poverty will play a crucial role in the conscientious and thorough implementation of the central government’s strategy for Tibetan governance, as well as theories and innovations for targeted poverty alleviation, while also providing an important foundation for key measures to promote coordinated regional development and achieve common prosperity. In recent years, Mao County has made remarkable achievements in its socioeconomic development. However, its lagging economic development, weak infrastructure, and harsh ecological environment have contributed to difficulties in eliminating poverty.

2.2. Factor selection, data sources, and processing

Studies have shown that the dominant factors affecting the differentiation of rural poverty include slope, cultivated land per capita, distance to main roads, and distance to county centre (Liu et al., 2017). Harsh natural environment, poor geographic conditions, outdated infrastructure, and uneven regional development are the crux of persistent poverty in rural China (Liu et al., 2016).

Major factors influencing the rural poverty of Shanyang County include river network density, distance to the nearest highway, and disposable income per capita of rural residents (Wu et al., 2008). Harsh natural conditions, outdated infrastructure, and a weak industrial foundation have also been found to be major factors constraining rural poverty (Liu, 2015). Although the factors affecting the differentiation of rural poverty are complex, the combined effect of natural and human factors has a profound impact. According to the principle of selecting a systematic, typical, dynamic, scientific, quantifiable, and accessible indicator system – combined with the national third-party evaluation of targeted poverty alleviation and actual local conditions – this study only included topographic, climatic, vegetation, and social factors, which gave 11 candidate factors (Table 1). A geographical detector model was also applied to explore the dominant factors affecting the differentiation of GDP density among poor villages in the Tibetan plateau region. The values of GDP density (yuan/km^2) were then combined with vector data analysis to reveal the spatial distribution characteristics and differentiation mechanisms of the economic conditions in poor villages.

The research data in this study included the normalised differential vegetation index (NDVI), digital elevation model (DEM), topographic features, climate, vegetation elements, and social elements (Table 1). DEM, climate, and NDVI are derived from the Data Center of Resources and Environmental Science, Chinese Academy of Sciences (http://www.resdc.cn). NDVI data originated from China 500 m vegetation NDVI synthesis products, which was calculated by MODND1D, and the daily maximum in a month was calculated. Data on topographic features, in other words, elevation, aspect, and slope, were derived from the DEM. The map of the town centre and main traffic road was digitised using a 1:10,000 vegetation map. Distance to the centre of town and distance to the main traffic road in Maoxian were calculated by GIS Euclidean Distance. Climate data, in other words, average annual temperature, average annual precipitation, accumulated temperature (≥10°C), and dryness index, were calculated by GIS. Land use comes from remote sensing interpretation. The vector boundary of village scale and 64 poor villages in 2015 was provided by the Maoxian People's Government.

Tab.1 Spatial influence factors of GDP density in pooor villages

Topographic features	Climate and vegetation elements	Social elements
Elevation（x_1）/m	Average annual temperature（x_4）/°C	Land use（x_9）/types
Slope（x_2）/°	Average annual precipitation（x_5）/mm	Distance to the center of town（x_{10}）/m
Aspect（x_3）/°	Caccumulated temperature (≥10^0)（x_6）/°C	Distance to main traffic road（x_{11}）/m

	Aridity index （x_7）/level
	NDVI（x_8）/level

2.3 Methods

2.3.1 Natural break point method

The natural break point method is based on the natural grouping inherent in the data. In order to reduce the mean discrete variance within the group and maximise the difference between classes, it completely follows the distribution law of data and avoids the interference of human factors. The elevation, slope, and aspect in poor villages were divided into nine levels; the average annual precipitation, average annual temperature, and accumulated temperature (≥10°C) were divided into six grades; the NDVI and dryness indices were divided into five grades and four grades, respectively, based on natural break point method.

2.3.2 GIS spatial analysis

The superposition of GDP density with topographic features, climate and vegetation elements, and social elements was used for analysing the spatial differentiation characteristics of each factor and GDP density.

2.3.3 Geographical detector

The geographical detector method was proposed by Wang et al. (2017), through the measurement index of ‘factors’, combined with GIS spatial superposition technology and set theory to identify the model of interaction between multiple factors, the basic idea of which is to assume that the study is divided into several subregions. If the sum of the variances of the subregions is less than the total variances of the regions, there is spatial differentiation. If the spatial distribution of the two variables tends to be consistent, the two variables are statistically correlated (Wang et al., 2016; Wang et al., 2010). The geographical detector includes risk detection, factor detection, ecological detection, and interactive detection. On the basis of the geographical detector model, this study calculates the explanatory power of each factor on the GDP density of poor villages and analyses the regional differentiation mechanism of rural poverty.

(1) Spatial differentiation and factor detection. The calculation method comprises the following steps: first, spatial overlay analysis was performed for the GDP density layer and factor layer in poor villages; second, factors were divided into different spatial types or subzones; third, a significance test for the differences of mean values of factors was conducted to detect the relative importance of factors. The calculation model for the explanatory power of each factor is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \quad (1)$$

where q is the explanatory power of factors on GDP density in poor villages, $h = 1, \ldots, L$ are the stratification of y or factor x, that is, classification or partition; N_h and N are the number of units in h and the whole region, respectively; N and σ^2 are the total number of samples and the variance of y value in the whole region; and N_h is the variance of units h.

The range of q value is [0, 1], the larger the q value, the more obvious the spatial differentiation of y. In the extreme case, the q value of 1 indicates that factor x completely controls the spatial distribution of Y; the q value of 0 indicates that the factor x has nothing to do with Y.

The variance calculation formula of the y value in the whole region is as follows:

$$\sigma^2 = \frac{1}{N-1} \sum_{i=1}^{N} (Y_i - \overline{Y})^2 \quad (2)$$

where Y_j and $\overline{Y}$ are the j_{th} sample and the mean value of region Y in the study area, respectively.

$$\sigma_h^2 = \frac{1}{N_h - 1} \sum_{i=1}^{N_h} (Y_{h,i} - \overline{Y}_h)^2 \quad (3)$$

where $Y_{h,i}$ and $\overline{Y}$ is the value of ith sample and the mean of Y in zone h, respectively.

(2) Detection of factor interaction. Interaction detection is used to identify the interaction between factors, that is, to evaluate the accountability of the combined effect (enhancing or weakening) and respective effect on GDP density in poor villages. First, the q values of two factors with respect to NDVI were calculated $q(x_i)$ and $q(x_j)$. Then, q values regarding the interaction between factors were calculated ($q(x_i \cap x_j)$) and compared with $q(x_i)$ and $q(x_j)$.

(3) Detection of risk zones. Risk detection is used to judge whether there is a significant difference in mean attribute values between the subzones of two factors, and it can be used to find regions with high vegetation coverage. The risk detection is examined by using t statistic value:

$$t = \frac{\overline{Y}_{h=i} - \overline{Y}_{h=j}}{\left[\frac{Var(Y_{h=i})}{n_h = 1} + \frac{Var(Y_{h=j})}{n_h = 2}\right]^{1/2}} \quad (4)$$

(4) Ecological detection. Ecological detection is used to determine whether there is a significant difference between two natural factors (x_1 and x_2) in terms of influence on the spatial distribution of GDP density in poor villages, in other words, whether xi will influence the spatial distribution of GDP density in poor villages more significantly than x_j.

$$F = \frac{N_{x_i} \times (N_{x_j} - 1) \times SSW_{x_i}}{N_{x_j} \times (N_{x_i} - 1) \times SSW_{x_j}} \quad (5)$$

$$SSW_{x_i} = \sum_{h=1}^{L_i} N_h \sigma_h^2, \quad SSW_{x_j} = \sum_{h=1}^{L_j} N_h \sigma_h^2 \quad (6)$$

where N_{xi}, N_{xj} represent the sample number of two factors, respectively. SSW_{xi}, SSW_{xj} represent the sum of intra-layer variance formed by two natural factors, respectively. L_i, L_j represent the stratification values of variables x_i and x_j, respectively.

3. Results and Analysis

3.1. Poor villages and the differences in their GDP density

The distribution of poor villages in Mao County showed the coexistence of concentrated, contiguous areas with a ‘floral arrangement’ pattern outside these areas; there were significantly more poor villages in the east–west direction than in other areas. Clustered distribution could be found along the provincial highway (S302)-Heishui River in the east–west direction, with clustering along the Heishui River in townships including Huilong, Baixi, Wadi, Sanlong, Qugu, Yadu, and Weicheng, and in townships west of the Weimen to Huilong section along national highway G213. Scattered distribution could be observed in the southernmost and northernmost sections of the county. This study found a large difference in the distribution of GDP density among townships and administrative villages in Mao County. The average GDP density of Mao County was 3,912 yuan/km^2, whereas the average GDP density of poor villages was 3,313.3 yuan/km^2. There were significant differences in the regional distribution of GDP density among poor villages, with a maximum of 12,169 yuan/km^2, a minimum of 1.18 yuan/km^2, and a standard deviation of 12,169.08. The GDP density of approximately 48.64% and 47.31% of poor villages was <2,411.45 yuan/km^2 and 7,268 yuan/km^2, respectively; poor villages with GDP density of >7,268.73 yuan/km^2 accounted for 3.92%. The GDP density was higher near the provincial highway (S302), whereas higher-elevation areas near the Heishui River showed lower GDP density. Therefore, the in-depth detection of dominant factors affecting the regional differentiation of rural poverty and their distribution characteristics are of great significance for the scientific implementation of policies for targeted poverty alleviation.

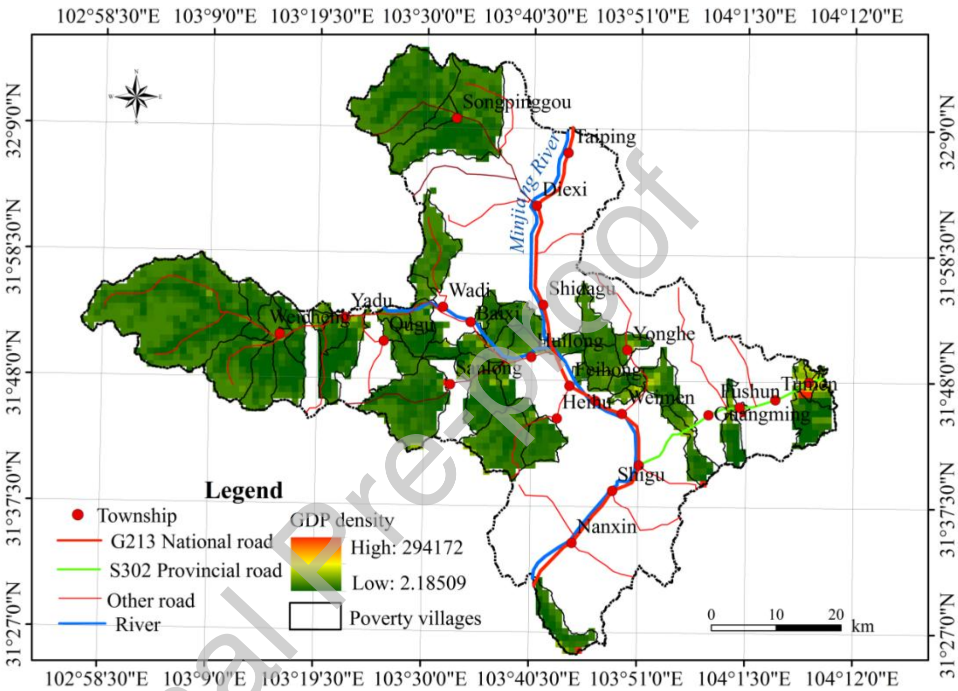

Fig. 2. Difference of GDP density in poor villages (yuan/km^2)

3.2. Impact of detection factors on GDP density in poor villages

Using the geographical detector, we calculated the size of the impact for each factor on GDP density, and the impact of each factor on GDP density was extracted (Table 2). The factors were then ranked according to their degree of impact on GDP density as follows: distance to main roads > NDVI > land-use type > average annual temperature > elevation > accumulated temperature ≥10°C > distance to township centre > aridity index > average annual precipitation > slope > aspect. With respect to the impact of the factors on GDP density, the q values of distance to main road, NDVI and land-use type were 80.76%, 12.8%, and 8.82%, respectively. Therefore, distance to main road, NDVI, and land-use type were dominant factors influencing the GDP density of poor villages. Although the q values of topographic and climatic factors were relatively low and the explanatory power of individual factors was very small, their interactions with the dominant factors (distance to main road, NDVI, and land-use type) showed non-linear or mutual enhancement effects, which augmented the effect of topographical and climatic factors on GDP density.

Tab.2 *q* values of factors in poor villages

Factors	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}
q	0.0 396	0.0 058	0.0 082	0.0 545	0.0 101	0.0 288	0.0 185	0.1 283	0.0 882	0.0 269	0.8 076
p value	0.000	0.5 814	0.2 904	0.000	0.0 932	0.000	0.000	0.000	0.000	0.000	0.000

3.3. Analysis on the significant differences among detection factors

The distance to main roads showed significant differences with all other factors in its effect on the spatial differentiation of GDP density (Table 3). NDVI showed significant differences in its effect on the spatial differentiation of GDP density with all other factors, except for land-use type and distance to township centre. Land-use type showed significant differences with slope, aspect, average annual temperature, NDVI, and distance to main roads in its effect on the spatial differentiation of GDP density; it did not show significant differences with elevation, accumulated temperature ≥10°C, aridity index, and distance to township centre.

Tab.3 Statistical significance of detection factors in poor villages (95% confidence level)

Factor	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}
x_1											
x_2	N										
x_3	N	N									
x_4	N	N	N								
x_5	N	N	N	N							
x_6	N	N	N	N	N						
x_7	N	N	N	N	N	N					

x_8	Y	Y	Y	Y	Y	Y	Y			
x_9	N	Y	Y	N	Y	N	N	N		
x_{10}	N	N	N	N	N	N	N	N	N	
x_{11}	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Y indicates that the influence of two factors on vegetation GDP density in poor villages is significantly different (confidence is 95%). N means no significant difference.

3.4. Analysis on the indicative effect of detection factors

The applicable range for each factor concerning changes in GDP density was calculated and analysed according to the geographical detector, and its statistical significance was tested at a 95% confidence level. As shown in Table 4, there were significant differences in the GDP density of different factors. Specifically, the smaller the distances to main roads and the township centre, the higher the GDP density of poor villages. Micro-landforms, such as low elevation, gentle slope, and south-facing aspect, had a relatively large impact on the GDP density of poor villages. Cultivated land was the main land type of the poor villages. Good temperature and moisture conditions, including the average annual temperature, accumulated temperature ≥10°C, and average annual precipitation, benefitted the development of agricultural and animal husbandry production, which promoted the economic development of poor villages.

Tab.4 The suitable limits of the factors in poor villages (95% confidence level)

Code	Factors	Suitable types or range	Mean value of GDP /yuan km^2
x_1	Elevation/m	<1 706	5954
x_2	Slope/°	<10.96	3670
x_3	Aspect/°	157.5~202.5	3258
x_4	annual average temperature/℃	8~13	5521
x_5	Average annual precipitation/mm	1 097~1 161	3524
x_6	Caccumulated temperature (≥10°)/℃	3 163~3 980	6505
x_7	Aridity index	-1~0	3596
x_8	NDVI	0.286~0.439	5035

x_9	Land-use type	cultivated land	7293
x_{10}	Distance to the center of town/m	<2 961	4480
x_{11}	Distance to main traffic road/m	<1 206	2956

3.5. Analysis on the interaction effect of detection factors

By identifying the interaction between different candidate factors x_i, the study analyses whether it will increase or decrease the explanatory power of the dependent variable, GDP density, or whether each of these factors has an independent influence on GDP density. In the natural and social environment, GDP density is the result of multiple factors acting together, and it is impossible for there to be a single factor or a factor of a single nature.

The vast majority of factor interactions had q values greater than those of single factors, and the factor interaction effects were non-linear enhancements (Table 5). The q values for the interaction effects among factors on GDP density indicate that the interactions of distance to main roads with land-use type, elevation, average annual temperature, accumulated temperature ≥10°C, average annual precipitation, and distance to township centre showed nonlinear enhancement relationships;: $x_9 \cap x_{11}$（0.889> $x_1 \cap x_{11}$（0.874> $x_4 \cap x_{11}$（0.853> $x_6 \cap x_{11}$（0.852> $x_5 \cap x_{11}$（0.842> $x_{10} \cap x_{11}$（0.835）. The results also indicate that the interactions of NDVI with aspect, slope, average annual precipitation, average annual temperature, elevation, and accumulated temperature ≥10°C showed nonlinear enhancement relationships: $x_3 \cap x_8$（0.8 389）> $x_2 \cap x_8$（0.8 284）> $x_5 \cap x_8$（0.4 772）> $x_4 \cap x_8$（0.4 573）> $x_1 \cap x_8$（0.4 595）> $x_6 \cap x_8$（0.2 039）.

In summary, the impact of factors on changes in GDP density was not independent but showed significant mutual effects. The impact of multi-factor interactions on GDP density was not a simple process of superposition but one of nonlinear or mutual enhancement effects. Therefore, the driving factors mainly exerted synergistic and nonlinear synergistic effects, none of which were mutually independent.

Tab.5 Interaction between factors that influence changes of GDP density in poor villages

C	A+B	Result	Interpretation	C	A+B	Result	Interpretation
$x_1 \cap x_2$ =0.0 829	＞0.0 454＝x_1＋x_2	C＞A＋B	↑↑	$x_4 \cap x_6$ =0.0 596	＜0.0 834＝x_4＋x_{10}	C＜A＋B	↑
$x_1 \cap x_3$ =0.1 054	＞0.0 477＝x_1＋x_3	C＞A＋B	↑↑	$x_4 \cap x_7$ =0.0 559	＜0.0 730＝x_4＋x_{11}	C＜A＋B	↑
$x_1 \cap x_4$ =0.3 061	＞0.0 941＝x_1＋x_4	C＞A＋B	↑↑	$x_4 \cap x_8$ =0.4 573	＞0.1 828＝x_4＋x_{12}	C＞A＋B	↑↑

$x_1 \cap x_5$ =0.0 821	$>$0.0 496=x_1+x_5	C$>$A+B	↑↑	$x_4 \cap x_9$ =0.1 964	$>$0.1 427=x_5+x_6	C$>$A+B	↑↑
$x_1 \cap x_6$ =0.0 503	$>$0.0 984=x_1+x_6	C$>$A+B	↑↑	$x_4 \cap x_{10}$ =0.1 172	$>$0.0 815=x_5+x_6	C$>$A+B	↑↑
$x_1 \cap x_7$ =0.0 468	$>$0.0 580=x_1+x_7	C$>$A+B	↑↑	$x_4 \cap x_{11}$ =0.8 526	$<$0.8 621=x_5+x_6	C$<$A+B	↑
$x_1 \cap x_8$ =0.4 595	$>$0.1 678=x_1+x_8	C$>$A+B	↑↑	$x_5 \cap x_6$ =0.0 488	$>$0.0 389=x_5+x_7	C$>$A+B	↑↑
$x_1 \cap x_9$ =0.1 247	$>$0.1 278=x_1+x_9	C$>$A+B	↑↑	$x_5 \cap x_7$ =0.0 424	$>$0.0 285=x_5+x_8	C$>$A+B	↑↑
$x_1 \cap x_{10}$ =0.0 981	$>$0.0 665=x_1+x_9	C$>$A+B	↑↑	$x_5 \cap x_8$ =0.4 772	$>$0.1 383=x_5+x_{10}	C$>$A+B	↑↑
$x_1 \cap x_{11}$ =0.8 748	$>$0.*8 471*= x_1+x_9	C$>$A+B	↑↑	$x_5 \cap x_9$ =0.1 232	$>$0.0 983=x_4+x_8	C$>$A+B	↑↑
$x_2 \cap x_3$ =0.0 886	$>$0.0 140=x_2+x_3	C$>$A+B	↑↑	$x_5 \cap x_{10}$ =0.1 531	$>$0.0 370=x_5+x_{10}	C$>$A+B	↑↑
$x_2 \cap x_4$ =0.2 118	$>$0.0 603=x_2+x_4	C$>$A+B	↑↑	$x_5 \cap x_{11}$ =0.8 415	$>$0.8 176=x_4+x_8	C$>$A+B	↑↑
$x_2 \cap x_5$ =0.0 559	$>$0.0 159=x_2+x_5	C$>$A+B	↑↑	$x_6 \cap x_7$ =0.0 320	$<$0.0 473=x_4+x_9	C$<$A+B	↑
$x_2 \cap x_6$ =0.1 587	$>$0.0 346=x_2+x_6	C$>$A+B	↑↑	$x_6 \cap x_8$ =0.2 039	$>$0.1 571=x_4+x_{10}	C$>$A+B	↑↑
$x_2 \cap x_7$ =0.0 434	$>$0.0 243=x_2+x_7	C$>$A+B	↑↑	$x_6 \cap x_9$ =0.1 079	$<$0.1 171=x_4+x_{11}	C$<$A+B	↑
$x_2 \cap x_8$ =0.8 284	$>$0.1 341=x_2+x_8	C$>$A+B	↑↑	$x_6 \cap x_{10}$=0.0 752	$>$0.0 558=x_4+x_{10}	C$>$A+B	↑↑
$x_2 \cap x_9$ =0.1 247	$>$0.0 940=x_2+x_9	C$>$A+B	↑↑	$x_6 \cap x_{11}$=0.8 519	$<$0.8 364=x_4+x_{11}	C$<$A+B	↑
$x_2 \cap x_{10}$ =0.1 092	$>$0.0 327=x_1+x_9	C$>$A+B	↑↑	$x_7 \cap x_8$ =0.1 901	$>$0.1 467=x_4+x_{12}	C$>$A+B	↑↑
$x_2 \cap x_{11}$ =0.8 183	$>$0.8 134=x_1+x_9	C$>$A+B	↑↑	$x_7 \cap x_9$ =0.1 016	$<$0.1 067=x_5+x_6	C$<$A+B	↑
$x_3 \cap x_4$ =0.1 142	$<$0.0 627=x_2+x_5	C$<$A+B	↑	$x_7 \cap x_{10}$=0.0 654	$>$0.0 454=x_4+x_{12}	C$>$A+B	↑↑
$x_3 \cap x_5$ =0.0 502	$>$0.0 183=x_2+x_6	C$>$A+B	↑↑	$x_7 \cap x_{11}$ =0.8 293	$<$0.8 260=x_5+x_6	C$<$A+B	↑
$x_3 \cap x_6$ =0.0 616	$>$0.0 370=x_2+x_7	C$>$A+B	↑↑	$x_8 \cap x_9$ =0.4 754	$>$0.2 165=x_4+x_{12}	C$>$A+B	↑↑
$x_3 \cap x_7$ =0.0 413	$>$0.0 266=x_2+x_8	C$>$A+B	↑↑	$x_8 \cap x_{10}$=0.8 472	$<$0.1 552=x_5+x_6	C$<$A+B	↑
$x_3 \cap x_8$ =0.8 389	$>$0.1 364=x_2+x_8	C$>$A+B	↑↑	$x_8 \cap x_{11}$ =0.8 276	$<$0.9 358=x_4+x_{12}	C$<$A+B	↑
$x_3 \cap x_9$ =0.1 674	$>$0.0 964=x_2+x_8	C$>$A+B	↑↑	$x_9 \cap x_{10}$=0.1 624	$>$0.1 152=x_4+x_{12}	C$>$A+B	↑↑
$x_3 \cap x_{10}$ =0.1975	$>$0.0 351=x_2+x_8	C$>$A+B	↑↑	$x_9 \cap x_{11}$=0.8 889	$<$0.8 958=x_5+x_6	C$<$A+B	↑
$x_3 \cap x_{11}$ =0.8240	$>$0.8 157=x_2+x_8	C$>$A+B	↑↑	$x_{10} \cap x_{11}$=0.8 350	$>$0.8 345=x_4+x_{12}	C$>$A+B	↑↑
$x_4 \cap x_5$ =0.1007	$>$0.0 646=x_4+x_9	C$>$A+B	↑↑				

Note: "C" represents the interaction of two factors, $x_i \cap x_j$; "A+B" represents the addition of two factor q values, $(q(x_i)+q(x_j))$; "↑" denotes x_i and x_j enhance each other; "↑↑" denotes a non-linear enhancement of x_i and x_j.

4. Discussion

4.1. Regional differentiation mechanism in poor villages

On the basis of the results of the geodetector analysis, distance to main roads, NDVI, and elevation were ultimately determined as the dominant factors affecting the GDP density of poor villages. Further comprehensive detection was conducted to analyse the mechanisms underlying the effects of the dominant factors on differences in the economic development of poor villages, which will provide a reference for achieving measures of scientific poverty alleviation and targeted poverty elimination tailored to local conditions.

(1) Distance to main roads

Transportation is an important channel forming the county's internal and external connections, while the distance to main roads is a key indicator reflecting its transportation location and serving as a key constraint on local economic development (Liu et al., 2016). Nineteen sub-provincial roads, one provincial highway (S302), and one national highway (G213) among poor villages in Mao County connect ten, four, and three townships, respectively (Fig. 3). On the basis of GIS spatial analysis and geographical detector analysis, we found that as the distance to main roads increased (Table 6) the trend of change in the GDP density of poor villages in Mao County followed the curve-fitting equation:

$$y = -168.92x + 2973, R^2 = 0.7395$$

It can be seen from the curve-fitting equation that GDP density showed an overall decreasing trend as the distance to main roads increased, and the two were highly correlated. Areas closer to main roads showed higher GDP density. In contrast, living in remote mountainous areas far from main roads made communication with the outside world less convenient, affecting the export of agricultural products, the movement of migrant workers, and the input of capital, resulting in slow economic development, fewer sources of income, and lower GDP density as a consequence. When the distance of poor villages to main roads was less than 1,226m, the GDP density was 2,956.56 yuan/km^2; when the distance exceeded 7,358m, the GDP density was reduced to 1,925.958 yuan/km^2. Therefore, the distance to main roads objectively reflected the convenience of transportation and closeness of communication with the outside world of the sample sites. A shorter distance indicates a higher degree of connection with the outside world, whereas the opposite indicates a lower degree of connection (Liu et al., 2016).

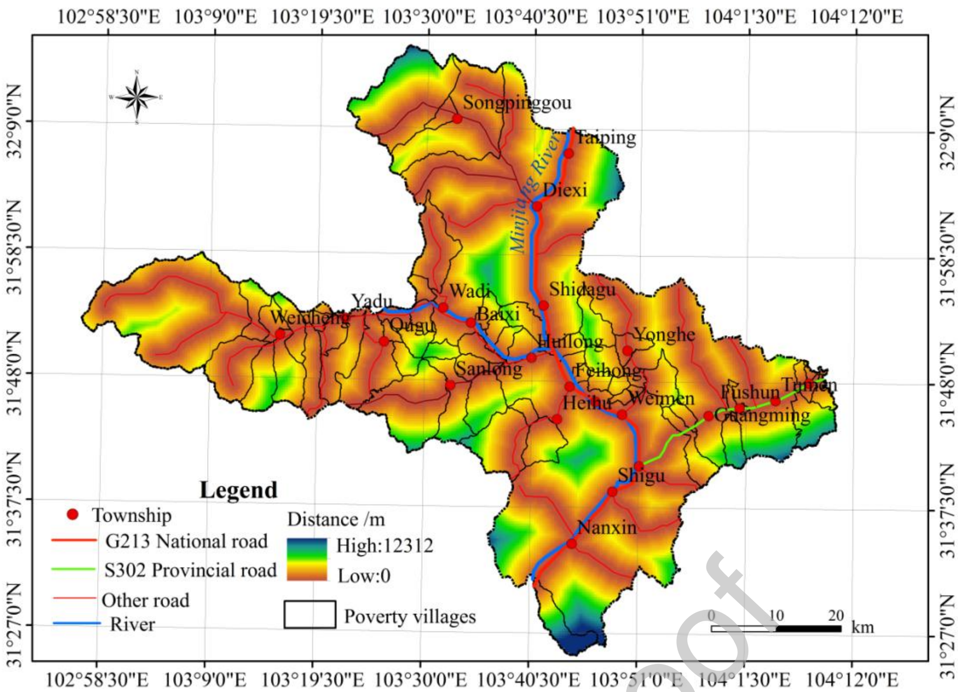

Fig.3 Distance to main traffic road

Tab.6 Area proportion and GDP density and distance to main traffic road in poor villages

Distance/m	<1 226	1 226~ 2 452	2 452~ 3679	3 679~ 4 905	4 905~ 6 131	6 131~ 7 358	7 358~ 11 037
Area proportion/%	46.496	44.892	33.378	17.636	0.875	0.000	0.000
GDP density /yuan/km^2	2 956.56	2 658.9	2 146.38	2 278.666	2 402.814	1 711.676	1 925.958

(2) NDVI

Vegetation is an important component of the ecosystem. It adapts to climatic, topographic, and soil conditions, and has a strong dependence and sensitivity to a variety of natural factors. We can see from Table 5 that the *q* values for the interaction effects of NDVI on GDP density indicate nonlinear and mutual enhancement relationships among factor interaction effects: $x_8 \cap x_{10}$ (0.847>$x_3 \cap x_8$ (0.838> $x_2 \cap x_8$ (0.828) >$x_5 \cap x_8$ (0.477) >$x_8 \cap x_9$ (0.475). This implies that the interaction effects of distance to main roads with slope and aspect significantly enhanced the impact of NDVI on GDP density. Table 7 shows that the greater the NDVI value, the more suitable the characteristics of natural geographic factors are for vegetation growth. Poor villages with

NDVI of 0.286~0.439 showed the highest GDP density at 5,035.503 yuan/km^2 but only accounted for 1.72% of the area of poor villages. Regions with NDVI>0.592 accounted for more than 90% of the area of poor villages, and the values of GDP density ranged from 2,270 to 4,008 yuan/km^2. Therefore, poor villages with better vegetation coverage had better temperature and moisture conditions, which are conducive to agricultural production, thus also resulting in higher GDP density.

Tab.7 NDVI, area proportion and GDP density in poor villages

NDVI	0.132~0.286	0.286~0.439	0.439~0.592	0.592~0.746	0.746~0.9
Area proportion/%	1.186	1.720	5.219	9.015	82.859
GDP density /yuan/km^2	3 761.379	5 035.803	4 000.309	4 008.26	2 270.163

(3) Land use

By land use, Mao County is 2.61% cultivated land, 67.5% forest land, and 21.6% grassland. Cultivated land is the material foundation on which agricultural production depends. The total area of cultivated land in the county was 6,395.36 ha, of which floodplains covered 1,415.343 ha, hillsides covered 4,480.022 ha, and the cultivated land per capita was 0.068 ha. The total area of grassland was 110,000 ha, of which the area of useable land was 86,000 ha. GIS spatial analysis indicates that cultivated land, forest land, and grassland account for 3.265%, 24.419%, and 49.828%, of the area of poor villages, respectively. Poor villages near the provincial highway had

lower elevations, better climate, and more convenient transportation. Thus, advantages of topography and location helped to support leading enterprises in agricultural industrialisation and to grow high-quality vegetables and specialty fruits, and build other industrial bases, furthering economic development. The poor villages near Heishui River were able to develop advantageous characteristic agriculture and establish integrated bases. Their crops included the crisp red plums of Luoshan Village, crisp plums of Nanzhuang Village, alpine green vegetables of Mu’er Village, and the fruits and vegetables of Kekezhai Village. However, unstable agricultural production and low yield have made it more difficult to increase the income of rural residents, thus causing a higher incidence of poverty.

(4) Climatic factors

In general, the rise in temperature will accelerate plant growth and development; when the temperature is lower or higher than the range of tolerance for plants, their growth will slow down and stop, their development will be blocked, and the plants will begin to experience damage or even death. Despite the low q values for the average annual temperature, average annual precipitation, accumulated temperature ≥10°C, and aridity index of poor villages, which were all lower than 0.05 (Table 4), the interaction effects among factors significantly enhanced the impact of climatic factors on GDP density. In other words, between average annual temperature and distance to main roads ($x_4 \cap x_{11}$ =0.8 526>x_4), elevation ($x_1 \cap x_4$ =0.3 061>x_4), and slope（$x_2 \cap x_4$ =0.2 118>x_4; between NDVI and average annual precipitation ($x_5 \cap x_8$ =0.4 772>x_5) and accumulated temperature ≥10°C ($x_6 \cap x_8$ =0.2 039>x_6); and between aridity index and distance to main roads（$x_7 \cap x_{11}$ =0.8 293>x_7）.

In addition to the shared characteristics of plateau-type monsoon climate, Mao County also has regional characteristics such as significant vertical climate differences, diverse local microclimates, large differences in precipitation, distinct wet and dry seasons, and 'foehn wind effects'. The poor villages in the eastern part of the county have a semi-humid warm temperate climate, and the alpine valleys have a semi-arid temperate climate, characterised by dryness and windiness, cold winters and cool summers, a large temperature difference between day and night, and large regional differences.Our study found that accumulated temperature ≥10°C within the range of 3.163 to 3.980°C and average annual temperature within the range of 8 to 13°C in Mao County had a greater impact on the GDP density of poor villages (6,505 yuan/km^2 and 5,521 yuan/km^2, respectively) than average annual precipitation within the range of 1,097 to 1,161mm and aridity index within the range of -1 to 0 (3,596 yuan/km^2 and 3,524 yuan/km^2, respectively). Therefore, climatic factors had a relatively large impact on poverty differentiation.

(5) Topographical factors

The rise in elevation will lead to changes in climate, causing the air to become colder and drier, which would have a corresponding impact on plant growth. Because of the combined effect of factors such as light, temperature, and rainfall, different slopes and aspects can affect plant growth, thus causing changes in the ecological relationship between plants and the environment (Table 4). Our analysis shows that despite the low q values of elevation, slope, and aspect of poor villages, which were all smaller than 0.03, there were nonlinear or mutual enhancement effects between elevation and NDVI ($x_1 \cap x_8$ = 0.4595>x_1、$x_1 \cap x_3$ =0.1054>x_1), between slope and distance to main roads ($x_2 \cap x_{11}$ =0.8183>x_2) and land use ($x_1 \cap x_9$ =0.12474>x_1), and between slope and NDVI ($x_3 \cap x_8$ =0.8 389>x_3), distance to main roads ($x_3 \cap x_{11}$ =0.8240>x_3), and distance to township centre ($x_3 \cap x_{10}$ =0.1975>x_3). These effects significantly enhanced the impact of elevation on GDP density, such that the increase in elevation caused the GDP density of poor villages to display a decreasing trend: GDP density was the highest when elevation <1,706m, reaching 5,954.722 yuan/km^2 (Table 8); GDP density was the highest when slope <10.96° and aspect was within the range of 157.5 to 202.5°, at 3,670 yuan/km^2 and 3,258 yuan/km^2, respectively. The impact of elevation was greater than that of slope and aspect on the GDP density of poor villages. Therefore, topographical factors had a relatively large impact on poverty-stricken regions.

Tab.8 Elevation and GDP density in poor villages

Elevation/m	<1 706	1 706~ 2 112	2 112~ 2 475	2 475~ 2 813	2 813~ 3 141	3 414~ 3 467	3 467~ 3 803	3 803~ 4 175	>3 807
GDP density /yuan/km^2	5954.722	3856.801	3280.646	2786.858	1692.974	1288.54	2704.116	2972.631	3881.337

4.2. Types of poverty-stricken regions and poverty alleviation policies and measures

The regional differentiation of poverty stems from the combined effects of natural and human factors. There are differences in the dominant factors of poverty differentiation in Mao County located in the Tibetan region of the Northwest Sichuan Plateau. However, the interaction effects of factors such as distance to main roads, land use, average annual temperature, and distance to township centre had a crucial impact on the agricultural product sales, production methods, agricultural structure, and basic public services and facilities. The interaction effects of the detection factors indicate that the interaction effects of natural, social, and economic factors in the Tibetan region of the Northwest Sichuan Plateau show nonlinear and mutual enhancement relationships, which have a key impact on the formation of rural poverty. On the basis of the detection results, the study area was divided into three types of poverty-stricken regions: regions with transportation location constraints, regions with natural resources and environmental constraints, and regions with economic location constraints.

(1) Regions with transportation location constraints

This type of region is mainly characterised by the significant impact of distance to main roads, featuring incomplete road infrastructure and poor basic conditions. The area of poor villages in Mao County with distances to main roads falling within the ranges of 8,584 to 9,810 m, 9,810 to 11,037 m, and 11,037 to 11,263 m accounted for 0.240%, 0.386%, and 0.291% of the total area, respectively. Road infrastructure is incomplete at greater distances from the main roads, which has become a challenge in achieving poverty alleviation. Therefore, special national poverty alleviation funds should be used to implement projects such as connecting villages, ensuring village road security, and hardening village-level roads, which will greatly improve the accessibility to county, township, and village roads, thereby maximising the role of transportation infrastructure in rural economic development, especially in eliminating poverty. In addition, resettlement policies should be adopted in remote mountainous areas where regional development is severely impeded.

(2) Regions with natural resources and environmental constraints

This type of region is significantly affected by regional natural resources and environmental factors. They are alpine regions, facing serious problems such as steep slopes, high elevation, fragile ecology, geological disasters, and debris flow disasters. These regions have barren land resources, low temperatures, and moisture resources, making them unsuitable for the development of the agricultural industry. The natural resources and environmental constraints of these regions are sufficiently severe to affect the effectiveness of poverty elimination. Therefore, the promotion of rural drinking-water safety, farmland irrigation, and medium-to-large-sized water conservancy projects should be accelerated, and the achievements of the ‘Hundred Villages, Thousand Pools, and Ten Thousand Pits Micro-Irrigation Project’ should be consolidated, in order to solve the problems of ‘instability, unrest and poverty caused by water’ faced by poor villages (People's Government in MAO County, 2017). Funding for national rural power grid support should be actively sought to improve the power supply capacity and quality of distribution networks. The relationship between ecological protection and poverty alleviation should be properly managed in poverty-stricken areas; and the protection, governance, and restoration of the ecological environment in poor villages should be strengthened, in order to improve the capability of poverty-stricken areas for sustainable development and to achieve green development.

(3) Regions with economic location constraints

This type of region is significantly affected by the distance to the township centre. The distance of poor villages to the township centre ranges from 0 to 24,900 m. Regions within the range of <11,150 m from the township centre account for 77.97% of the total area of poor villages, and regions within the range of > 11,150m account for 22.03%. This type of region is located far from the county-level city or township centre and has inadequate rural infrastructure and public service facilities, which makes it difficult to meet the consumption, healthcare, education, and other essential needs of rural households in poor villages. Regional water improvement and drinking water safety projects should be strengthened, along with the construction of infrastructure and public service facilities, such as building township health centres, improving radio and television communication, and establishing rural social security. By following the principles of ‘adopting agriculture, tourism, or business where suitable’, significant efforts should be invested in fostering and developing characteristic pillar industries in poor villages. It is also necessary to fully demonstrate the roles of new business entities, such as cooperatives, specialised households, and leading enterprises, and strive to improve the ability of the poor population to escape from poverty, thereby achieving sustainable and stable poverty elimination. In addition, e-commerce should be vigorously developed in order to fully utilise modern information technology to expand the sales channels of characteristic products, thus transforming the ecological resource advantages of poor villages into economic advantages and further expanding the population's channels to increase income.

Tab.9 GDP density, area proportion and distance to the center of villages and towns in poor villages

Distance/m	>2981	2981~ 5021	5021~ 6966	6966~ 8985	8985~ 11150	11150~ 13 933	13933~ 17959	17959~ 23074	>23074
Area proportion/%	11.589	21.893	18.664	14.441	11.383	8.403	6.261	4.711	2.655
GDP density /yuan/km^2	4 221	2314	2294	1726	2449	2780	4480	3051	3528

5. Conclusion

In this study, we quantified the individual and interactive influences of impact factors on GDP density changes and identified the most suitable characteristics of each principal factor for stimulating GDP density growth based on the geographical detector method. This is a new spatial statistical approach based on remotely sensed data. It is both timely and necessary to understand changes in GDP density, its driving forces, and the implications for scientific promotion of precise approaches to poverty alleviation innovation, comprehensive strategy, and earnest implementation of the central government's strategy for governing Tibet in the Northwest Sichuan Plateau.

We illustrated the individual influences of impact factors on GDP density changes in poor villages. Impact factors can be ranked in descending order by the magnitude of their influence on GDP density: distance to main roads > NDVI > land-use type > average annual temperature > elevation > accumulated temperature ≥10°C > distance to township centre > aridity index > average annual precipitation > slope > aspect. The distance to main road, NDVI, and land-use types account for more than 80%, 12%, and 8% of variation in GDP density in poor villages, respectively, meaning that they are the primary factors affecting GDP density changes.

We found that the interactive influence of factors on GDP density in poor villages changes, and the synergistic effect of impact factors is manifested as mutual and nonlinear enhancement.

This study reveals the optimal characteristics of key natural factors beneficial to growth of GDP density in poor villages, thus attaining a more in-depth understanding of the influence exerted by factors on GDP density. This is a critical step towards discovering the driving mechanism of GDP density change. To some extent, the findings of this study may benefit intervention in and promotion of GDP density by determining a favourable value range for factors.

We proposed different types of poverty-stricken regions and poverty alleviation policies and measures, which have significant implications for implementing targeted poverty alleviation measures in other poverty-stricken areas. Poor villages are the most basic unit for the regional differentiation of rural poverty and play an important role in the research on poverty elimination systems. Based on the explanatory power of different dominant factors for poverty differentiation, this study identified different regional types of rural poverty and proposed measures such as strengthening the construction of public infrastructure and cultivation of industries. It focused on the comprehensive integration of multiple models, fully utilising the basic effects of characteristic agriculture and animal husbandry and implementing stratified policies according to local conditions. This will facilitate the establishment of an eco-industrial system suited to poverty-stricken areas that integrates natural-economic-social composite systems, thus forming a higher-level, comprehensive model of poverty alleviation. This study provided stratified guidance for targeted poverty alleviation according to the types of poverty-stricken regions in townships and promoted a characteristic model and sustainable mechanism for targeted poverty alleviation of townships in the Tibetan region of the Northwest Sichuan Plateau, western China. These findings have provided scientific support and referential basis for the implementation of poverty elimination decision-making in other poverty-stricken minority areas.

Finally, this study highlights the advantages of the geographical detector in detecting spatial heterogeneity and identifying driving factors. The detection of risks, factors, ecology, and interactions has provided crucial support for detecting the dominant factors and studying the poverty mechanisms of rural poverty differentiation in the Tibetan region of the Northwest Sichuan Plateau. Unlike traditional methods, such as principal component analysis and classical regression models, which are usually based on certain assumptions or limitations (e.g. normal distribution and linear assumptions), the geographical detector does not have linear assumptions, which has clear physical implications.

Conflict of Interest Statement

This manuscript has not been published or presented elsewhere in part or in entirety, and is not under consideration by another journal**.** All of the authors contributed materially to the study, have reviewed and approved the manuscript, and agreed with submission to the journal. The authors have no conflicts of interest to declare.

All of the authors:

Guangjie Wang,Wenfu Peng, Shuai Tao

The Institute of Geography and Resources, Sichuan Normal University, Chengdu 610068, P. R. China

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References

Liao C,＆Fei D,2019. Poverty reduction through photovoltaic-based development intervention in China: Potentials and constraints. World Development.122,1-10.

Liu D P, 2015. Factors restricting the entry of rural poverty groups into the comprehensive well-off society and countermeasures. Rural Economy. (7),55-59.

Wang J F,＆Xu C D, 2017. Geodetector: Principle and prospective. Acta Geographica Sinica. 72(1),116-134.

Wang J F,＆Zhang T L,＆Fu B J, 2016. A measure of spatial stratified heterogeneity. Ecological Indicators. 67,250-256.

Wang J F,＆Li X H, ＆Christakos G, et al,2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. International Journal of Geographical Information Science.24(1),107-127.

Qiu L L, ＆Zeng W Z,2017. Research on rural income gap in counties from the perspective of precise poverty alleviation,based on the analysis of 88 poverty-stricken counties in Sichuan Province. China agricultural resources and zoning.38(8),151-157.

Wang P, ＆Yan J Z,＆Hua X B,＆Yang L,2019. Determinants of livelihood choice and implications for targeted poverty reduction policies: A case study in the YNL river region, Tibetan Plateau. Ecological Indicators. 101,1055-1063.

Prabhakar Yadav,＆Peter J.Davies,＆Sabah Abdullah,2019. Reforming capital subsidy scheme to finance energy transition for the below poverty line communities in rural India. Energy for Sustainable Developmen.45,11-27.

Sewell S J,＆Desai S A, ＆Mutsaa E,＆Lottering R T,2019. A comparative study of community perceptions regarding the role of roads as a poverty alleviation strategy in rural areas.Journal of Rural Studies.71,73-84.

Somvang Phimmavong,＆Rodney J.Keenan,2019. Forest plantation development, poverty, and inequality in Laos: A dynamic CGE microsimulation analysis. Forest Policy and Economics.111.https://doi.org/10.1016/ j.forpol.2019.102055.

Qu W,＆Tu Q,＆Niu SW,et al,2012. Poverty effect test of physical and geographical environment-empirical analysis of the impact of physical and geographical conditions on rural poverty. China rural economy.(2),21-34.

Peng W F,＆Kuang T T,＆Tao S,2019. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China.Journal of Cleaner Production. 233,353-367.

Peng W,＆Li TS,＆Li W M,2008. Spatial differentiation of rural poverty in county areas and its influencing factors -- a case study of Shanyang County, Shaanxi Province. Journal of Geography.37(3),593-606.

Wang X Y, 2015. Development of introspection and anti-poverty in minority areas-a case study based on northwest yunnan and guizhou. Journal of China agricultural university (social science edition).32(4): 1-14.

Hua X B,＆Yan J Z,＆Zhang Y L,2017. Evaluating the role of livelihood assets in suitable livelihood strategies: Protocol for anti-poverty policy in the Eastern Tibetan Plateau, China.Ecological Indicators.78,62-74.

Lai Y H, 2016. Predicament and countermeasures of targeted poverty alleviation in ethnic minority areas. Rural economy and science and technology.27(20),175-176.

Liu Y S,＆Li J T, 2017. Geographical exploration and optimization of rural poverty differentiation mechanism in

China. Acta geographica sinica.72(1),161-173.

Liu Y S,＆Liu J L,＆Zhou Y, 2017. Spatio-temporal patterns of rural poverty in China and targeted poverty alleviation strategies.Journal of Rural Studies.52,66-75.

Zhou Y,＆Guo L Y, ＆Liu Y S,2019.Land consolidation boosting poverty alleviation in China: Theory and practice. Land Use Policy.82,339-348.

Zhou Y,＆Li Y R,＆Zhou Y,＆Liu Y S, 2019.The nexus between regional eco-environmental degradation and rural impoverishment in China. Habitat International.https://doi.org/10.1016/j.habitatint.2019.102086.

Liu Y S,＆Zhou Y,＆Liu J L,2016. Regional differentiation of rural poverty in China and its targeted poverty alleviation strategies. Proceedings of the Chinese academy of sciences. 31(3),269-278

Wang Y S,＆Li Y H,2019. Promotion of degraded land consolidation to rural poverty alleviation in the agro-pastoral transition zone of northern China. Land Use Policy.

https://doi.org/10.1016/j.landusepol.2019.104114.

Li Y H,＆Wang Y F,＆Liu Y S,2016. Mechanism and effect of social capital in poverty alleviation in China. Proceedings of the Chinese academy of sciences.(3),302-308.