Article

Exploring the Spatial Determinants of Rural Poverty in the Interprovincial Border Areas of the Loess Plateau in China: A Village-Level Analysis Using Geographically Weighted Regression

Tao Li, Xiaoshu Cao *, Menglong Qiu and Yu Li

Northwest Land and Resources Research Center, Shaanxi Normal University, Xi'an 710119, China; ltao@snnu.edu.cn (T.L.); mlqiu@snnu.edu.cn (M.Q.); yuli-2019@snnu.edu.cn (Y.L.)
* Correspondence: caoxsh@snnu.edu.cn

Abstract: The spatial pattern of rural poverty and its influencing factors are unique in regions located in the "double zone", overlaying the Loess Plateau landform and interprovincial border socioeconomic zone. Using Huining County, located in the interprovincial border area of the Loess Plateau, as a case study, this paper examines the spatial heterogeneity of rural poverty patterns and poverty-causing factors by using geographically weighted regression (GWR) modeling. The potential accessibility indicator is employed to identify the formative mechanism of rural poverty. The results show that rural poverty is significantly correlated with county-level accessibility, water resource accessibility, and town-level accessibility. County-level accessibility and town-level accessibility have significant border effects on rural poverty. The arid characteristics in certain areas of the Loess Plateau mean that the impact of water resource accessibility on the incidence of rural poverty is second only to that of county-level accessibility. Forestland resources have a positive correlation with the incidence of rural poverty in the region dominated by farming. Finally, targeted poverty reduction policies are proposed based on the results of the analysis of poverty-causing factors. The findings derived from this paper can help other developing countries in designing their own poverty reduction policies.

Keywords: Loess Plateau; interprovincial border areas; rural poverty; village; geographically weighted regression; China

1. Introduction

Poverty is a global social problem. Poverty alleviation and elimination are a major focus of global concern and among the main issues of the 17 Sustainable Development Goals of the United Nations (UN) 2030 Agenda [1,2]. From 1978 to 2015, the number of impoverished populations in rural areas of China dropped from 250 million to 55.75 million, and the incidence of poverty fell from 30.7% to 5.7% nationally, contributing more than 70% to global poverty reduction and representing a very large contribution to poverty reduction internationally [3,4]. However, due to the comprehensive influence of the natural environment, resource endowment, regional differences, and other factors, rural poverty in China has become increasingly complex [5]. There are still 14 contiguous low-income areas in China [6]. Therefore, further systematic analyses to improve the understanding of poverty-causing factors and the typical spatial heterogeneity of rural poverty have important reference value for targeted policy implementation and improved poverty reduction benefits. These analyses are also important for other developing countries facing poverty.

Poverty research, driven by the pursuit of poverty alleviation, has been a focus in the fields of geography, economics, and sociology. Most studies have carried out systematic and in-depth studies on poverty measurements, the spatial differentiation of poverty, poverty-causing mechanisms, and poverty reduction strategies [7]. Poverty research in the field of geography mainly focuses on the spatial pattern of poverty, its relationship with the geographical environment, and the formative mechanism of regional poverty [8]. Both individual poverty and regional poverty are affected by socioeconomic conditions and natural and livelihood capital, and these poverty-influencing factors vary across different time scales and geographical regions [7]. The occurrence of rural poverty and poverty reduction strategies has obvious regional characteristics [9]. The spatial pattern of rural poverty and its influencing factors are unique in regions located in the "double zone", overlaying the Loess Plateau landform and interprovincial border socioeconomic zone. The Loess Plateau is a compound region, with a fragile ecological environment and a relatively undeveloped, rural economy, thus making it a key and challenging area in the process of poverty alleviation [10]. Regions located at the junction of two or more provincial administrative regions tend to develop slowly and gradually become impaired and weak [11]. Consequently, the rural-poverty-causing and poverty-causing factors in this "double zone" are unique. They both reflect the general rules of the same causes of poverty as in other poor areas and special rules of the cause of poverty due to the overlay of the Loess Plateau landform and interprovincial border socioeconomic zone, respectively. It is thus of great significance to scientifically identify the poverty factors and spatial heterogeneity of rural poverty in such regions.

Therefore, the main objective of this paper is to explore the spatial pattern and spatial determinants of rural poverty at the village scale in the interprovincial border areas of the Loess Plateau in China. More specifically, this paper will contribute to the existing literature by examining the contribution of three important factors influencing rural poverty and their spatial heterogeneity: socioeconomic accessibility, resource accessibility, and the natural environment. To this end, we apply geographically weighted regression (GWR) analysis [12] to examine the effect of these three factors on poverty at the village-level. We select Huining County in Gansu Province as the case study. This county is located in the northwestern region of the Loess Plateau and in the border area between Gansu and Ningxia Provinces.

The remainder of this paper is structured as follows: Section 2 presents a brief review of the extant literature on poverty, followed by discussions on the study area, methodology, and data used in our poverty analysis framework in Section 3. Section 4 presents the results of the descriptive analysis of spatial patterns of poverty in the study area. Section 5 presents the results of the GWR analysis, which examines the spatial determinants of rural poverty. Finally, in Section 6, we present an overview of our key findings and provide policy implications.

2. Literature Review

2.1. Understanding Poverty

Poverty has multidimensional and spatial characteristics. There is wide variation in the definitions of poverty. Early poverty studies focused mainly on poverty caused by income poverty itself; namely, poverty is when income level is not high, consumption ability is insufficient, there is a lack of food and an inability to maintain a condition in which a person's basic needs are met [13]. Poverty involves not only having low income but also a deprivation of basic capacity [14]. The World Bank defined poverty as the lack of opportunity of part of a group without the ability to gain the socially recognized and generally enjoyed diet and living conditions of others and to participate in societal activities [15]. With the deepening of the research in this area, poverty has been acknowledged to include economic shortages, social exclusions, lack of opportunity or public services, and vulnerability or exposure to the risk of those deficits [4,16,17]. Since the 1990s, the World Bank and developed countries have attached great importance to space poverty research. Spatial poverty traps (SPTs) refer to the spatial agglomeration of poverty regions or impoverished population caused by a lack of geographical capital [18]. SPTs are usually distributed in remote

geographical locations, fragile ecological environments, poor infrastructure, and politically disadvantaged areas [8]. Poverty mainly includes absolute and relative poverty [19], spatial and individual poverty [20], and urban and rural poverty [21]. With the promotion of poverty reduction efforts and the precision of objectives, the poor will gradually gather to form an island group [22].

Over the past several decades, the Chinese Government has long been committed to eradicating poverty. During the process, the overall aim of antipoverty has transformed from focusing initially on basic needs (food and clothing) to comprehensive guarantees (food, clothing, compulsory education, basic medical care, and housing security) of poor groups [1]. The definition of multidimensional and spatial poverty provides a key basis for the determination of the impoverished population in practice. For instance, since the end of 2013, various regions in China have organized and carried out the work of identifying and registering the impoverished population (Jiandang LiKa). According to the national rural poverty alleviation standard of a per-capita net income of 2736 RMB for farmers in 2013 (equivalent to 2300 RMB per capita in 2010), comprehensively taking into account the conditions of housing, health care, education, and medical care, 89 million impoverished people were identified across the country. The poverty data in this paper were obtained from the work of identifying and registering the impoverished population in 2014.

2.2. Poverty Measurement and Mapping

As the basis of poverty mapping and poverty targeting, poverty identification includes the identification of poor areas and impoverished populations [8]. The main focus of poverty identification and spatial differentiation has been the creation of multidimensional poverty measures and spatial pattern analysis through the construction of comprehensive poverty models [13,23,24], vulnerability-sustainability livelihood models [4], unit-level models [25], temporal and spatio-temporal area level models [26], hierarchical Bayes estimation [27], and BP (Back Propagation) neural network models at the county-level [28]. In fact, the multiple dimensions of poverty are often correlated and mutually reinforced. As a result, the measurement of poverty needs to establish a multi-index system and mechanism-based model of comprehensive poverty [29], which is usually influenced by the cognitive level, research scale, and data availability [4,29].

Poverty mapping can reveal the spatial pattern of poverty and its spatial heterogeneity, which can guide priority-setting and target-alleviation policy [30]. Disparate data sources such as census data [31], night light, satellite image, and big data have been used to map poverty [32,33]. Poverty mapping has been used on a variety of scales, including the subnational scale in Zambia, the district scale in Poland [34], Vietnam [31] and India [30], and the individual scale in Africa [32].

2.3. Geographical Environment and Poverty

Poverty is closely related to the geographical environment [35,36]. The geographical conditions affecting poverty involve location, resource endowment, ecological environment, public service, etc. [37]. Approximately 78% of the world's poor people are concentrated in mountainous areas with ecologically fragile environments, remote geographical locations, and insufficient public services and facilities [7]. Thus, the research on poverty-causing mechanisms and poverty reduction strategies involves the exploration of the relationships among poverty and geographical location, natural environments (including resource endowment), social and cultural factors, uneven public infrastructure, and public services [35,38–40]. Both the mechanisms underlying the occurrence of rural poverty and the basic model for reducing poverty in China have a clear regional basis [5,41]. Inadequate natural endowments, ecological degradation, and natural disasters play a significant role in the relative poverty found in rural China [40]. Poverty is significantly related to the distance between counties and towns. A remote geographical location is usually regarded as the main cause of the high incidence of poverty in the semiarid region of Zimbabwe [18]. Moreover, rural poverty in developed countries such as the United States and Britain is closely related to geographical location, which means that poverty incidence rises with increased distance from metropolitan areas [42]. In other words, the more remote a geographical location, the more distinct its poverty [43]. Complex natural environmental conditions have a positive driving effect on the spatial distribution of the

poorest counties. Specifically, 70% of poverty-stricken counties are located in areas with an average ground gradient of more than 10 degrees [44]. Compared with valley plains and hilly areas, where eroded silt accumulates, eroded mountainous areas have higher poverty levels and are thus key areas for poverty reduction [13]. In 2014, more than 40% of China's rural poor population was distributed in ecologically fragile areas [22]. The unique values, religious beliefs, traditional customs, and languages of regions (especially those of ethnic minorities) also affect the level of poverty [43]. In terms of the regional poverty model and poverty reduction strategy, there are obvious differences in the mechanisms leading to rural poverty in different regions, which can be categorized into four types: natural environment constraints, resource endowment constraints, traffic location constraints, and economic location constraints [45].

From this brief review of the existing literature, it can be inferred that many existing studies contribute to our understanding of the spatial patterns of rural poverty and its influencing factors in China. As mentioned above, the problem of poverty also has regional and systematic characteristics. However, relatively little attention has been paid to socioeconomic accessibility at different scales and its boundary effect, which is very important in the above-mentioned "double zone", overlaying the Loess Plateau landform and interprovincial border socioeconomic zone. Additionally, the increasing complexity of the poverty problem highlights the importance of carrying out poverty research at the village scale to realize targeted policy implementation and improve the effects of poverty reduction. As the smallest administrative unit, the village is the basic "cell" of socioeconomic and cultural activity in poor mountainous areas. Furthermore, since the Twelfth Five-Year Plan was approved in 2010, "hamlet advancement (Zhengcun Tuijin)" has been an important means of poverty alleviation. It is therefore extremely important to carry out research on the mechanisms driving poverty at the village scale.

Therefore, this paper attempts to contribute to the literature by exploring the spatial pattern and spatial determinants of rural poverty at the village scale in the interprovincial border area of the Loess Plateau of China.

3. Methodology and Data

3.1. Study Area

Huining County lies in central Gansu Province and at the southern end of the Baiyin municipality, at 35°24′N~36°26′N and 104°29′E~105°31′E (Figure 1). Located in a typical provincial boundary area between Gansu and Ningxia, Huining County borders Xiji County and Haiyuan County in Ningxia to the east. The county is 140 km long from north to south and 90 km wide from east to west and covers a total of 6439 km². Sitting at the junction of the northwestern Loess Plateau and Qinghai–Tibet Plateau, it is part of the hill and gully region of the Loess Plateau in central Gansu; this region in China suffers from serious water shortages and soil loss. The topography is higher in the south and lower in the north, inclining from the southeast to the northwest. The southern and middle parts of the county are mountainous. The landforms (long berms and loess hillocks) are formed by loess accumulation and erosion. The Zuli River runs through the northern and southern parts of the region. The average elevation of the county is 2025 m, while that for the county's town is 1723 m. The annual average temperature is 7.9 °C, with a range of 37.5 °C to –26.5 °C, while the average annual precipitation is 150~450 mm, and the average annual evaporation is 1800 mm [46].

The county comprises 28 towns, 284 administrative villages, and 16 communities. In 2018, the county had a total population of 580,300, of which 492,200 lived in rural areas, accounting for 84.8% of the total population. In 2016, the county's total gross domestic product (GDP) was 6142.12 million RMB, and the per capita GDP was 11,418 RMB. The per capita disposable income of the urban residents was 15,683.02 RMB, while that of rural residents was 6283.44 RMB [47]. Huining is also a part of the Liupan Mountain contiguous poverty-stricken areas. In 2011, China implemented the new Outline for Development-Oriented Poverty Alleviation for China's Rural Areas (2011–2020). The Chinese State Council Group Office of Poverty Alleviation and Development (CPAD) determined 14 contiguous low-income areas with special difficulties and set these areas as the main battlefield for

poverty alleviation efforts in the new period. Huining has wide-ranging and profound poverty and a large number of poor people, and there are substantial challenges to poverty alleviation and development. Of all the countries in Gansu Province, 50% were classed as poverty-stricken counties, Huining County included, by the Chinese State Council Group Office of Poverty Alleviation and Development and were therefore considered to be in need of poverty alleviation and development. According to the statistics sheet of the registered poverty (Jiangdang Lika) rate in 2014, the county had 130 poor villages, 39,042 poor households, 172,285 poor people, and a poverty incidence of 36.37% in its total population. The poor population in Huining County accounts for 5% of the poor population in Gansu Province, although Gansu has 43 poverty-stricken counties. Additionally, Huining County is close to Xiji–Haiyuan–Guyuan of Ningxia Province, which was identified as one of the most inhospitable areas to human life by the United Nations World Food Programme (WFP) in 1972. Therefore, the incidence of poverty in Huining County is very high and can be regarded as a typical county in Gansu Province and northwest China.
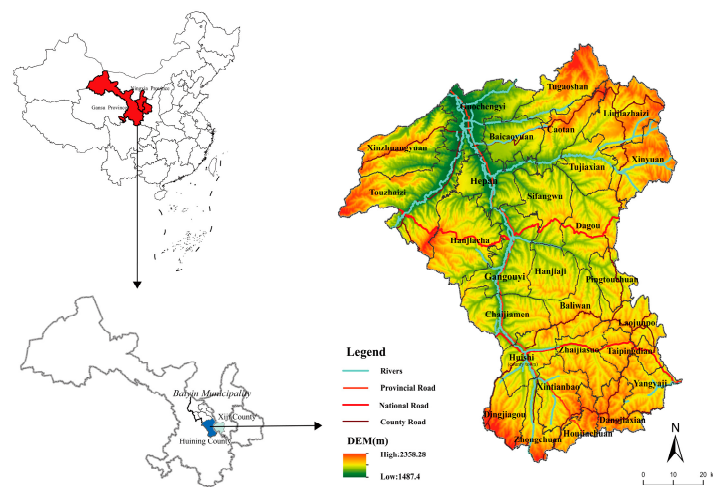

Figure 1. Study area.

3.2. Methodology

3.2.1. Socioeconomic Accessibility

Socioeconomic accessibility, a comprehensive index reflecting the accessibility of transportation networks and socioeconomic development, is a very effective metric for identifying the formative mechanism of rural poverty [48]. Many previous studies have reviewed and classified accessibility indicators or measures [49,50]. In this paper, the potential accessibility index was used, as it measures the aggregate access of a region's catchment area. The classical mathematical equation of *PA* is as follows:

$$PA_i = \sum_{j=1}^{n} \frac{M_j}{T_{ij}^a} \qquad (1)$$

where PA_i is the potential accessibility value of village i and T_{ij} is the shortest travel time between village i and destination j. In this research, the shortest travel time is obtained from the Baidu map LBS (Location Based Services) open platform [51]. Compared to network analysis in the ArcGIS 10.0, travel time data acquired from big data sources can reflect real-time speed, congestion, and other traffic conditions. M_j is the mass of the destination, which is measured using the square root of the product of the population and GDP of destination j based on a relatively comprehensive

consideration of economic and social factors [52], and *a* is the parameter gauging the distance decay rate, which is set as 1 following previous studies [53].

Socioeconomic accessibility in this paper was calculated three ways: municipal-level accessibility, county-level accessibility, and town-level accessibility. These measures reflect the convenience of maintaining external contact for rural units or, in other words, the barriers to receiving the diffusive and driving positive socioeconomic effects from central places at different levels. Therefore, these three accessibility indexes reflect the degree of convenience for villages in Huining to receive resources from the city, county town, and town of Baiyin. The 28 towns in Huining and three towns in Xiji bordering Huining are considered the destinations for measuring town-level accessibility. Huining and Xiji are considered the destinations for measuring county-level accessibility. Baiyin is considered the destination for measuring municipal-level accessibility.

3.2.2. Global Spatial Autocorrelation

Poverty often occurs in geographical clusters. This paper uses Moran's *I* index to carry out spatial autocorrelation analysis on rural poverty and reveal its spatial distribution [54]. The formula used is as follows:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (X_i - \bar{X})^2} \qquad (2)$$

where W_{ij} is the spatial weight matrix revealing the proximity between locations *i* and *j* (for adjacent areas, the value is 1, and for nonadjacent areas, it is 0); X_i and X_j are the observed values of locations *i* and *j*, respectively; $\bar{X}$ is the average value of variable *x*; and *n* is the number of villages in the study area. The range of values for *I* is [–1,1]. An interval of [0,1] means a positive correlation; that is, the elements tend to have a spatially aggregated distribution. Conversely, an interval of [–1,0] means a negative correlation, and the distribution of the variables tends to be scattered. Thus, the greater the value tends toward 1 or –1, the greater the difference there is in the spatial distribution of rural poverty.

3.2.3. Geographically Weighted Regression Model

Poverty and poverty-causing factors have spatial characteristics, and there are also interregional spatial correlations and spatial heterogeneity in geographical space. However, the spatial heterogeneity of spatial regression parameters is not considered in general global regression models and thus individual situations cannot be explained by using global parameters. Geographically weighted regression (GWR) modeling incorporates spatial attribute data into regression models for the estimation of local parameters and is widely used to carry out local regression estimation [12]. Hence, this paper uses GWR modeling to analyze poverty-causing factors and the spatial heterogeneity of rural poverty. The specific formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k a_k(u_i, v_i) x_{ik} + \varepsilon_i \qquad (3)$$

where y_i is the rural poverty incidence of village *i*; $\beta_0(u_i, v_i)$ is the local estimated intercept of village *i*; x_{ik} is the value of the kth independent variable associated with a_k; *k* is the independent variable count; *i* is the sample village count; ε is the residual error; (u_i, v_i) is the spatial coordinate of the ith village; and $a_k(u_i, v_i)$ is the effect of the kth independent variable for village *i*. In this paper, the AIC (Akaike information criterion) method is adopted to determine the optimal model.

3.3. Variable Selection and Data Source

A total of 13 potential explanatory variables were selected according to previous studies [5,43], the analysis scale in this research, and data availability (Table 1). These explanatory variables can be divided into two categories: exogenous variables, which are unlikely to be affected by the level of economic development or rural poverty, and endogenous variables, which may both influence and be influenced by rural poverty. For instance, the topography variable may influence poverty, but it is unlikely to be influenced by poverty. In contrast, socioeconomic accessibility is determined partly by the level of economic development, and a low poverty rate may influence the development of transport infrastructures in the long run. To carry out a regression analysis, the topography, soil type, and land use variables in Table 1 should be expressed as specific variables. The calculation method of each variable is shown in the variable description of Table 1.

An exploratory regression analysis was conducted on the sample data to determine the optimal combination of variables for analyzing rural poverty characteristics. The results show that the optimal number of variables was 7, as the maximum adjusted R^2 reached 0.73, and the variance inflation factor (VIF) value was 1.62. Multicollinearity did not present a problem, and the goodness of fit reached the highest level (73%). On this basis, seven significant variables in the exploratory regression analysis were selected as final explanatory variables.

Table 1. Potential factors influencing rural poverty.

| Type	Explanatory variable		Description	Expected relationship with poverty
Exogenous variables	Topography	Elevation	Mean village elevation[*]	Positive correlation
		Slope	Mean village slope	Positive correlation
	Soil resources	Soil type	Proportion of village area with alluvial soils	Not known
			Proportion of village area with loessal soils	
			Proportion of village area with calcareous soils	
			Proportion of village area with loam soils	
	Land resources	Land use	Proportion of village area with arable land[*]	Not known
			Proportion of village area with forestland[*]	
			Proportion of village area with grassland	
	Water resources	Water resource accessibility	Distance to the nearest river[*]	Positive correlation
Endogenous variables	Socioeconomic resources	Socioeconomic accessibility	Highest accessibility value to the prefecture-level city[*], county town[*], and town[*]	Positive or negative

Note: [*] final explanatory variables of this study.

The land-use and digital elevation model (DEM) data were obtained from the 1:4 M fundamental element version of the National Fundamental Geographic Information System. Socioeconomic data, including population and GDP, on the prefecture-level cities, counties, and towns involved in this study were derived from the Gansu Development Yearbook (2015), Huining Statistics Yearbook (2015), and China's County-scale Statistics Yearbook-Villages and Towns volume (2015), respectively. Poverty incidence data for each village in 2014 were obtained from a statistics sheet of the registered poverty (Jiandang Lika) rate. Poverty incidence refers to the proportion of the impoverished population in a given village. As previously mentioned, Huining is located in an interprovincial border area. The eastern and northeastern parts of the county border Xiji in Ningxia. To accurately and scientifically determine the impact of socioeconomic accessibility on the incidence of rural poverty, this research simultaneously considers Xiji County town and the towns adjacent to Huining when calculating accessibility at the county- and town-levels. In fact, during field investigations, it was found that a large proportion of the tools needed for production, maintaining daily life, and fundamental public services in the villages in Xinyuan town and Dagou town were obtained from towns in Xiji County.

4. Spatial Patterns of Rural Poverty

In 2014, the average incidence of rural poverty in Huining was 36.37%, with a range of 87.47% to 0.11%. Figure 2 presents the spatial distribution of rural poverty rates at the village-level, which was generated using the inverse distance weighted (IDW) interpolation procedure built in ArcGIS 10.0. The discrepancies in rural poverty in Huining are striking and show prominent agglomeration characteristics. In general, rural poverty in Huining follows a pattern of "low in the middle and high in the surrounding regions" (Figure 2). Villages with low poverty rates were spread out to the north and south in the form of belts and concentrated in low-lying valley plateau areas, such as the Zuli River and Guanchuan River in the northwestern region, Zuhe River in the county town, and Lihe River in the southern region. These villages include Guochengyi, Hepan, Baicaoyuan, Gangouyi, Chaijiamen, and Huishi. The villages with high poverty rates are widely distributed but are mainly concentrated in the southern, eastern, and northeastern areas. Within these territories, various classic loess landforms, such as berms and tablelands, are formed by loess accumulation and erosion. These villages include Xinzhuangyuan, Tugaoshan, Caotan, Xinyuan, Tumenya, and Dagou.
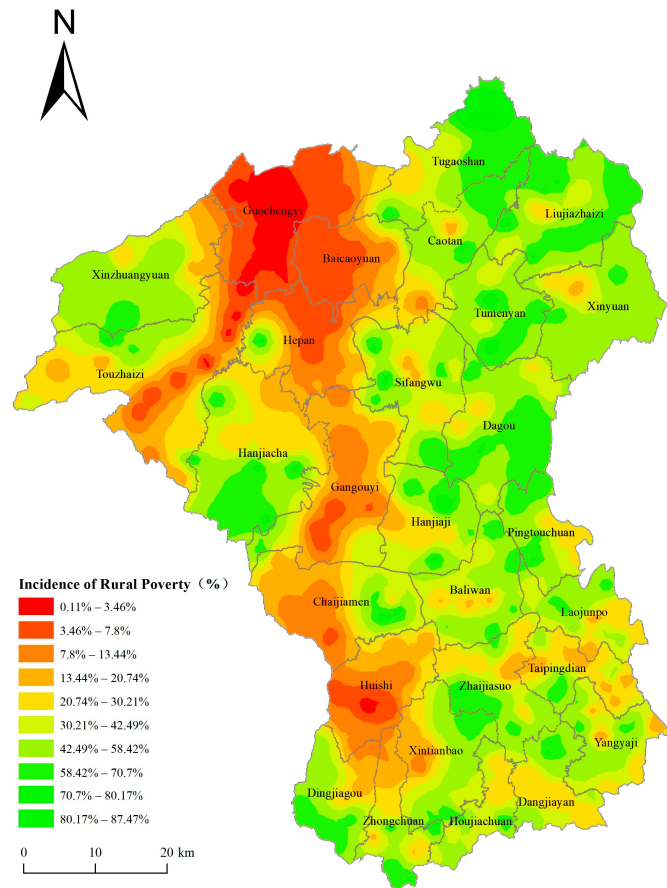
Figure 2. Spatial pattern of rural poverty rates in Huining.

The spatial autocorrelation analysis of the rural poverty rates in Huining in 2014 showed that Moran's *I* index is equal to 0.17, and the value of *Z* is greater than 1.96. According to tests at the 0.01% significance level, the rural poverty rates in Huining present significant positive spatial correlation and agglomeration characteristics, and therefore, they are not spatially independent. The spatial concentration of rural poverty incidence is further analyzed using hotspot analysis tools (Figure 3). The results show that the cold spots are mainly distributed along the Zuli River, which runs from the north to the south of the county in a belt shape and includes the towns of Guochengyi, Baicaoyuan, Hepan, Gangouyi, and Huishi. These villages and towns are distributed in the flat tableland of the low-lying valley, and the main trunk road corridor (provincial highway (S207)) runs through them. The overall levels of transportation and socioeconomic accessibility are relatively high, which means that the economy in this area is relatively developed and that there is a low incidence of poverty. This finding relates to the above-mentioned spatial distribution of poverty. The hotspots are mainly distributed in the form of islands in peripheral areas and include the towns of Xinzhuangyuan, Tugaoshan, Hanjiacha, and Dagou. The next section introduces the GWR model, which was used to perform a quantitative analysis of the pattern of rural poverty in Huining and to measure the factors influencing the incidence of rural poverty and its spatial heterogeneity.
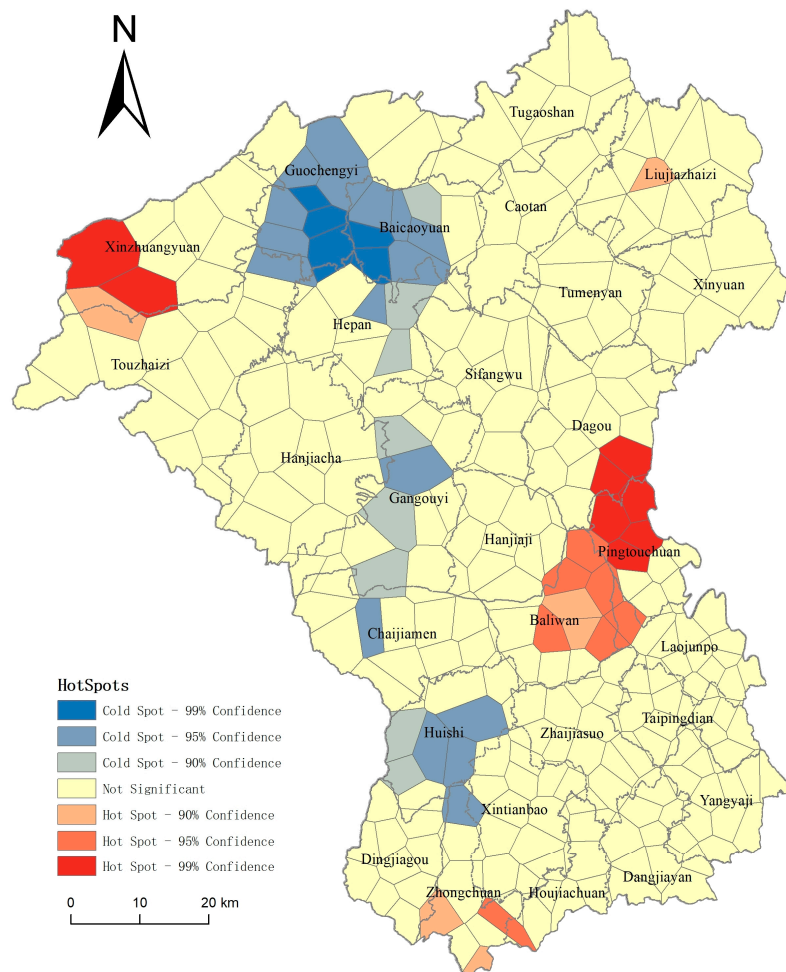
Figure 3. Spatial differentiation of rural poverty rates in Huining.

5. Spatial Determinants of Rural Poverty

5.1. Ordinary Least Squares (OLS) Analysis

Before applying the GWR model to the analysis, a global OLS regression model was used to test the relationship between rural poverty rates and the previously determined explanatory variables. The results of the OLS model are shown in Table 2. The variance inflation factor (VIF) was used to determine the multicollinearity between the explanatory variables. All the regression coefficients were significant at the 5% level, and the VIF values were less than 7.5, which indicates that the model was free from collinearity. The R^2 and adjusted R^2 values of the model are 0.486 and 0.469, respectively, indicating that the global OLS model can explain 46.9% of the incidence of rural poverty in the study area. Specifically, except for elevation and water resource accessibility, the rest of the explanatory variables are negatively correlated with the incidence of rural poverty. Three explanatory variables, namely, socioeconomic accessibility, water resource accessibility, and average elevation, have a significant correlation with rural poverty rates, which implies that these three variables are the main factors affecting the incidence of rural poverty in the study area. As some of the main sources of livelihood in villages, it is necessary to include these land use variables in the spatial heterogeneity analysis framework of influencing factors. However, the Koenker test shows that the global OLS regression model is unstable in the research area; that is, there is spatial heterogeneity between the

incidence of rural poverty and the explanatory variables in the study area. Therefore, the GWR model is used for the analysis.

Table 2. Ordinary least squares (OLS) summary statistics.

	Coefficient	Std. error	*t* statistics	VIF
Intercept	0.367	0.016	22.610	—
Proportion of village area with arable land	–0.183*	0.017	–1.339	1.066
Proportion of village area with forestland	–0.166*	0.017	–0.924	1.150
Average village elevation	0.229**	0.018	2.961	1.250
Water resource accessibility	0.231**	0.016	1.780	1.087
Municipal-level accessibility	–0.163*	0.019	1.274	1.394
County-level accessibility	–0.239**	0.017	2.907	1.064
Town-level accessibility	–0.249**	0.019	2.087	1.317
R^2	0.486			
Adjusted R^2	0.469			
AIC	76.813			
Koenker (BP) statistic	35.368			

Note: The Koenker test ($p < 0.000$) shows that the statistical significance of the explanatory variables needs to be evaluated with a robust probability. ** and * represent significance at the 1% and 5%, levels, respectively. VIF = variance inflation factor; AIC = Akaike information criterion; BP = Bruesch-Pagan.

5.2. GWR Analysis

GWR was carried out with the model described in Section 2.3. The calculation results are shown in Table 3. The R^2 and adjusted R^2 values of the model are 0.58 and 0.56, respectively, both of which are higher than the corresponding values from the aforementioned global OLS regression model. The goodness of fit greatly improved, the value of AIC is lower than it is for the OLS model, and the fitting performance is also improved in the GWR analysis. The condition number of the model is less than 30, and there is no multicollinearity between the variables. Table 3 presents the statistics on the mean value, minimum value, maximum value, and upper and lower quartile values based on the regression coefficient of the GWR model, as applied to the influencing factors for each village. Looking at the median values, the variables significantly correlated with rural poverty rates are county-level accessibility, water resource accessibility, town-level accessibility, average village elevation, and municipal-level accessibility. The proportions of arable land area and forestland area in the villages show negative correlation trends.

**Table 3.** Geographically weighted regression (GWR) summary statistics for local coefficients.

	Minimum	25% quantile	Median	75% quantile	Maximum
Intercept	0.361	0.368	0.276	0.386	0.396
Proportion of village area with arable land	–0.335	–0.129	–0.221	–0.113	–0.053
Proportion of village area with forestland	–0.303	–0.134	–0.217	–0.101	0.088
Average village elevation	0.076	0.113	0.333	0.194	0.387
Distance to nearest river	0.056	0.140	0.352	0.176	0.523
Municipal-level accessibility	–0.297	–0.174	–0.200	–0.138	–0.053
County-level accessibility	–0.599	–0.286	–0.398	–0.209	0.069
Town-level accessibility	–0.583	–0.257	–0.374	–0.201	–0.089
R^2	0.583				
Adjusted R^2	0.564				
AIC	69.805				
Bandwidth	38,335.705				

5.2.1. Socioeconomic Accessibility

There is a significant negative correlation between socioeconomic accessibility and the incidence of rural poverty, with a greater impact apparent for county-level accessibility and town-level accessibility. The negative correlations between the three types of accessibility and the incidence of rural poverty also show obvious spatial heterogeneity (Figure 4a–c), indicating that the higher the accessibility level (i.e., the higher the accessibility value), the lower the incidence of poverty. This is because markets, industries, and public service facilities at all levels are mainly located in prefecture-level cities, counties, and town areas. The higher the accessibility level of villages, the better the socioeconomic location conditions, and the more easily they are driven by the diffusion of positive effects from economic centers at all levels. In turn, these factors lead to a lower incidence rate of rural poverty. The degree of the effect of the variables on rural poverty ranked from large to small is as follows: county-level accessibility > town-level accessibility > municipal-level accessibility. This suggests that giving priority to the diffusing and driving role of county and town administrative units is important for improving the efficiency of poverty reduction at the village-level.

Huining's particular location at provincial boundaries means that the counties of the neighboring provinces have significant impacts on the incidence of rural poverty. From the perspective of spatial heterogeneity, the regression coefficient for municipal-level accessibility shows a decreasing trend from the northwest to the southeast, indicating that municipal-level accessibility has a greater impact on the reduction of rural poverty in towns in northwestern Huining, such as Guochengyi, Xinzhuang, Baicaoyuan, and other places that are relatively close to Baiyin City. This may be due to the radiation effect of Baiyin City on these towns. Correspondingly, the regression coefficient of county-level accessibility generally shows a decreasing trend from the south to the north. The incidence of poverty in the villages close to the counties in the south, such as Renyu, Zhaijiasuo, and Dingjiagou, tends to be more affected by county-level accessibility. It should be noted that in contrast to the southern region, Xinyuan and other places in the northeastern area are also affected by county-level accessibility. This region is adjacent to Xiji County in Ningxia, which has a more significant driving effect on the daily socioeconomic development of this region. This effect was also proven in the process of field work, primarily due to the special location of the provincial boundary region.

The functions of the agglomeration and diffusion of towns in reducing poverty are mainly concentrated in rural areas on the edges of counties. The regression coefficient for town-level accessibility shows a declining tendency from the north to the south. The villages in the north that are greatly affected by town-level accessibility can be divided into two types. The first type of villages, including Guochengyi, Hepan, and Gangouyi, are located in the valley plateau area in the part of Huining with relatively flat terrain; the provincial road (S207) connecting the north and south runs through villages of this type. The towns are relatively well developed socioeconomically and play a significant role in driving the development of the surrounding villages in the area. The second type includes villages and towns, such as Xinzhuangyuan and Touzhaizi, that are distributed around the first type of town. These towns are relatively underdeveloped and mainly undertake basic management functions, which have a limited effect on driving their development. Moreover, they are far away from the county town, which thus has a limited effect on such towns in terms of daily life and production. As a result, nearby more well-developed towns, such as Guochengyi and Hepan, have become socioeconomic centers for these towns. Accordingly, in areas distant from county towns (e.g., Huishi), factors that can support production, livelihood, and poverty alleviation work should focus on the agglomeration and diffusion functions of small towns and give priority to the poverty reduction effect of town units on rural poverty through measures such as optimizing the layout of villages and towns, cultivating special small towns, and giving more power to town governments.
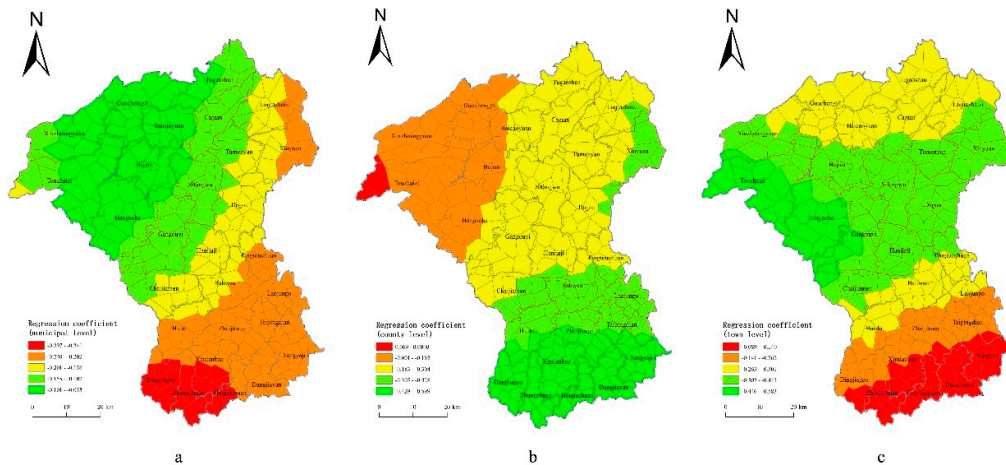
Figure 4. The GWR coefficients between rural poverty and socioeconomic accessibility in the GWR model: (**a**) municipal-level accessibility, (**b**) county-level accessibility, and (**c**) town-level accessibility.
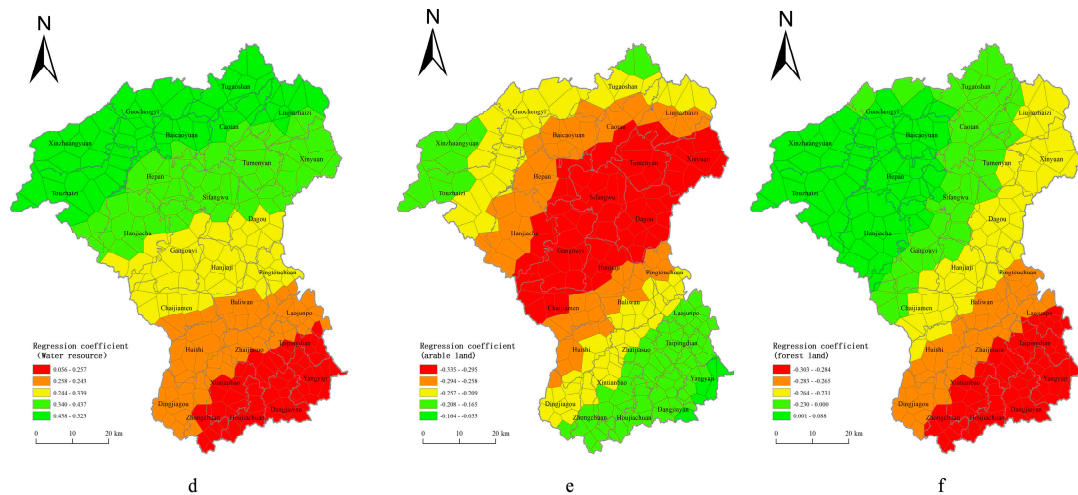
5.2.2. Water Resource Accessibility

This paper uses the distance to the nearest river to characterize water resource accessibility and measure its impact on rural poverty. The GWR results show that the distance to the nearest river has a positive correlation with the incidence of rural poverty; that is, the shorter the distance to the nearest river, the lower the incidence of poverty. Table 3 shows that the impact of the distance to the nearest river is inferior only to accessibility at the county-level, indicating the importance of water resources for socioeconomic development and poverty reduction in Huining. As a drought-prone agricultural area with very poor water resources, Huining faces severe water shortages. Furthermore, the accessibility of water resources presents obvious spatial heterogeneity, with the regression coefficient gradually decreasing from the north to the south (Figure 5a). In the northern and central-northern regions of the Loess Plateau, the elevation is relatively low, and farming is the main industry. Agricultural production creates high water demand and is limited by the poor water conditions for production and livelihood and the lack of agricultural water resources. Attempts to address the rural poverty problem in this area are therefore directly constrained by water resources. In other words, it would be of great value to strengthen the supply of water resources for poverty alleviation in this region.

5.2.3. Land Resources

The impact of land resources, as characterized by arable land use and forestland use, shows a negative correlation overall; that is, the larger the proportions of the two types of land use are, the lower the incidence rate of poverty, and vice versa. Compared with the other explanatory variables, these two variables have the least impact on the incidence rate of poverty. Specifically, the regression coefficient for arable land use shows an increasing trend from the central northern area to the northern and southern areas (Figure 5b). The per-capita arable land resources in the central and northern regions are high, and a planting regime of mainly wheat, corn, and potatoes has been established. Therefore, arable land resources have a relatively large impact on the incidence rate of poverty in this region. Correspondingly, the regression coefficient for forestland use shows an increasing tendency from the southern region to the northern region (Figure 5c). As previously mentioned, in the southern part of the county there are many tall mountain peaks with high elevations, and due to vertical joint development, soil erosion is very severe. In 1999, an ecological conservation project for returning farmland to forestland was implemented in this area. The project had an important impact on farmers' production and lives through measures such as restructuring land use and improving the efficiency of the intensive farming of arable land, thus positively

impacting the incidence of rural poverty and the significant forest resources in the southern region. It is important to note that there is a positive correlation between forestland use and the incidence of rural poverty in the northwestern area of the county; that is, the greater the proportion of forestland resources, the higher the incidence of rural poverty. The reason for this pattern is that farming in this area is the mainstay, and the goal of returning farmland to forest has further reduced arable land resources and restricted the development of local agricultural production [10].
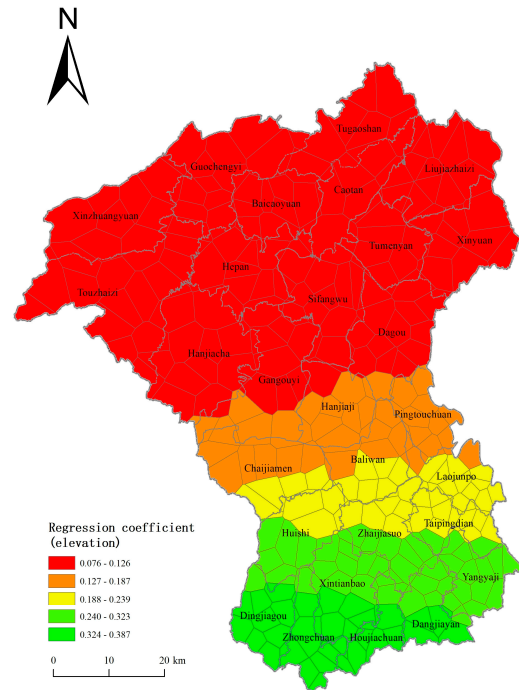

Figure 5. The GWR coefficients between rural poverty and water resources and land resources in the GWR model: (**a**) water resource accessibility, (**b**) arable land use, and (**c**) forestland use.

5.2.4. Topography

Elevation is the main measure reflecting the overall characteristics of regional topography. The GWR model shows a positive correlation between the topographic features expressed by the average village elevation and the incidence of rural poverty; that is, the higher the average village elevation, the greater the constraints on accessibility and infrastructure construction, and the higher the incidence of rural poverty. In terms of spatial heterogeneity, the regression coefficient for average village elevation shows a decreasing trend from the south to the north (Figure 6); that is, the influence of topography (as represented by elevation) on the incidence of rural poverty gradually decreases from the south to the north. This result is directly related to the topography of Huining County. This complex topography further impacts agricultural production through its effects on local climate, soil, hydrology, biology, and other factors. Moreover, the complex terrain also has major impacts on the construction of transportation infrastructure and socioeconomic development. As shown in Figure 2, the incidence of rural poverty in the southern region is relatively high. In contrast, the northern part of the county comprises mostly low Loess Plateau areas, with relatively low elevations. Compared with socioeconomic accessibility, water resources, and other factors, topography has a fundamental impact on rural poverty in this area.

Figure 6. The GWR coefficients between rural poverty and topography in the GWR model

6. Policy Implications and Conclusion

The existing literature on rural poverty reported the effect of accessibility and other spatial determinants but did not consider socioeconomic accessibility at different scales. Moreover, the spatial pattern of rural poverty and its influencing factors is unique in regions located in the "double zone", overlaying the Loess Plateau landform and interprovincial border socioeconomic zone. Using Huining County, located in the interprovincial border zone of the Loess Plateau as an example, this paper considered in detail and systematically explored the spatial pattern of rural poverty and the spatial heterogeneity of the factors influencing poverty. Generally, rural poverty is significantly correlated with county-level accessibility, water resource accessibility, town-level accessibility, municipal-level accessibility, and topography. The scale-effect can be found in the socio-economic accessibility factors of rural poverty. The results show that the main causes of rural poverty in different regions of Huining are also different. Huining's particular location at provincial boundaries means that the counties of neighboring provinces have significant impacts on the incidence of rural poverty. The elevation and water resources are the two important basic conditions, leading to the basic spatial pattern of rural poverty between central and surrounding regions in Huining. Water resources are of particular importance for socioeconomic development and poverty reduction in contiguous poor areas of the Loess Plateau.

The whole procedure of the proposed approach in this study is supported by GIS software. The proposed framework can be easily applied to other regions. The findings derived from this paper can also help other developing countries in designing their own policies on poverty reduction. Based on the above-mentioned empirical results, the relevant policy implications are as follows: (1) County-level and town-level accessibility should be given more attention during the process of poverty reduction. Based on the experience of Huining, villages should focus on the beneficial radiating effect of town agglomerations through the development of marginal regional towns. In the process of poverty reduction, in addition to considering economic, infrastructure, and other policies, optimizing the layout of villages and towns, cultivating special small towns, and giving more power to township administrative agencies should also be considered. For villages located in border areas, further attention should be paid to the positive radiating effects of the socioeconomic functions of neighboring towns in border areas. (2) There should be a focus on strengthening and improving the

supply and utilization efficiency of water resources, ensuring the supply of water for production and daily use, and recognizing the important role of water accessibility in poverty reduction. (3) In the northwestern region of the county, which is dominated by farming, the conversion of cropland to forest has further reduced arable land resources and limited the development of local agricultural production. The return of cropland to forestland (and grassland) has led to remarkable social and ecological benefits that should be intensified by raising subsidy levels; but in areas where arable land is the main resource for farming, attention should be paid to the increase in poverty caused by the sharp reduction in arable land area due to the return of farmland to forestland.

While this paper has explored the primary factors affecting the occurrence of poverty at the village-level, due to the limited availability of data, multidimensional factors related to poverty, such as housing, education, and policies, have not been considered. Therefore, the spatial heterogeneity of these explanatory variables should be explored in subsequent research to more comprehensively analyze the influencing factors of rural poverty and its spatial heterogeneity in interprovincial border areas.

References

1. Liu, Y.; Guo, Y.; Zhou, Y. Poverty alleviation in rural China: Policy changes, future challenges and policy implications. *China Agric. Econ. Rev.* **2018**, *10*, 241–259.
2. UNDP. *Transform our World:2030 Agenda for Sustainable Development ;* United Nations: New York, NY, USA, 2016.
3. UNDP. *The Millennium Development Goals Report*; United Nations: New York, NY, USA, 2015.
4. Liu, Y.; Xu, Y. A geographic identification of multidimensional poverty in rural China under the framework of sustainable livelihoods analysis. *Appl. Geogr.* **2016**, *73*, 62–76, doi:10.1016/j.apgeog.2016.06.004.
5. Liu, Y.; Li, J. Geographic detection and optimizing decision of the differentiation mechanism of rural poverty in China. *Acta Geogr. Sin.* **2017**, *72*, 161–173.
6. Xu, J.; Song, J.; Li, B.; Liu, D.; Wei, D.; Cao, X. Do settlements isolation and land use changes affect poverty? Evidence from a mountainous province of China. *J. Rural Stud.* **2020**, doi:10.1016/j.jrurstud.2020.04.018.
7. Ding, J.; Zhiming, L. Regional poverty analysis in a view of geography science. *Acta Geogr. Sin.* **2018**, *73*, 232–247.
8. Zhou, Y.; Liu, Y. The geography of poverty: Review and research prospects. *J. Rural Stud.* **2019**, doi:10.1016/j.jrurstud.2019.01.008.
9. Li, Y.; Cao, Z.; Zheng, X.; Liu, Y. Regional and Sustainable Approach for Target-Poverty Alleviation and Development of China. *Bull. Chin. Acad. Sci.* **2016**, *31*, 279–287.
10. Wen, Q.; Shi, L.; Ma, C.; Wang, Y. Spatial heterogeneity of multidimensional poverty at the village level: Loess Plateau. *Acta Geogr. Sin.* **2018**, *73*, 1850–1864.
11. Cao, X.; Xu, J. Spatial heterogeneity analysis of regional economic development and driving factors in China's provincial border counties. *Acta Geogr. Sin.* **2018**, *73*, 1065–1075.
12. Fotheringham, A.; Charlton, M. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*; Wiley: New York, NY, USA, 2002.
13. Liu, X.; Li, Y.; Wang, Y.; Guo, Z.; Zheng, F. Geographical identification of spatial poverty at county scale. *Acta Geogr. Sin.* **2017**, *72*, 545–557.
14. Sen, A. Well being, agency and freedom: The dewey lectures. *J. Philos.* **1985**, *82*, 169–122.
15. Bank, W. *World Development Report*; Oxford University Press: New Work, NY, USA, 1981.
16. Bourguignon, F.; Chakravarty, S. The Measurement of Multidimensional Poverty. *J. Econ. Inequal.* **2003**, *1*, 25–49.

17.　UNDP. *Human Development Report 2010: The Real Wealth of Nations: Pathways to Human Development*; Palgrave Macmillan: New York, NY, USA, 2010.

18.　Bird, K.; Shepherd, A.J.W.D. Livelihoods and Chronic Poverty in Semi-Arid Zimbabwe. *World Dev.* **2003**, *31*, 591–610.

19.　Foster, J.E. Absolute versus Relative Poverty. *Am. Econ. Rev.* **1998**, *88*, 335–341.

20.　Milbourne, P. The Geographies of Poverty and Welfare. *Geogr. Compass* **2010**, *4*, 158–171.

21.　Amato, P.R.; Zuo, J. RURAL POVERTY, URBAN POVERTY, AND PSYCHOLOGICAL WELL-BEING. *Sociol. Q.* **1992**, *33*, 229–240.

22.　Liu, Y.; Li, Y. Revitalize the world's countryside. *Nature* **2017**, *548*, 275–277.

23.　Alkire, S.; Foster, J. Counting and Multidimensional Poverty Measurement.*J. Public Econ.* **2011**, 95(7-8):476-487.

24.　Wagle, U. Rethinking poverty: Definition and measurement. *Int. Soc. Sci. J.* **2002**, *54*, 155–165.

25.　Elbers, C.; Lanjouw, J.O.; Lanjouw, P. Micro–Level Estimation of Poverty and Inequality. *Econometrica* **2003**, *71*, 355–364, doi:10.1111/1468-0262.00399.

26.　Esteban, M.D.; Morales, D.; Pérez, A.; Santamaría, L. Small area estimation of poverty proportions under area-level time models. *Comput. Stat. Data Anal.* **2012**, *56*, 2840–2855, doi:10.1016/j.csda.2011.10.015.

27.　Pratesi, M.; Giusti, C.; Marchetti, S. Small Area Estimation of Poverty Indicators. In *Survey Data Collection and Integration*; Davino, C., Fabbris, L., Eds.; Springer: Berlin/Heidelberg, Germany, 2013; doi:10.1007/978-3-642-21308-3_6pp. 89-101.

28.　Feng, Z.; Wang, S.; Jin, S.; Yang, J. Effects of urban morphology and wind conditions on land surface temperature in Changchun. *Acta Geogr. Sin.* **2019**, *74*, 902–911.

29.　Edward, P.; Sumner, A. Estimating the Scale and Geography of Global Poverty Now and in the Future: How Much Difference Do Method and Assumptions Make? *World Dev.* **2014**, *58*, 67–82, doi:10.1016/j.worlddev.2013.12.009.

30.　Erenstein, O.; Hellin, J.; Chandna, P. Poverty mapping based on livelihood assets: A meso-level application in the Indo-Gangetic Plains, India. *Appl. Geogr.* **2010**, *30*, 112–125, doi:10.1016/j.apgeog.2009.05.001.

31.　Minot, N.; Baulch, B. Poverty Mapping with Aggregate Census Data: What is the Loss in Precision? *Rev. Dev. Econ.* **2005**, *9*, 5–24, doi:10.1111/j.1467-9361.2005.00261.x.

32.　Blumenstock, J.; Cadamuro, G.; On, R. Predicting poverty and wealth from mobile phone metadata. *Science* **2015**, *350*, 1073–1076, doi:10.1126/science.aac4420 %J Science.

33.　Min, B.; Gaba, K.M.; Sarr, O.F.; Agalassou, A. Detection of rural electrification in Africa using DMSP-OLS night lights imagery. *Int. J. Remote Sens.* **2013**, *34*, 8118–8141, doi:10.1080/01431161.2013.833358.

34.　Marchetti, S.; Beresewicz, M.; Salvati, N.; Szymkowiak, M.; Wawrowski, Ł. The use of a three-level M-quantile model to map poverty at local administrative unit 1 in Poland. *J. R. Stat. Soc. Ser. A (Stat. Soc.)* **2018**, *181*, 1077–1104.

35.　Jalan, J.; Ravallion, M. Geographic poverty traps? A micro model of consumption growth in rural China. *J. Appl. Econ.* **2002**, *17*, 329–346, doi:10.1002/jae.645.

36.　Kraay, A.; Mckenzie, D. Do Poverty Traps Exist? Assessing the Evidence. *J. Econ. Perspect.* **2014**, *28*, 127–148.

37.　Bigman, D.; Dercon, S.; Guillaume, D.; Lambotte, M.J.T.W.B.E.R. Community Targeting for Poverty Reduction in Burkina Faso. *World Bank Econ. Rev.* **2000**, *14*, 167–193.

38.　Liu, Y.; Liu, J.; Zhou, Y. Spatio-temporal patterns of rural poverty in China and targeted poverty alleviation strategies. *J. Rural Stud.* **2017**, *52*, 66–75, doi:10.1016/j.jrurstud.2017.04.002.

39.　Okwi, P.O.; Ndeng'e, G.; Kristjanson, P.; Arunga, M.; Notenbaert, A.; Omolo, A.; Henninger, N.; Benson, T.; Kariuki, P.; Owuor, J. Spatial determinants of poverty in rural Kenya. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 16769–16774, doi:10.1073/pnas.0611107104.

40.　Glauben, T.; Herzfeld, T.; Rozelle, S.; Wang, X. Persistent Poverty in Rural China: Where, Why, and How to Escape? *World Dev.* **2012**, *40*, 784–795, doi:10.1016/j.worlddev.2011.09.023.

41.　Liu, Y.; Yang, Z.; Jilai, L. Regional differentiation characteristics of rural poverty and targeted poverty alleviation strategy in China. *Bull. Chin. Acad. Sci.* **2016**, 269-278.

42.　Partridge, M.D.; Rickman, D.S. Distance from Urban Agglomeration Economies and Rural Poverty. *J. Reg. Sci.* **2008**, *48*, 285–310.

43.　Epprecht, M.; Müller, D.; Minot, N. How remote are Vietnam's ethnic minorities? An analysis of spatial patterns of poverty and inequality. *Ann. Reg. Sci.* **2011**, *46*, 349–368, doi:10.1007/s00168-009-0330-7.

44. Zhou, L.; Xiong, L.; Wang, Y.; Zhou, X.; Yang, L. Spatial Distribution of Poverty-Stricken Counties in China and Their Natural Topographic Characteristics and Controlling Effects. *Econ. Geogr.* **2017**, *37*, 157–166.

45. Guo, Y.; Yang, Z.; Zhi, C. Geographical patterns and anti-poverty targeting post-2020 in China. *J. Geogr. Sci.* **2018**, *28*, 1810–1824.

46. HCPG. *Huining Yearbook*; People's Publishing House of Gansu Province: Huining, China, 2018.

47. HCBS. *Huining Statistics Yearbook*; Huining County Bureau of Statistics: Huining, China, 2017.

48. Ahlström, A.; Pilesjö, P.; Lindberg, J. Improved accessibility modeling and its relation to poverty–A case study in Southern Sri Lanka. *Habitat Int.* **2011**, *35*, 316–326, doi:10.1016/j.habitatint.2010.11.002.

49. Gutiérrez, J. Location, economic potential and daily accessibility: An analysis of the accessibility impact of the high-speed line Madrid–Barcelona–French border. *J. Transp. Geogr.* **2001**, *9*, 229–242, doi:10.1016/S0966-6923(01)00017-5.

50. Geurs, K.T.; van Wee, B. Accessibility evaluation of land-use and transport strategies: Review and research directions. *J. Transp. Geogr.* **2004**, *12*, 127–140, doi:10.1016/j.jtrangeo.2003.10.005.

51. Yang, W.; Chen, B.Y.; Cao, X.; Li, T.; Li, P. The spatial characteristics and influencing factors of modal accessibility gaps: A case study for Guangzhou, China. *J. Transp. Geogr.* **2017**, *60*, 21–32, doi:10.1016/j.jtrangeo.2017.02.005.

52. Jiao, J.; Wang, J.; Jin, F.; Dunford, M. Impacts on accessibility of China's present and future HSR network. *J. Transp. Geogr.* **2014**, *40*, 123–132, doi:10.1016/j.jtrangeo.2014.07.004.

53. Li, T.; Zhang, S.; Cao, X.; Witlox, F. Does a circular high-speed rail network promote efficiency and spatial equity in transport accessibility? Evidence from Hainan Island, China. *Transp. Plan. Technol.* **2018**, *41*, 779–795, doi:10.1080/03081060.2018.1504186.

54. Dziauddin, M.F.; Powe, N.; Alvanides, S. Estimating the Effects of Light Rail Transit (LRT) System on Residential Property Values Using Geographically Weighted Regression (GWR). *Appl. Spat. Anal. Policy* **2015**, *8*, 1–25, doi:10.1007/s12061-014-9117-z.

.