

## Comparative Analysis of Differentiation Mechanisms of Spatial Poverty Traps under Different Geographical Environments: An Empirical Post-print Based on the Dabie Mountains and Loess Plateau

**Authors:** Sun Jianwu

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### Abstract

The victory of the poverty alleviation campaign has shifted the focus of poverty governance toward alleviating relative poverty. The overlap between the population that has been lifted out of poverty and the relatively poor population determines that contiguous destitute areas will remain the main battlefield for China to solve poverty problems. Taking Xin County in the Dabie Mountains and Yanchang County in the Loess Plateau region as examples, this study uses poverty incidence rate as the dependent variable and selects independent variables from three dimensions of “people”, “industry”, and “land”, comprehensively employing methods such as spatial autocorrelation and geographical detector to analyze the spatial differentiation patterns and mechanisms of poverty in different geographical environments. The results show that: In the Dabie Mountains, poverty spatial agglomeration is mainly characterized by an alternating distribution of point-like and cluster-like patterns, while in the Loess Plateau region, it is mainly cluster-like. In the Dabie Mountains, the two dimensions of “land” and “industry” have significant effects on spatial poverty, whereas in the Loess Plateau region, the three dimensions of “people”, “industry”, and “land” are relatively balanced. The difference in survival pressure brought by the resource abundance of the carrying space “land” is where the difference in poverty formation mechanisms between the two regions lies. In the Loess Plateau region, based on sufficient survival resources, a negative cyclic accumulation of the three dimensions is formed in a relatively closed space, while in the Dabie Mountains, under the effect of resource scarcity, individuals make rational survival choices to seek employment elsewhere, thereby breaking the cycle of poverty accumulation.

## Full Text

### Comparison of Spatial Poverty Trap Differentiation Mechanisms in Different Geographical Environments: An Empirical Study Based on the Dabie Mountains and Loess Plateau

SUN Jianwu<sup>1</sup>, GAO Junbo<sup>2,3</sup>, MA Zhifei<sup>1,3</sup>, YU Chao<sup>1,3</sup>, ZHANG Xinyi<sup>1,3</sup>

<sup>1</sup>School of Geographic Sciences, Xinyang Normal University, Xinyang 464000, Henan, China

<sup>2</sup>School of Tourism, Xinyang Normal University, Xinyang 464000, Henan, China

<sup>3</sup>The Center of Targeted Poverty Alleviation and Rural Revitalization, Xinyang Normal University, Xinyang 464000, Henan, China

## Abstract

The successful completion of poverty eradication campaigns has shifted the focus of poverty governance toward alleviating relative poverty. The substantial overlap between populations that have been lifted out of absolute poverty and those experiencing relative poverty means that concentrated contiguous impoverished regions will remain the primary battleground for addressing poverty in China. Taking Xinxian County in the Dabie Mountains and Yanchang County on the Loess Plateau as examples, this study employs poverty incidence as the dependent variable and selects independent variables from three dimensions—"human," "industry," and "land." Using spatial autocorrelation and geographic detector methods, we analyze the spatial differentiation patterns and mechanisms of poverty in different geographical environments. The results indicate that the "land" and "industry" dimensions significantly influence spatial poverty in the Dabie Mountains, while all three dimensions—"human," "industry," and "land"—play relatively balanced roles in the Loess Plateau region. Spatial poverty in the Dabie Mountains exhibits a pattern of alternating point-like and cluster distributions, whereas the Loess Plateau shows predominantly cluster distributions. The difference in survival pressure created by varying resource abundance in the "land" dimension constitutes the key distinction in poverty formation mechanisms between the two regions. The Loess Plateau, endowed with sufficient survival resources, forms a three-dimensional negative circular accumulation within relatively enclosed spaces, while the Dabie Mountains, constrained by resource scarcity, sees individuals rationally choose labor migration, thereby breaking the cycle of poverty accumulation.

**Keywords:** spatial autocorrelation; geographic detector; Dabie Mountains; Loess Plateau

## 1 Introduction

Poverty represents a major global social challenge, and eliminating poverty while narrowing urban-rural gaps constitutes a crucial objective for sustainable human development [?]. Since China's reform and opening-up, poverty reduction has progressed through three distinct stages: poverty alleviation driven by rural reforms, poverty reduction propelled by industrialization, urbanization, and development-oriented poverty alleviation, and poverty elimination aimed at completing the building of a moderately prosperous society [?]. By the end of 2020, China had eradicated absolute poverty. However, the elimination of absolute poverty does not signify the end of poverty reduction efforts; relative poverty will persist long-term. Moreover, significant overlap exists between absolute and relative poverty populations, making the elimination of absolute poverty a prerequisite for alleviating relative poverty [?]. The Fourth Plenary Session of the 19th CPC Central Committee proposed "winning the final battle against poverty, consolidating achievements, and establishing a long-term mechanism for addressing relative poverty," indicating that poverty will remain a long-term focus in China, with concentrated contiguous impoverished areas continuing to serve as the main battlefield.

Extensive theoretical and empirical research on poverty has been conducted by scholars worldwide. Studies have examined poverty causes, spatiotemporal evolution, formation mechanisms, and poverty reduction pathways from various perspectives [?]. Methodologically, research has transitioned from single-dimensional income-based approaches to multidimensional frameworks incorporating education, health, housing, and social security [?]. Spatially, analyses span national, provincial, municipal, county, township, village, and household scales, with increasing attention to multi-scale studies [?]. Methodologically, geographic weighted regression, multilevel linear models, geographic detectors, and spatial lag models have been widely applied [?]. As research deepens, spatial poverty has emerged as a key focus. Guided by spatial poverty theory, numerous scholars have constructed spatial poverty geographic capital indicator systems based on economic, social, and environmental dimensions to investigate spatial poverty identification methods, differentiation characteristics, and formation mechanisms [?]. Overall, existing research has yielded rich theoretical and practical insights. However, most studies focus on single regions, with limited comparative research across different areas at the same scale. The factors causing poverty and the mechanisms of poverty occurrence vary significantly across different natural geographical environments [?]. Analyzing and comparing rural poverty-causing factors and differentiation mechanisms across different geographical environments at the same scale can more clearly reveal both the prominent issues of regional poverty and the common challenges of comprehensive regional poverty.

This study selects the Dabie Mountains and Loess Plateau—two key national poverty alleviation regions—to examine spatial poverty trap existence using spatial autocorrelation tests and employs geographic detector models to explore

the causes of spatial poverty traps and poverty mechanism differences across geographical environments, aiming to provide insights for regional poverty reduction pathway selection and poverty differentiation research.

## 2 Methods

### 2.1 Global Spatial Autocorrelation

Global autocorrelation examines overall correlations among study objects, primarily using Moran's  $I$  index, Geary's  $C$  index [?], and Getis-Ord  $G$  coefficient. The formulas are as follows:

**Moran's  $I$  index:**

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

**Geary's  $C$  index:**

$$C = \frac{(n-1)}{2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (Y_i - Y_j)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}$$

**Getis-Ord  $G$  coefficient:**

$$G = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} Y_i Y_j}{\sum_{i=1}^n \sum_{j=1}^n Y_i Y_j}$$

Where  $n$  represents the number of spatial units;  $W_{ij}$  denotes the spatial weight matrix;  $Y_i$  and  $Y_j$  are poverty incidence rates in units  $i$  and  $j$ ;  $\bar{Y}$  is the mean poverty incidence; and  $S^2$  is the variance of poverty incidence.

Moran's  $I$  ranges from  $[-1, 1]$ , with values greater than 0 indicating positive spatial correlation, less than 0 indicating negative spatial correlation, and equal to 0 indicating independent random distribution. Significance testing uses  $Z$ -values calculated as [?]:

$$Z(I) = \frac{I - E(I)}{\sqrt{VAR(I)}}$$

where  $E(I)$  is the expected value and  $VAR(I)$  is the variance of Moran's  $I$ . A larger absolute  $Z$ -value indicates higher significance.

### 2.2 Local Spatial Autocorrelation

Local spatial autocorrelation examines local spatial correlations of poverty incidence. The local Moran's  $I$  formula is [?]:

$$I_i = \frac{Y_i - \bar{Y}}{S^2} \sum_{j=1}^n W_{ij} (Y_j - \bar{Y})$$

Significance testing follows the same Z-value calculation as global autocorrelation. Significant positive local Moran's  $I$  indicates high-high or low-low clustering, while significant negative values indicate high-low or low-high clustering.

### 2.3 Geographic Detector

Geographic detector is a statistical method for detecting spatial differentiation and revealing its driving forces by comparing variance sums across strata [?]. It can detect spatial stratified heterogeneity and statistical associations between variables based on spatial distribution consistency. This study applies factor detection and interaction detection to identify dominant factors and interactions affecting spatial poverty differentiation:

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

where  $L$  represents strata of poverty incidence  $Y$  or influencing factor  $X$ ;  $N_h$  and  $\sigma_h^2$  are the unit count and variance within stratum  $h$ ;  $N$  and  $\sigma^2$  are the total unit count and overall variance;  $SSW$  is the within-stratum variance sum; and  $SST$  is the total variance. The  $q$  value, ranging from  $[0,1]$ , measures the contribution of independent variables to the dependent variable, with larger values indicating stronger influence.

### 2.4 Factor Selection and Data Sources

Regional poverty emergence is influenced by natural environment, social conditions, resource endowments, livelihood capital, location, and economic vitality. Drawing on human-environment relationship theory, regional poverty components can be categorized into three dimensions: the subjective "human" dimension, the intermediary "industry" dimension, and the objective "land" dimension. This framework guides our analysis of spatial poverty trap formation mechanisms.

Combining regional characteristics of Xinxian and Yanchang counties with available survey data, we constructed a spatial poverty trap cause detection index system across three dimensions (Table 1).

**Human Dimension:** As poverty subjects, households' livelihood sustainability determines poverty occurrence. Education level, health status, and family burden constitute human capital, while natural resources like farmland and forestland form natural capital [?]. Based on data availability, we selected the proportion of family members with serious illness ( $X_{\{1\}}$ ), proportion of children under 15 ( $X_{\{2\}}$ ), proportion with education above primary school ( $X_{\{3\}}$ ), and per capita farmland area ( $X_{\{4\}}$ ) as detection indicators.

**Industry Dimension:** Industrial development capacity, reflected by income structure and level, significantly influences regional poverty. In poor areas,

household income primarily derives from farming and migrant work. We selected the proportion of crop income ( $X_{\{5\}}$ ), proportion of migrant work income ( $X_{\{6\}}$ ), and per capita net income ( $X_{\{7\}}$ ) as detection indicators.

**Land Dimension:** Location conditions and topography, being non-malleable at the regional level, constitute key reasons for spatial poverty traps [?]. We used distance to roads ( $X_{\{8\}}$ ), distance to rivers ( $X_{\{9\}}$ ), distance to county government ( $X_{\{10\}}$ ), and distance to township government ( $X_{\{11\}}$ ) to represent location conditions. Given the diversity of regional resource elements and difficulty in quantifying endowments with few indicators, we used village total population ( $X_{\{12\}}$ ) to reflect resource availability under finite regional constraints.

**Table 1** Spatial poverty trap cause detection index system

| Dimension               | Indicator                                                                                                                                                                                                                          |
|-------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Human (Subject)         | Proportion of family members with serious illness ( $X_{\{1\}}$ )<br>Proportion of children under 15 ( $X_{\{2\}}$ )<br>Proportion with education above primary school ( $X_{\{3\}}$ )<br>Per capita farmland area ( $X_{\{4\}}$ ) |
| Industry (Intermediary) | Proportion of crop income ( $X_{\{5\}}$ )<br>Proportion of migrant work income ( $X_{\{6\}}$ )<br>Per capita net income ( $X_{\{7\}}$ )                                                                                            |
| Land (Object)           | Distance to roads ( $X_{\{8\}}$ )<br>Distance to rivers ( $X_{\{9\}}$ )<br>Distance to county government ( $X_{\{10\}}$ )<br>Distance to township government ( $X_{\{11\}}$ )<br>Village total population ( $X_{\{12\}}$ )         |

**Data Sources:** Data for 205 administrative villages in Xinxian County and 149 villages in Yanchang County, including total population, household attributes, and farmland resources for 2017, were obtained from local government departments. Per capita farmland area was calculated from total population and farmland area. Based on field survey data, we calculated per capita net income, income structure proportions, family illness proportions, child proportions, and education proportions. Following geographic detector requirements, we established 1 km interval data points (Figure 2), assigned values in ArcGIS, and calculated distances to major roads, rivers, county government, and township government using spatial proximity analysis. DEM data from the National Geographic Information Center provided slope and elevation information.

### 3 Spatial Poverty Distribution Differences Between Dabie Mountains and Loess Plateau

#### 3.1 Dabie Mountains: Alternating Point and Cluster Patterns

Xinxian County exhibits predominantly high-high clustering characteristics, forming obvious cluster distributions in mountainous areas far from the county seat with poor transportation in the southeast, northeast, and west. Other areas show scattered point-like and small cluster distributions (Figure 3). High-high clustering covers  $226 \text{ km}^2$ , accounting for 14.0% of the county's territory, indicating that high poverty incidence areas cluster and influence each other, forming "spatial poverty traps." Additionally, low-low clustering appears around the county seat, suggesting single-core county development where economic levels gradually decline from the center outward, and demonstrating the county seat's "trickle-down effect" on surrounding areas.

Global autocorrelation results show Xinxian's Moran's  $I$  is 0.179, passing significance tests, indicating that poverty populations in both counties exhibit significant high-poverty or low-poverty clustering—clear evidence of spatial poverty traps. Local Moran's  $I$  cluster maps further reveal the specific distribution patterns (Figure 3).

#### 3.2 Loess Plateau: Prominent Cluster Patterns

Yanchang County shows more significant high-high clustering, forming four obvious agglomeration blocks in northern, southern, and remote northeastern/southwestern mountainous areas, with only individual point distributions elsewhere (Figure 3). High-high clustering covers  $463 \text{ km}^2$ , reaching 19.6% of county territory, indicating more pronounced mutual influence among high poverty incidence areas and more prominent spatial poverty traps. Low-low clustering appears around the county seat and township centers, forming more obvious cluster distributions near township centers, demonstrating township economies' significant driving effects on surrounding areas.

#### 3.3 Comparative Analysis of Spatial Poverty Trap Clustering

Both regions show clear spatial poverty clustering and trap formation, but with significant differences in aggregation degree and spatial structure. The Loess Plateau's poverty spatial aggregation is markedly higher than the Dabie Mountains', with Xinxian's Moran's  $I$  at 0.179 and Yanchang's at 0.198. In terms of distribution, Xinxian's spatial poverty traps are relatively dispersed, with alternating point and cluster patterns averaging  $66.1 \text{ km}^2$  per block. Yanchang's traps show concentrated cluster distributions averaging  $115.8 \text{ km}^2$  per block, indicating more significant trap effects. Low poverty incidence clustering in Xinxian concentrates near the county seat due to its single-core development model, while Yanchang's low-poverty areas are more dispersed, constrained by topography that limits the county seat's radiation capacity.

## 4 Causes of Spatial Poverty Traps in Dabie Mountains and Loess Plateau

### 4.1 Spatial Heterogeneity Analysis

**4.1.1 “Land” and “Industry” Dimensions Dominate Dabie Mountains Poverty Differentiation** Factor detector results show that for Xinxian County, the highest contributing factors are distance to county government ( $q = 0.124$ ), proportion of migrant work income ( $q = 0.070$ ), distance to township government ( $q = 0.070$ ), and per capita net income ( $q = 0.070$ ), all significant at the 0.01 level. The average contribution rate across all factors is 0.059. Distance to county government and village total population contribute over 10%, indicating concentrated causes of spatial poverty differentiation. Interaction detection results (Table 3) show that interactions between geographic detection factors enhance their influence on poverty incidence, with larger interaction values (0.179, 0.124, 0.098), primarily showing bi-factor enhancement and non-linear enhancement.

**4.1.2 Balanced Effects of “Human,” “Industry,” and “Land” in Loess Plateau** For Yanchang County, high-contribution factors include distance to county government ( $q = 0.198$ ), proportion of children under 15 ( $q = 0.162$ ), proportion of crop income ( $q = 0.159$ ), per capita net income ( $q = 0.159$ ), and proportion with primary school education or above ( $q = 0.140$ ), all significant at the 0.01 level. The average contribution rate is 0.119, with all three dimensions contributing relatively balanced effects. Interaction detection (Table 3) again shows enhanced effects under interaction, with values of 0.198, 0.162, and 0.159, primarily through bi-factor and non-linear enhancement.

**Table 2**  $q$  values for each indicator in Xinxian and Yanchang counties

| Indicator                                                      | Xinxian $q$ | Yanchang $q$ |
|----------------------------------------------------------------|-------------|--------------|
| Proportion with serious illness ( $X_{\{1\}}$ )                | 0.059**     | 0.119**      |
| Proportion of children under 15 ( $X_{\{2\}}$ )                | 0.059**     | 0.162**      |
| Proportion with education above primary school ( $X_{\{3\}}$ ) | 0.059**     | 0.140**      |
| Per capita farmland area ( $X_{\{4\}}$ )                       | 0.059**     | 0.119**      |
| Proportion of crop income ( $X_{\{5\}}$ )                      | 0.059**     | 0.159**      |

| Indicator                                         | Xinxian $q$ | Yanchang $q$ |
|---------------------------------------------------|-------------|--------------|
| Proportion of migrant work income ( $X_{\{6\}}$ ) | 0.070**     | 0.119**      |
| Per capita net income ( $X_{\{7\}}$ )             | 0.070**     | 0.159**      |
| Distance to roads ( $X_{\{8\}}$ )                 | 0.059**     | 0.119**      |
| Distance to rivers ( $X_{\{9\}}$ )                | 0.059**     | 0.119**      |
| Distance to county government ( $X_{\{10\}}$ )    | 0.124**     | 0.198**      |
| Distance to township government ( $X_{\{11\}}$ )  | 0.070**     | 0.119**      |
| Village total population ( $X_{\{12\}}$ )         | 0.059**     | 0.119**      |

Note:  $q$  measures contribution; lower  $P$  values indicate higher significance. \*\* indicates significance at 0.01 level.

## 4.2 Formation Mechanisms

**4.2.1 Dabie Mountains Mechanism** Spatial poverty differentiation in the Dabie Mountains is primarily influenced by the “land” dimension, followed by “industry.” Xinxian’s nested hilly terrain creates complex geography with scarce fertile land, hindering modern cultivation. Transportation accessibility between villages and urban centers lags far behind plain areas, while the county seat’s central role in economic, cultural, educational, and medical services is particularly prominent. Distance to the county seat constrains remote villages’ access to public services, hindering industrial development and becoming a key poverty factor (Figure 4). Limited usable resources and large population create acute human-land contradictions. Under existing production conditions, rural resources cannot generate sufficient livelihood outcomes. Ecological protection policies reduce farmland while technological development creates surplus labor, increasing survival pressure. Driven by survival rationality, labor migration becomes the primary choice for youth. Households supporting local low-level survival or with heavy family burdens typically remain in farming, but remote location and high public service costs limit off-farm opportunities. This results in point-like and cluster distributions of high poverty incidence in areas with poor location conditions.

**4.2.2 Loess Plateau Mechanism** The Loess Plateau experiences relatively balanced effects from all three dimensions. Yanchang County’s loess hilly-

gully region, characterized by yuan, liang, and mao landforms, creates multiple relatively enclosed sub-spaces that extend actual communication distances. Although abundant land resources support basic survival, enclosed spaces foster backward fertility concepts, creating heavy child-rearing burdens and low education levels that lead to human capital scarcity. High costs of new technology and industrial development offset demands for modern agriculture development (Figure 5). Meanwhile, prominent urban-rural gaps and weak rural infrastructure in healthcare, education, social security, and banking—highly concentrated in towns—further raise costs and reduce quality of public service access for remote households, constraining their ability to obtain external resources for production transformation and limiting non-agricultural industry development. This forces residents to follow traditional, single production-lifestyles, creating stable negative circular accumulation and low-level equilibrium in relatively enclosed spatial units.

## 5 Discussion and Conclusion

### 5.1 Discussion

The analysis reveals that survival pressure differences caused by resource endowment variations constitute the key distinction between the two regions' spatial poverty mechanisms. Limited livelihood capital from "land" and high external resource acquisition costs force "human" to adapt to traditional, backward, single livelihood strategies, creating path dependence in "industry" development that is low-level and uncompetitive. Weak competitiveness further constrains job provision and public service improvement [?], forming a "low-level, inefficient, disordered, stable regional economic and social operation system" [?] that constitutes a spatial poverty trap—the pattern evident in the Loess Plateau.

However, Xinxian presents an external breakthrough: under China's unified labor market and price mechanism, migrant work yields relatively high returns [?]. The acute human-land contradiction and survival pressure drive large-scale youth out-migration, creating a new breakthrough in the negative poverty cycle, though constrained by age, family structure, education, and communication costs. The "land" dimension's foundational role and its resource abundance differences create the distinct spatial poverty formation mechanisms between the Dabie Mountains and Loess Plateau.

### 5.2 Conclusions

Using spatial autocorrelation and geographic detectors, this study analyzed spatial poverty differentiation and its influencing factors in the Dabie Mountains and Loess Plateau, yielding four main conclusions:

- 1) Despite both being mountainous, the two regions show significant differences in poverty spatial clustering and distribution patterns. The Dabie Mountains exhibits alternating point and cluster distributions, while the

Loess Plateau shows predominantly cluster patterns, with significantly higher clustering levels in the Loess Plateau.

- 2) In terms of poverty causes, the Dabie Mountains is strongly influenced by “land,” followed by “industry,” while the Loess Plateau experiences relatively balanced effects across “human,” “industry,” and “land” dimensions that form circular accumulation. However, the Loess Plateau’s lower poverty incidence suggests that spatial poverty occurrence depends not on the number of poverty dimensions but on their modes and depth of action.
- 3) Distance to county government ranks first in factor contribution in both regions (0.179 and 0.198 respectively). Additionally, village total population (0.124), distance to township government (0.070), and proportion of migrant work income (0.070) are main factors in the Dabie Mountains, while proportion of children under 15 (0.162), proportion of crop income (0.159), per capita net income (0.159), and proportion with primary school education or above (0.140) are key factors in the Loess Plateau.
- 4) Differences in survival pressure from “land” resource abundance constitute the source of divergent poverty formation mechanisms. The Loess Plateau forms three-dimensional negative circular accumulation in relatively enclosed spaces based on sufficient survival resources, while the Dabie Mountains, under resource scarcity, sees individuals rationally choose labor migration, breaking the poverty accumulation cycle.

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