Chin. Geogra. Sci. 2018 Vol. 28 No. 2 pp. 296–312
https://doi.org/10.1007/s11769-018-0943-9

Springer Science Press
www.springerlink.com/content/1002-0063

Multi-scale Spatial Patterns and Influencing Factors of Rural Poverty: A Case Study in the Liupan Mountain Region, Gansu Province, China

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Abstract: The important role of spatial scale in exploring the geography of poverty as well as its policy implications has been noticed but with limited knowledge. To improve such limited understanding, we mainly investigated the spatial patterns and influencing factors of rural poverty (indicated by poor population and poverty incidence) at three different administrative levels in the Liupan Mountain Region, one of the fourteen poorest regions in China. Our results show that from a global perspective, poor areas are clustered significantly at the county-, township-, and village-level, and more greatly at a lower level. Locally, there is spatial mismatch among poverty hotspots detected not only by the same indicator at different levels but also by different indicators at the same level. A scale effect can be found in the influencing factors of rural poverty. That is, the number of significant factors increases, but the degree of their association with poverty incidence decreases at a lower level. Such scale effect indicates that poverty incidence at lower levels may be affected by more complex factors, including not only the new local ones but also the already appeared non-local ones at higher levels. However, the natural conditions tend to play a scale-independent role to poverty incidence. In response to such scale-dependent patterns and factors, anti-poverty policies can be 1) a multilevel monitoring system to reduce incomplete or even misleading single-level information and understanding; 2) the village-based targeting strategy to increase the targeting efficiency and alleviate the mentioned spatial mismatch; 3) more flexible strategies responding to the local impoverishing factors, and 4) different task emphasises for multilevel policymakers to achieve the common goal of poverty reduction.

Keywords: poverty; spatial scale; spatial patterns; anti-poverty policy; China

Citation: MA Zhenbang, CHEN Xingpeng, CHEN Huan, 2018. Multi-scale Spatial Patterns and Influencing Factors of Rural Poverty: A Case Study in the Liupan Mountain Region, Gansu Province, China. *Chinese Geographical Science*, 28(2): 296–312. https://doi.org/10.1007/s11769-018-0943-9

1 Introduction

Poverty is one of the biggest challenges for the developed and especially developing countries, as well as the leading and especially lagging areas (World Bank, 2000; 2009; Bird and Shepherd, 2003; Sunderlin et al., 2008). This is largely, but not completely, because that poverty is a multi-dimensional, complex, stubborn and recurring phenomenon (World Bank, 2000; Grant et al., 2004; Alkire and Foster, 2011; Liu and Li, 2017). The poor status is not only owing to the individual variations (i.e., physical disability, lack of education, outdated thinking), but also because of the non-homogeneous context since one can not live without the interactions with the

Received date: 2017-05-10; accepted date: 2017-09-08

Foundation item: Under the auspices of National Natural Science Foundation of China (No. 41401204, 41471462), Fundamental Research Funds for the Central Universities (No. lzujbky-2013-128)

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physical and socio-economic circumstances (Ravallion and Wodon, 1999; Bird and Shepherd, 2003; Carter and Barrett, 2006; Xu et al., 2006; Rupasingha and Goetzb, 2007; Liu et al., 2016). For instance, households may respond similarly to terrain, industrial structure or cultural influence. Therefore, the place may play a great role in rural poverty. The poor are found to be more likely living in certain places (Ravallion and Wodon, 1999; Minot, 2000; Bird et al., 2002; Jalan and Ravallion, 2002), and such places tend to be geographically clustered (Ravallion and Wodon, 1999; Amarasinghe et al., 2005; Voss et al., 2006; Annim et al., 2012; Luo et al., 2016). Thus, the question of 'where are the poor, and why' (namely the geography or spatial dimension of poverty) arouse great interest among researchers since the 1990s.

At first, the geographic variables (i.e., rainfall, slope or location of the settlements) were introduced into the models which were based on household survey data to evaluate the potential geographic effect on the living standards of households. Many works strongly suggested the existence of spatial poverty trap, which suggests that the productivity of a household's own capital can be reduced in less-endowed areas (Jalan and Ravallion, 1997; Ravallion and Wodon, 1999; Bird and Shepherd, 2003). In a case study in rural China, Jalan and Ravallion (1997) found the evidence of spatial poverty trap on a six-year panel of farm-household data. Ravallion and Wodon (1999) detected significant and sizable geographic differences in the living standard by controlling a wide range of nongeographic household characteristics (i.e., land and education). Bird and Shepherd (2003) also suggested that remote rural areas were more likely to be geographic pockets of poverty due to the disadvantages (i.e., difficult climate, limited water resource and steep terrain) and the marginalization.

Obviously, it is not enough to policy-making with only the detection of spatial poverty trap based on household survey data. There are several reasons. Firstly, constraints in the sample size prevent the use of such data for estimating the poverty of a large number of small geographic units (i.e., townships or villages) (Minot, 2000; Elbers et al., 2003). Thus the policymakers can not get a panoramic view of the geographical poverty for identifying poor areas, especially at lower geographical levels. Moreover, since poverty may be related to the locations or places, the possible spatial patterns, the influencing factors, and the underlying mechanisms of the rural poverty will be crucial for the efficiency of policy intervention.

Fortunately, poverty mapping technology provides an opportunity in the visualization of poverty. It can address those issues mentioned above by combining census and survey data to yield statistically reliable estimates of poverty at lower geographical levels (Hentschel et al., 2000; Minot, 2000; Elbers et al., 2003; Erenstein et al., 2010; Olivia et al., 2011). So this technology coupled with spatial statistical methods was gradually employed to investigate the spatial dimension of poverty. The spatial statistic, such as Moran's statistic, can quantify and clarify the patterns seen in the poverty maps (Amarasinghe et al., 2005; Farrow et al., 2005; Epprecht et al., 2011). Unsurprisingly, many results showed that the poor areas (with high poverty incidence) tend to be spatially clustered, suggesting that the geographic effects arising probably from the structuring forces (i.e., agro-ecological environment, physical infrastructure, or feedback between households) can not be ignored (Ravallion and Wodon, 1999; Amarasinghe et al., 2005; Palmer-Jones and Sen, 2006; Rupasingha and Goetzb, 2007; Epprecht et al., 2011). Meanwhile, the spatial regression models and geographically weighted regression (GWR) were used to explore the global and local relationships between the spatially auto-correlated poverty and its determinants (Benson et al., 2005; Farrow et al., 2005; Kam et al., 2005; Okwi et al., 2007; Epprecht et al., 2011). Consequently, it was observed that the determinants of poverty were spatially non-homogeneous (Benson et al., 2005; Kam et al., 2005; Okwi et al., 2007).

However, previous works were mostly carried out at a single geographic or administrative level. The role of scale on the spatial patterns and influencing factors of rural poverty may be underestimated or ignored. It has been recognized for decades that spatially heterogeneous pattern changes with spatial scale due to a joint effect of structuring forces across multiple scales (Dungan et al., 2002; Wu, 2004; Okwi et al., 2007; Ward and Kaczan, 2014; Kim et al., 2016; Li et al., 2016). Hence, from a theoretical perspective, the spatial scale will help to get a comprehensive understanding of the interaction between poverty patterns and natural/human processes. In practice, the spatial scale plays an important role in the area-based policies. Firstly, the degree of the coverage of the poor and the leakage to the non-poor depends largely on the geographical level of targeting (Park et al., 2002; Amarasinghe et al., 2005), thus bringing the different costs of area-based targeting (Elbers et al., 2007). Moreover, with the consideration of spatially heterogeneous causes, the spatial scale contributes to the efficiency of anti-poverty policies. For instance, the experiences from Kenya and Niger River Basin suggested that the nation-level determinants of poverty were not necessarily congruent with the sub-national ones (Okwi et al., 2007; Ward and Kaczan, 2014). Based on a multilevel study, Kim et al. (2016) suggested that identifying the specific contextual determinants of poverty at the state and village levels were more helpful to reduce India's poverty. Again, policymakers or enforcers at different administrative levels tend to have different interest going against actual efficiency (Park et al., 2002; Park and Wang, 2010; Ward and Kaczan, 2014). Hence, the consideration of spatial scale should be taken into account in policy-making, especially in the area-based policies (Amarasinghe et al., 2005; Pijanowski et al., 2010; Ward and Kaczan, 2014; Liu et al., 2016).

Based on multilevel dataset (namely the village-, township-, and county-level) in the Liupan Mountain Region in Gansu Province, China, the objective of this study is to investigate the differences in the spatial patterns and influencing factors of rural poverty among three spatial scales. Firstly, comparison of multilevel patterns of rural poverty was made to find how the global and local patterns are changed with the administrative level. Then, Spearman's correlation and bivariate spatial correlation analysis were employed to detect the factors influencing poverty incidence at different levels. Finally, the anti-poverty policies, especially area-based ones, were suggested with the considerations of spatial scale. This paper's contribution can be: 1) it attempts to enrich the understanding of 'scale' in spatial dimension of rural poverty from the aspects of both spatial patterns and its underlying factors; 2) it allows for scale-differentiating policies against poverty, thus supporting the policymakers both at home and abroad, especially for those in developing countries where rural poverty, to a great extent, persists and is clustered spatially.

2 Materials and Methods

2.1 Study area

Liupan Mountain Region (LPMR), named after Liupan Mountain, is one of the fourteen poorest regions designated by the State Council of the People's Republic of China (2011). LPMR covers 69 counties across Gansu Province, Shaanxi Province, Qinghai Province and Ningxia Autonomous Region. In this paper, we selected the Gansu's 46 counties in LPMR (LPMR-GS) as the study area (Fig. 1). In 2013, the number of poor people in LPMR-GS accounts for approximately 5% of that in China. Thus, a good understanding of the geography of poverty in this area greatly benefits in the China's current 'Targeted Poverty Alleviation Strategy', which devotes to target both the poor areas (14 regions, 592 counties, 128 000 villages) and about 70.0 $\times 10^6$ poor people (in 2014) nationwide (Liu et al., 2016).

LPMR-GS covers about 11.5×10^4 km^2 with a population of about 17.2×10^6 in 2013. The administrative division system includes 8 prefecture-, 46 county-, 711 township- and 9684 village-level divisions (Fig. 2). It has the same 30 nation-level poor counties which were officially designated in 1986, 1994, 2001 and 2011, suggesting the existence of spatial poverty trap.

The study area has a harsh and heterogeneous environment. It has an average elevation of 1850 m (ranging from 775 to 4516 m), and the gradient in near 60% of surface area is above 10 degrees. The average annual precipitation and temperature range from 177 to 701 mm (mean: 435 mm) and from –7.4℃ to 11.4℃ (mean: 6.3℃), respectively. With sparse vegetation in most areas, the soil erosion is serious.

Obviously, the less-favored environment contributes to the lagging development of society and economy (State Council of the People's Republic of China, 2011; Liu and Xu, 2016). In 2013, the GDP of this study area was 2.55×10^{11} yuan (accounting for 40.4% of GDP in Gansu), and GDP per capita was 14 889 yuan (accounting for only 60.7% of that in Gansu). Since the agricultural sector accounts for just 17.2% of GDP, the rural households, up to 80.7% of the population, have limited opportunities to improve their livelihoods through agricultural activities. Therefore, most young adults go to cities and towns hunting for jobs in the industry and service sectors (Zhang and Huang, 2008). Hence, the study area is feasible for the investigation of a scale-related geography of rural poverty because of the spatially heterogeneous environments and socio-economic conditions.

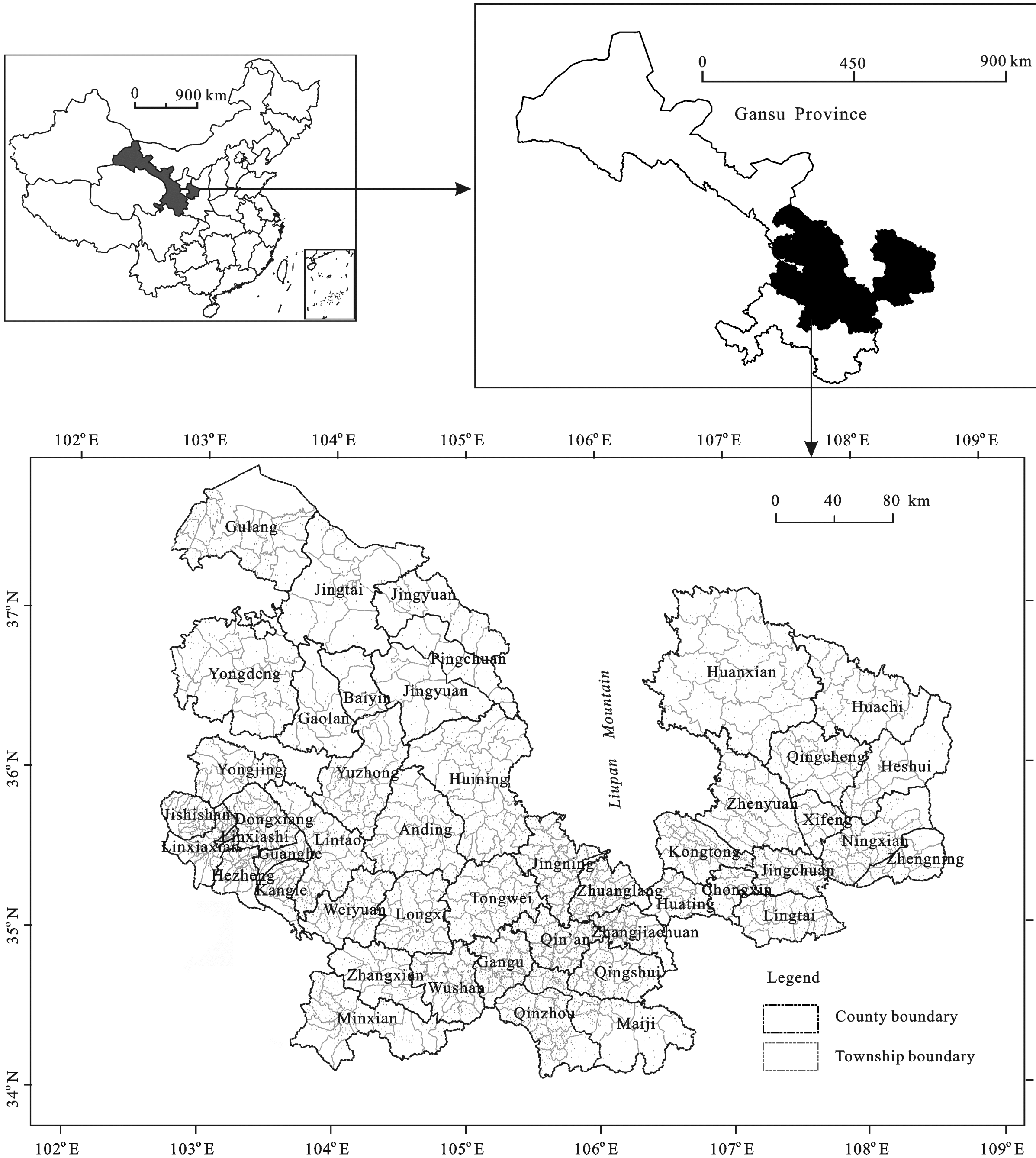

Fig. 1 Location and administrative divisions of the study area. Data source: (Wu, 2012)

2.2 Selection of the variables and data collections

Since this work focuses on whether and how spatial scale plays a role in the geography of rural economic poverty, we drew the theoretical understanding to guide our analysis from the concept of risk chain. The risk-chain is a common framework for analyzing first poverty of a household and then the links with risk and vulnerability (Alwang et al., 2001; Dercon, 2001; Benson et al., 2005). The risk chain decomposes household's economic vulnerability into three links: 1) the risk, or risky events, 2) the options for coping risk, or the risk responses, and 3) the outcome in terms of welfare loss. That is, a household is said to be vulnerable to future loss of welfare caused by risky events. The degree of vulnerability to poverty depends on the characteristics of the risk and the household's ability to respond to risk. Then, a household's current status (whether it is poor or not) is the outcome. However, this

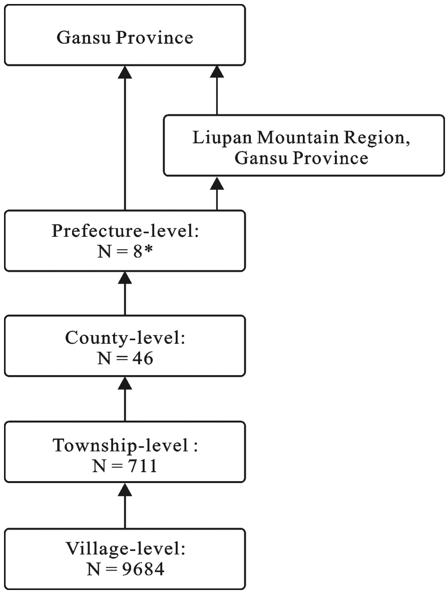

Fig. 2 Structural hierarchy of the administrative divisions of the study area. * LPMR-GS covers all the prefectures' whole area except Lanzhou and Wuwei. The involved counties are Gaolan, Yongdeng, Yuzhong in Lanzhou, and Gulang in Wuwei, respectively

conceptual framework can be expanded to the vulnerability-related poverty of communities or regions, if more attention is paid to covariant risks affecting the population at the meso- or macro-level (World Bank, 2000; Benson et al., 2005). Such covariant risks can be environmental risk (droughts, *etc*.), market risk (price fluctuations, *etc*.), social risk (the breakdown of social ties during a social transformation, *etc*.), political risk (income transfers, *etc*.), health risk (epidemics, *etc*.) and so on. Furthermore, the risk-chain refers to the dynamics of poverty (Dercon, 2001), thus being able to capture the link between spatial pattern of poverty and the related natural processes, human activities, or both. For example, a drought can cause crop failure, then the place where people rely mainly on agriculture for their living will suffer increased prevalence of poverty more easily.

Based on the risk-chain framework, the variables possibly related to the covariant risks and the risk responses are considered as the influencing factors of multilevel poverty. Moreover, three criteria were used to select the variables. Firstly, given agricultural income is the major source of income for rural households in 2013 (accounting for 46.2% of family income, Gansu Province Bureau of Statistics, 2014b), we mainly introduced the variables representing the possible risks and the coping strategies related to agricultural activities. Note that the variables related to nonagricultural activities are judged to be coping factors rather than risk factors. This is because wage income from non-farm work accounts for 41.8% of family income and is important to respond to more risky agriculture-based livelihoods. Meanwhile, it is unreasonable and unpractical, to some extent, to found a clear link between wage-related risks (illness, unemployment and other labor market risks) and rural poverty in local villages, townships, or even counties, since the rural labors are usually migrant workers and tend to work in cities (Zhang and Huang, 2008). Secondly, they are available for the entire study area. Finally, for the comparability of results across different administrative levels, the variables, if possible, can be processed in a geographic information system (GIS) and aggregated from village-level to township-, and county-level. Overall, a total of 24 variables were selected and categorized by their general nature (listed in Table 1).

The poverty data for this study are provided by Gansu Office of Poverty Alleviation and Development. Both village-level poor population (PP, the number of rural people falling below the poverty line, namely per capita net income 2736 yuan in 2013) and head-count ratio (HCR, or poverty incidence, % of rural people falling below the poverty line) in 2013 are available as poverty indicators, which can be aggregated to the township-, and county-level divisions.

The administrative divisions, or spatial analysis units at different levels, are derived from basic geographic data set of Gansu province at the scale of 1∶100 000 (Wu, 2012). This data set consists of points and polygons. The points include the locations of the cities, county towns, and villages. The polygons are the boundaries of the cities, counties, and townships. Note that the villages' boundaries are based on Thiessen polygons.

As for the influencing factors, the topographical, agro-climatic and land-use variables were compiled in GIS and then sampled to provide average values in each analysis unit (village, township, and county). In contrast, variables representing the accessibility to roads for each village were measured in GIS as the minimum Euclidean distance between its location and the road network. Then, the average values were assigned for the corresponding townships, and counties. The accessibility to the expressway, as an exception, was calculated as the distance between a village and the nearest entrance/-exit ramp. Note that in many cases, a village could be far from the branch road but nearby the main road, the layer of the main road was integrated into the layer of the branch road so that a reasonable result can be obtained for the lower-grade road. Similarly, variables representing the accessibility to urban areas were measured with the vector layer of the urban systems.

Table 1 The selected variables possibly related to rural poverty in the study area

Variable	Risk or coping factor	Unit
Topographical[1] (30 m × 30 m)[c]		
Mean elevation	Risk: crop failure caused by soil erosion, low temperature, *etc*. (Okwi et al., 2007)	m
Mean slope	Risk: crop failure caused by soil erosion, landslides, *etc*. (Benson et al., 2005; Okwi et al., 2007)	°
Agro-climatic[2] (500 m × 500 m)[c]		
Annual temperature	Risk: crop failure caused by low temperature, *etc*. (Olivia et al., 2011)	℃
Annual rainfall	Risk: crop failure caused by drought, *etc*. (Benson et al., 2005; Okwi et al., 2007)	mm
Accessibility to roads[3]		
Distance to the nearest expressway	Coping: response to price fluctuations, diseases, lack of information, *etc*. (Li et al., 2016)	km
Distance to the nearest main road	Coping: response to price fluctuations, diseases, lack of information, *etc*. (Li et al., 2016)	km
Distance to the nearest branch road	Coping: response to price fluctuations, diseases, lack of information, *etc*. (Li et al., 2016)	km
Accessibility to urban areas[3]		
Distance to the nearest urban center	Coping: response to diseases, poor education, lack of information, *etc*. (Benson et al., 2005)	km
Distance to the nearest county town [d]	Coping: response to diseases, poor education, lack of information, *etc*. (Benson et al., 2005)	km
Land-use [2] (1 km × 1 km)[c] (in 2010)		
Grassland area (% of land area)	Risk: loss of livestock products caused by climate variability, pests (Okwi et al., 2007)	%
Forest land area (% of land area)	Risk: loss of forest products caused by climate variability, pests (Okwi et al., 2007)	%
Farmland area (% of land area)	Risk: crop failure caused by climate variability, pests, *etc*. (Okwi et al., 2007)	%
Built-up area (occupied by buildings, % of land area)	Coping: more built-up area implies tendencies toward urbanization which is in response to composite risk related to agriculture-based livelihoods (Okwi et al., 2007)	%
Demographic[4] (in 2013)		
Total population	Risk/coping: larger population implies both higher risks of crop failure, epidemic, *etc*. and more reliable recovery from such risks thanks to more social capital, *etc*. (Ward and Kaczan, 2014)	people
Population density	Risk/coping: greater density implies both higher risk of crop failure, epidemic, *etc*. and more reliable recovery from such risks thanks to improved agricultural technologies, more social capital, *etc*. (Benson et al., 2005; Okwi et al., 2007)	people/km^2
Non-agricultural population (% of total population)[b]	Coping: more social capital or job opportunities in response to composite risk related to agriculture-based livelihoods (Erenstein et al., 2010)	%
Employees in the industry, service sectors (% of employees)[a]	Coping: income source diversification in response to a single resource of income from agricultural activities (Benson et al., 2005; Kam et al., 2005)	%
Agricultural[4] (in 2013)		
Irrigated area per capit [a]	Coping: response to drought. (Kam et al., 2005; Palmer-Jones and Sen, 2006)	ha
Grain-sown area (% of total sown area)[a]	Coping: crop and income source diversification in response to crop failure. (Benson et al., 2005; Palmer-Jones and Sen, 2006)	%
Socio-economic[4] (in 2013)		
GDP in primary industry (% of GDP)[b]	Risk: composite risk related to agricultural economy (World Bank, 2009)	%
GDP in secondary industry (% of GDP)[b]	Coping: response to composite risk related to agriculture-based livelihoods (World Bank, 2009)	%
GDP in tertiary industry (% of GDP)[b]	Coping: response to composite risk related to agriculture-based livelihoods (World Bank, 2009)	%
GDP per capita[b]	Coping: response to composite risk related to lagging development (World Bank, 2009)	yuan (RMB)
Village with network broadband (% of total villages)[a]	Coping: response to lack of information. (Ward and Kaczan, 2014)	%

Notes: Data source: [1] Geospatial Data Cloud (2016); [2] Data Center for Resources and Environmental Sciences (2016); [3] Wu (2012); [4] Editorial Board of Gansu Development Yearbook (2014a), Gansu Rural Yearbook Editorial Board (2014b), National Bureau of Statistics of China (2014). [a] No statistical data can be found at the village-level; [b] No statistical data can be found both at both the township- and village-level; [c] The spatial resolution of the data set; [d] Usually, a county town is not an urban area, but it is a county's political, economic and cultural center

2.3 Methods

Since poverty often exhibits the spatial association, Exploratory Spatial Data Analysis (ESDA) is frequently employed to evaluate the spatial autocorrelation of the rural poverty (Moran, 1948; Anselin, 1995; Amarasinghe et al., 2005). The Global Moran's I helps to examine whether the spatial autocorrelation exists over the entire study area, whereas Local Indicators of Spatial Autocorrelation (LISA) can characterize local patterns by identifying the statistically significant hotspots, the coldspots, and the spatial outliers.

The Global Moran's I is defined as follow:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \mu)(x_j - \mu)}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \mu)^2} \quad (1)$$

where x_i and x_j are values of variable x for spatial units i and j, μ is the mean value of x with the total number of n, and w_{ij} is the spatial weight matrix (W) defining the proximity between units i and j. W is usually row standardized for lattice data. As it is argued that the choice of the spatial weights matrix is an important analytical decision but with little formal guidance (Anselin, 2002), we undertook a suggested sensitivity analysis of the results using different weighting schemes for the resultant explanatory power (Benson et al., 2005), namely the largest value of Moran's I. Finally, we used a first-order Queen-based contiguity, which was also proved to be appropriate in the analysis of the areal administrative unit (Palmer-Jones and Sen, 2006). Within the –1 to 1 range, positive values of Moran's I suggest spatial clustering of similar values, whereas negative values suggest that high values tend to be near low values. Being similar to the familiar Pearson's correlation coefficient, Moran's I is comparable among different indicators or spatial scales when the study area is fixed. Thus, a graph, which shows how Moran's I varies as a function of distance or spatial scale, helps to get a sense of the intensity of spatial clustering (Oden, 1984; Legendre and Fortin, 1989; Mitchell, 2005).

LISA has the form as (Anselin, 1995):

$$I_i = \frac{x_i - \mu}{\sigma^2}\sum_{j=1, j\neq i}^{n} w_{ij}(x_j - \mu) \quad (2)$$

where σ^2 is the variance of variable x. When the standard score (z-score) of I_i is higher than the critical value of 1.96, it is concluded at a 95 percent confidence level that the unit is clustered with the surrounding units and can be considered as hotspot (High-High) or coldspots (Low-Low). If the z-score of I_i is lower than –1.96, the unit is significantly different from the surrounding units and can be considered to be a spatial outlier. Then, High-Low (Low-High) indicates a high (low) value surrounding by low (high) values.

In this study, ESDA was conducted, using the spatial data analysis package GeoDa 9.0 (Anselin, 2003), for the two indicators, i.e. PP and HCR. The Empirical Bayes adjustment in GeoDa was used to take account of the variance instability of HCR in the Moran's I statistics.

As for testifying the multilevel relationships between poverty incidence and the selected variables spatially, a bivariate spatial correlation analysis was performed by GeoDa. The bivariate spatial correlation coefficient, bivariate Moran's I (BI), can be regarded as an extension of univariate Global Moran's I. Similarly, BI identifies the extent of neighbor-based correlation of one variable at a location with that of the average neighboring values of the other variable (Anselin et al., 2010). And also, positive (or negative) values of BI suggest spatially positive (or negative) corrections of two variables. Here, the method selection was based on three aspects. Firstly, there are no sufficient cases to model poverty incidence as a function of selected 24 variables at the county-level. Secondly, the scale-dependent relationships between rural poverty and the selected variables could be examined by BI, which is effective due to its standardized values ranging from –1 to 1. Furthermore, the significance of BI can be assessed using a spatial randomization (or permutation) approach (Anselin, 2003; Anselin et al., 2010). Thus, the possibly biased estimation of the usual (non-spatial) correlation between the two spatially autocorrelated variables can be avoided to some extent.

Even so, it is necessary to see if there are any general relationships between poverty incidence and the selected variables at the same location. The reason is that BI will be less helpful in case of the absence of a neighbor-based correlation. Namely, the poverty of a place is attributed to its own reasons more than the contextual ones. Thus, the less-than-optimal Spearman's correlation analysis was considered in addition to the neighbor-based correlation (Sunderlin et al., 2008), when the focus is on whether and how the degree of correlation changed with the spatial scale.

3 Results

3.1 Spatial association of rural poverty at multiple administrative levels

3.1.1 Global spatial autocorrelation

Spatial association of rural poverty over the study area was measured at the county-, township- and village-level by calculating global Moran's I of the two indicators, PP and HCR. As seen in Fig. 3, the positive values of Moran's I (0.215–0.339, 0.270–0.402 for PP and HCR respectively) indicate that rural poverty exhibits statistically significant clustering at all the three levels, with P-value of < 0.05 at the county-level and < 0.01 at the other two levels. The degree of the spatial association is higher at a lower level with a larger value of Moran's I. It can also be noted from Fig. 3 that Moran's I value for HCR is higher than those for PP at the village- and county-level, suggesting that poverty incidence is more likely clustered than poor population at these two levels.

3.1.2 Local spatial autocorrelation

Multilevel LISA cluster maps of the two indicators are shown in Fig. 4, and the statistical characteristics of LISA cluster types are given in Table 2. Obviously, the detected hotspots deserve more attention for policy interventions.

It can be observed (Fig. 4) that there is an obvious spatial mismatch between hotspots detected by either indicator at different levels. That is, most High-High

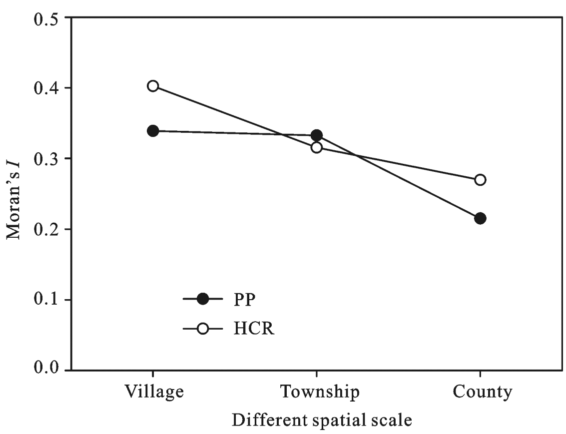

Fig. 3 Comparison of Moran's I coefficients for the indicators at the three levels. PP, poor population; HCR, head-count ratio

units may disappear at a lower level, followed by the emerging sub-units in somewhere else. By comparing Fig. 4a with Fig. 4b, a spatial mismatch can also be found between PP- and HCR-based hotspots at a certain level. This indicates that a hotspot of poor population is not necessarily the same one of poverty incidence. To some extent, this spatial mismatch tends to be improved at the village-level (Fig. 4).

As shown in Table 2, while HCR-based hotspots capture 17.7%, 7.8%, 9.0% of the poor population, the poverty incidence is 22.7%, 16.5%, and 2.3% higher than that of not-significant type (NS) at the village-, township-, and county-level, respectively. In contrast, PP-based hotspots can capture more poor people but have lower poverty incidences.

It should be noted from Table 2 that the NS type covers at least 67.9% of the poor population, and has the similar HCR of around 30% no matter which indicator is used at any level. This suggests most poor people are not significantly clustered despite locally distributed hotspots, and poverty is prevalent throughout the study area from a much broader spatial perspective.

3.2 Factors influencing rural poverty at multiple administrative levels

3.2.1 Non-spatial Spearman's correlation

As shown in Table 3, GDP per capita is most associated with HCR at the county-level, with the greatest significant coefficient of –0.63 ($P < 0.001$). It suggests economic development can, as reported in most cases, be helpful for poverty reduction in a county. The coefficients of built-up area, non-agricultural population, and GDP in secondary industry are significantly negative, suggesting that poverty incidence tends to higher in a less urbanized and industrialized county. By contrast, the positive coefficients of GDP in primary industry (0.45), farmland area (0.37) and grain-sown area (0.35) indicate a positive relationship between poverty and agricultural activities.

At the township-level, some variables start being significantly correlated to the poverty incidence (Table 3). Such variables are mainly distributed in the demography and accessibility. For instance, the coefficient increases from –0.14 to 0.27 for distance to branch road, from 0.00 to 0.21 for distance to county town, and from 0.12 to –0.33 for total population at the township-level. Note that for most variables the values of coefficients at the township-level are not much different from those at the

Table 2 Statistical characteristics of LISA cluster types at the three levels

	Cluster type	Village-level		Township-level		County-level	
		% of poor population (%)	Poverty incidence (%)	% of poor population (%)	Poverty incidence (%)	% of poor population (%)	Poverty incidence (%)
PP-based	NS[1]	71.8	30.0	71.5	28.8	67.9	28.9
	High-High	19.7	40.5	19.2	33.1	26.4	31.1
	Low-Low	4.5	10.4	4.8	20.2	3.0	20.3
	Low-High	1.8	19.3	3.3	24.8	0.0	0.0
	High-Low	2.2	37.0	1.3	33.7	2.7	21.8
HCR-based	NS[1]	72.2	30.7	83.0	30.0	76.5	29.1
	High-High	17.7	53.4	7.8	46.5	9.0	31.4
	Low-Low	7.0	10.4	7.2	15.1	6.1	21.6
	Low-High	1.4	18.2	0.3	13.0	0.0	0.0
	High-Low	1.7	47.5	1.8	43.6	8.5	31.8

Note: [1] Not significant.

village-level, suggesting that the relationships are comparable at these two levels.

3.2.2 Spatial neighbor-based correlation

The significant values of *BI* suggest spatial neighbor-based correlations between poverty incidence and the selected variables at all the three levels (Table 4), even though most coefficients are small. This indicates that the poverty incidence of an administrative unit is related to the neighbors' physical or socio-economic conditions. The number of significant variables increase firstly and then keep stable from high to low level if the unavailable variables are not counted. The new entrants at the township-level are mainly those representing accessibility for the villages. For instance, the coefficients increase from 0.08 to 0.20 (P < 0.001) for distance to expressway, from 0.14 to 0.19 (P < 0.001) for distance to unban center. It is worth noting that some variables are consistently correlated to poverty incidence at all the three levels. Such variables include mean elevation, mean slope, annual temperature and farmland area.

By comparing Table 3 with Table 4, some neighbor-based coefficients differ significantly from the Spearman's ones at the county-level. For instance, the values of *BI* for built-up area, non-agricultural population, and GDP per capita are 0.02, 0.02, and –0.15 respectively. These coefficients are either non-significant or much smaller than the corresponding Spearman's ones. This suggests that the level of urbanization and economic development in a county may be of little benefit to poverty reduction in the neighboring counties. By contrast, such differences are not remarkable for variables representing physical conditions (i.e., altitude, gradient, temperature, and rainfall).

4 Discussion

4.1 Characterizing multilevel patterns of rural poverty: which indicator works better?

PP and HCR are two of the traditional and popular indicators measuring poverty (Ravallion and Wodon, 1999; World Bank, 2000; Amarasinghe et al., 2005; Holt, 2007). Based on household income and expenditure surveys, those two indicators enable to obtain a broader picture of well-being in a place. That is, PP can tell us the size of poor population while HCR can show the incidence of poverty. However, it is a dilemma for policymakers that which indicator is better for area-based poverty targeting: focusing on places with larger poor population or places with higher incidence of poverty (Ravallion and Wodon, 1999; Partridge and Rickman, 2008; Park and Wang, 2010).

In this study, PP and HCR were used to characterize the multilevel patterns of rural poverty. As a result, larger values of Moran's I at the village-level (Fig. 3) can be observed as 0.402 for HCR but 0.339 for PP, indicating that the poor population tends to be less spatially associated than poverty incidence. Further, HCR-based hotspots can locate villages with higher poverty incidence while a similar poor population is targeted (Table 2). In this context, it seems that HCR is more efficient to characterize village-level pattern of rural poverty by taking account of targeting efficiency. Thus, our finding supports the practice that HCR is usually employed in studying spatial dimension of poverty (Cattell, 2001; Bird et al., 2010; Erenstein et al., 2010), and targeting the poor areas (Park and Wang, 2010; Olivia et al., 2011).

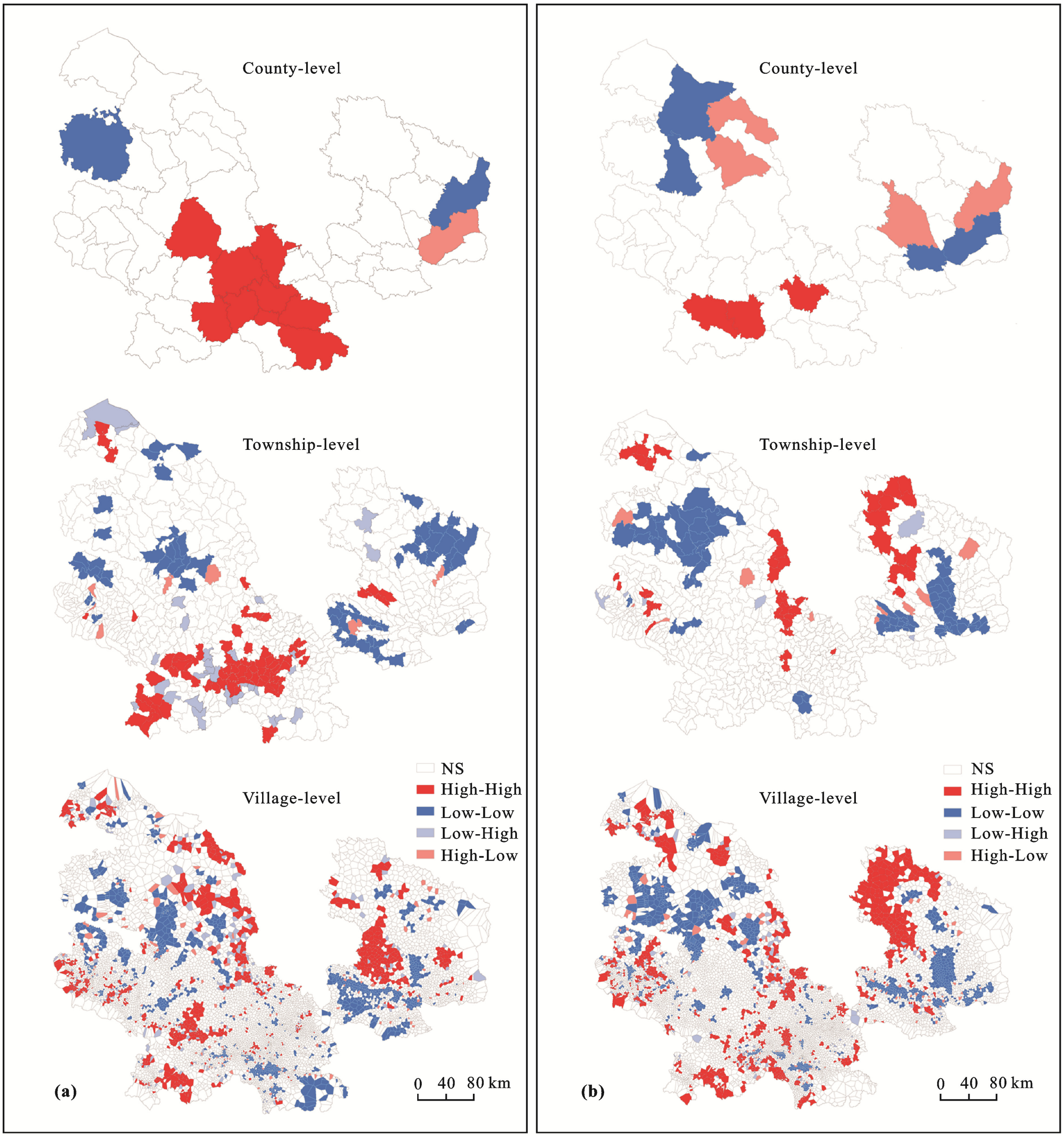

Fig. 4 Local Moran cluster maps for PP (a) and HCR (b) at the three levels. NS, not significant

However, there is a spatial mismatch between hotspots of poor people and those of poverty incidence (Fig. 4). This indicates if the hotspots detected by HCR are targeted and given support, there must be some hotspots, detected by PP with a greater number of poor people, being left out in consideration of limited anti-poverty resources (i.e., government funds and financial aids). For instance, the number of poor people living in overlapping hotspots (namely, located by both HCR and PP) is 37.0%, 7.4% and 27.7% of that in PP-based hotspots at the village-, township- and county-level, respectively. Since similar phenomena have been observed in other places or countries (Minot and Baulch, 2005; World Bank, 2009), policymakers should be more careful with this mismatch. For the study area, the current village-based targeting would be to some extent a better choice in reducing the spatial mismatches.

4.2 Characterizing multilevel patterns of rural poverty: does the scale effect exist?

The scale effect, a key theme in geographical studies such as how the observed patterns vary with the spatial

Table 3 Spearman's correlation coefficient between HCR and the selected variables at different administrative levels

Variable	Administrative levels			Variable	Administrative level		
	County (n=46)	Township (n=711)	Village (n=9684)		County (n=46)	Township (n=711)	Village (n=9684)
Topographical				Farm land area	0.37*	0.14***	0.09***
Mean elevation	0.32*	0.32***	0.25***	Built-up area	–0.48**	–0.52***	–0.34***
Mean slope	0.32*	0.34***	0.35***	Demographic			
Agro-climatic				Total population	0.12	–0.33***	–0.32***
Annual temperature	–0.33*	–0.29***	–0.23***	Population density	0.12	–0.22***	–0.40***
Annual rainfall	0.15	–0.08*	0.01	Non-agricultural population	–0.45**	–	–
Accessibility to roads				Employees in industry, service sectors	–0.33*	–0.14***	–
Distance to expressway	0.44**	0.29***	0.22***	Agricultural			
Distance to main road	0.21	0.31***	0.25***	Irrigated area per capita	–0.36*	–0.06	–
Distance to branch road	–0.14	0.27***	0.24***	Grain-sown area	0.35*	0.04	–
Accessibility to urban areas				Socio-economic			
Distance to urban center	0.35*	0.22***	0.17***	GDP in primary industry	0.45**	–	–
Distance to county town	0	0.21***	0.15***	GDP in secondary industry	–0.40*	–	–
Land-use				GDP in tertiary industry	0.21	–	–
Grass land area	0.02	0.04	0.03**	GDP per capita	–0.63***	–	–
Forest land area	0.11	0.02	0.08***	Village with network broadband	–0.32*	–0.08*	–

Note: ***, significant at 1‰; **, significant at 1%; *, significant at 5%; –, there is no data for such variables

Table 4 *BI* between HCR and the selected variables at different administrative levels

Variables	Administrative levels			Variables	Administrative levels		
	County (n=46)	Township (n=711)	Village (n=9684)		County (n=46)	Township (n=711)	Village (n=9684)
Topographical				Farm land area	0.30***	0.13***	0.07***
Mean elevation	0.31***	0.20***	0.22***	Built-up area	0.02	–0.11***	–0.18***
Mean slope	0.25**	0.16***	0.26***	Demographic			
Agro-climatic				Total population	0.05	–0.10***	–0.19***
Annual temperature	–0.30***	–0.21***	–0.21***	Population density	0.15*	–0.05**	–0.13***
Annual rainfall	0.11	0.00	0.02*	Non-agricultural population	0.02	–	–
Accessibility to roads				Employees in industry, service sectors	0.07	–0.06**	–
Distance to expressway	0.08	0.20***	0.18***	Agricultural			
Distance to main road	0.03	0.12***	0.19***	Irrigated area per capita	–0.27**	0.00	–
Distance to branch road	–0.12	0.05**	0.15***	Grain-sown area	0.19*	0.04*	–
Accessibility to urban areas				Socio-economic			
Distance to urban center	0.14	0.19***	0.17***	GDP in primary industry	0.13	–	–
Distance to county town	–0.11	0.13***	0.15***	GDP in secondary industry	–0.19*	–	–
Land-use				GDP in tertiary industry	0.17*	–	–
Grass land area	0.05	–0.01	0.00	GDP per capita	–0.15*	–	–
Forest land area	–0.07	–0.01	0.07***	Village with network broadband	–0.10	–0.05**	–

Note: ***, significant at 1‰; **, significant at 1%; *, significant at 5%; –, there is no data for such variables

scale, should not be absent in describing the spatial heterogeneity of rural poverty. This is because the identification of scale-dependent patterns could help understand multi-scale nature of spatially heterogeneous poverty (i.e., the interacting effects of underlying and complex processes) (Pijanowski et al., 2010). A change of scale may indicate a change in grain (the spatial resolution or unit of a map), a change in extent (the map size), or both (Wu, 2004). Our study focuses on the first one by examining the variation of spatial autocorrelation (indicated by global Moran's I and local Moran cluster map) at three administrative levels, namely spatial grain or unit.

Spatial patterns of rural poverty do change with the administrative level. Taking HCR for example, we found a smaller value of global Moran's I at a higher level (Fig. 3). Moreover, Moran's I value exhibits a bigger decrease from the village- to township-level. As shown in Fig. 4 also, the hotspots detected at different levels do not necessarily coincide spatially. Therefore, spatial analysis of poverty pattern at a single scale may provide incomplete, or even misleading information. Since most current studies are conducted at a single scale (Benson et al., 2005; Minot et al., 2006; Curtis et al., 2012; Epprecht et al., 2011), an examination of scale effects, whenever feasible, is desirable. Given such scale effects, careful attention should be paid to the area-based policy interventions.

For the study area, if HCR-based hot-spots are targeted for helping the poorest areas, a greater poverty incidence appears at a lower level (31.4%, 46.5% and 53.4% at the county-, township- and village-level, respectively in Table 2). This indicates the poor may benefit more from area-based policies by targeting smaller administrative units. Such policies can be local roads, irrigation systems and so on, which are likely to be inherent attributes of a poor area that foster poverty. The attendant benefit will be budgetary savings since there will always be limited anti-poverty funding.

4.3 Detecting multilevel factors influencing rural poverty: what are the implications?

An increasing number of studies have shown that of all dimensions of rural poverty, spatial dimension should not be ignored since the poor are inextricably linked with place or space (Bloom et al., 2003; Palmer-Jones and Sen, 2006; Annim et al., 2012; Curtis et al., 2012; Amara and Ayadi, 2013; Donohue and Biggs, 2015). For instance, every country has poor areas at all times, even spatial poverty traps where poverty prevails persistently (Bird et al., 2010; Burke and Jayne, 2010). In other words, poverty always shows spatial heterogeneity, which can result from interactions among a variety of physical, ecological, and socio-economic determinants (Kam et al., 2005; Voss et al., 2006; Rupasingha and Goetzb, 2007; Epprecht et al., 2011). Such interactions cannot be understood well without addressing the effects of changing scale on the factors influencing rural poverty, the ultimate aim of which is the policy implications.

From both non-spatial and spatial perspectives, we observe an increasing number of variables which are significantly ($P < 0.05$) associated with HCR at a lower level, when the unavailable variables are not counted (Tables 3–4). This suggests that the incidence of poverty at a lower level is likely to result from more complex factors, each of which may play a major role in some places, but less important or even unimportant in other places (namely the site-dependent effect). This supports a common view of spatially varying determinants of poverty as reported by Okwi et al. (2007) from Kenya, Amara and Ayadi (2013) from Tunisia, Annim et al. (2012) from Ghana and Farrow et al. (2005) from Ecuador. Alternatively, perhaps, some factors come into play directly or indirectly at a lower level. For instance, distance to the main road, distance to county town and total population begin to work at the township-level.

Therefore, from a perspective of landscape ecology, a scale effect can be found in the factors influencing rural poverty. That is, for instance, poverty incidence of a township or village is affected no only by local factors but also by non-local conditions. The local ones can be the village's remoteness and low population, which do not help to get good provision of government services and infrastructure (Bird and Shepherd, 2003), or reduce the likelihood of producers engaging with non-local markets. The non-local ones can be GDP per capita, or the non-agricultural population at the county-level, which are more associated with economic growth, or urbanization.

Note that the variables representing physical conditions (i.e., mean elevation, mean slope, and annual temperature) are consistently correlated to poverty incidence at all the three levels, no matter what kind of correlation coefficients (namely Spearman or BI) is used. This suggests that the natural environment tends to play a scale-independent role to poverty incidence in the study area.

The spatial relationships detected by BI can offer a neighbor-related perspective on spatial poverty trap.

That is, the spatially auto-correlated poverty may due to the combined effect of the grouping responses to the contextual physical forces (i.e., harsh topography) and the socio-economic interactions (i.e., geographical spillovers), since most significant values of BI suggest general neighbor-based correlations. In this sense, the county-level is worthy of more attention. For a county, the impact of the contextual physical forces on poverty incidence is weaker than that of its own levels of urbanization and economic development, but greater than that of the neighbor-related socio-economic interactions (Tables 3–4). This is consistent with the widespread perception that a county is a basic unit for social bonds and economic activities in China. Thus, enhancing the socio-economic interactions among the counties may be an effective way for the study area to escape the spatial poverty trap.

All the above findings have at least three policy implications. First, it will be more difficult for the central or provincial government to estimate poverty and to make policy at the lower levels because both of site-dependent and neighbor-related factors. For instance, the difficulties will be how to allocate the anti-poverty funding to local governments, or the mismatch between the top-down unified policy and the place- specific demands. To address those challenges, a multilevel monitoring system should be developed to reduce the information asymmetry. What's more, there is a need to develop more flexible antipoverty strategies in response to the locally impoverishing factors. Such strategies include more market-oriented interventions (Bird et al., 2002), decentralization of power to local governments (Park and Wang, 2010), the demand-driven participatory approaches (Francis and James, 2003) and so on. It should be noted that to what extent these strategies work depends on the degree of collaboration between different levels of governments and between governments of different places. On the one hand, the spatial mismatch between multilevel hotspots (Fig. 4) would bring out the conflict of interests. Namely, multilevel hotspots suggest different targeting schemes, then different allocations of anti-poverty resources, and finally different benefits for local governments in the current assessment system for government performances. On the other hand, a cross-regional hotspot may require joint efforts of neighboring townships or counties because the factors were spatially associated, but it is more likely to subject to a different understanding on when and how to response to these factors from their own perspective.

Second, different levels of government should not only share a common goal but also put a different emphasis on their tasks because of the scale-dependent relationships between poverty incidence and the factors. Generally speaking, the province- and prefecture-level governments should be focused on the global socio-economic development, since a lower incidence of poverty can be easily found in a county with higher GDP per capita (economic growth), higher proportion of the non-agricultural population (urbanization), or less GDP in primary industry (industrialization). The county-level government can be committed to both the socio-economic development and the improvement of accessibility for the villages. By contrast, given the relatively similar performance of factors, the township-level government and village-level organization may help the poor to escape poverty principally by overcoming the innate disadvantages (i.e., harsh environment). The possible ways include the out-migrating to well-endowed areas (Bird and Shepherd, 2003; Liu and Li, 2017) or making the profits through exploiting the distinctive features. In this sense, the scale-dependent strategy not only accords with but also supplements The World Bank's framework for regional development and anti-poverty policies (World Bank, 2009). That is, for the study area, Gansu province and the prefectures should pay more attention to develop spatially blind institutions (i.e., regulations influencing land and labor, universal education and health programs) to facilitate economic density. Thus, the increase of non-agricultural job opportunities and the poor's ability to work can be more helpful in consideration of the spatially non-clustered poor population (at least 67.9%). With the decentralized power, the counties can do more on the improvement in spatially connective infrastructures (i.e., roads, communication facilities) to help the poor hunting for jobs and services more easily in the cities and towns. With the more accurate information about the fostering-poverty factors, the townships and villages can devote to the bottom-up spatially targeted incentives (i.e., irrigation systems, out-migration, or rural tourism).

Third, the spatial sampling method should be employed in China's current third-party assessment of local government's performance in poverty alleviation. At present, because of its professionalism, objectivity, and impartiality, the third-party assessment is utilized to estimate if a county has escaped poverty and can be no longer targeted (Li et al., 2016; Liu et al., 2016). Usually, a certain number of villages are selected using the classical (non-spatial) sampling methods (i.e. systematic sampling, random sampling), which can bring about biased estimation considering the neighbor-related relationship between poverty and its underlying factors. For instance, if the spatially clustered villages suffering from the same constraints (i.e. poor soils, water shortage) are not selected, the assessors will not clearly know if this area has moved out of poverty by taking effective measures. Therefore, the non-uniform spatial sampling will be more suitable, only after a careful investigation of the spatial pattern of poverty and its affecting factors have been done.

4.4 Limitations

There are some limitations to be considered when interpreting the findings of our study. Firstly, the spatial pattern of poverty depends not only on the spatial scale as observed in this work but also on the type of geographic division to some extent (Imran et al., 2014). Meanwhile, as the poverty in rural areas is strongly related to the natural factors (Bird and Shepherd, 2003; Xu et al., 2006; Epprecht et al., 2011; Imran et al., 2014), we can not claim that our analysis, based on administrative divisions, are fully exhaustive. Nevertheless, this work helps a lot for local governments to get a good understanding from a policy-oriented perspective. Secondly, the contribution of this work is mainly to identify the possible factors that explain the variation in aggregate poverty across the study area at different spatial levels. However, to better understand how the factors contribute to spatial pattern of rural poverty, panel data will be more helpful than cross-sectional data as it can offer dynamic imformations. Actually, the current poverty status itself is a result of multi-scale spatio-temporal process (i.e., raifall, soil erosion, economic collapse). In this work, the introduction of the risk chain framework helps to offer a dynamic perspective, of course, but it is not enough. Lastly, the common problem of correlation analysis can not be unavoidable. That is, the correlation relationships between the variables and rural poverty do not necessarily reflect the causal relationships. For the purposes of developing more targeted policies, the exploring of causal relationships from cross-level and integrated perspectives will be more helpful in future.

5 Conclusions

In this paper, we mainly assessed the effects of spatial scale (namely administrative level) on the spatial patterns and influencing factors of rural poverty in the Liupan Mountain Region, Gansu province, China. The results showed that from a global perspective, rural poverty exhibits significant spatial clustering at the county-, township-, and village-level, and the degree of the spatial association is more likely higher at a lower level. Locally, multilevel LISA cluster maps indicated that there is a spatial mismatch among poverty hotspots detected by the same indicator at different levels. A spatial mismatch can also be found among poverty hotspots detected by different indicator at a certain level, and such spatial mismatch tends to be alleviated at the village-level. A scale-effect can be found in the factors of rural poverty. That is, an increased number of variables but a decreased degree of correlation can be observed at a lower level. However, the natural conditions tend to play a scale-independent role in poverty incidence in the study area.

Besides, some feasible policies are suggested for the study area. The current village-based targeting strategy is a better choice in increasing the targeting efficiency and reducing the spatial mismatch. If possible, a multilevel monitoring system should be developed to reduce incomplete or even misleading single-level information and understanding. More flexible antipoverty strategies, such as market-oriented interventions, local decentralizations, and participatory approaches are needed in response to the locally and spatially associated impoverishing factors. Policy drafted by different levels of policymakers should emphasize on the different perspectives: 1) the province-, prefecture-level spatially blind institutions to facilitate economic density for the purpose of creating the non-agricultural job opportunities and enhancing the poor's ability to work; 2) the county-level spatially connective infrastructures to improve the accessibility for the villages; 3) the township-, village-level spatially targeted incentives to overcome the harsh environment or to explore the distinctive features. Lastly, the spatial sampling method should be employed in China's current third-party assessment of local government's performance in poverty alleviation.

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