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What factors affect sustainable poverty reduction capacity in the Alpine-Gorge regions? Evidence from China

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Abstract
The COVID-19 pandemic has exacerbated the number of individuals who have reverted to poverty globally, underscoring the significant influence of sudden external disturbances on the global poverty reduction process. Nevertheless, the risk of reversion to poverty has often been overlooked in regions grappling with persistent internal challenges and insufficient capacity for sustainable poverty reduction. Consequently, this study utilized Lushui City, a representative alpine-gorge region in China, as a case study. It selected three pivotal time points in China's poverty reduction timeline (2000, 2010, and 2019) and integrated multi-source geospatial data to establish a regional sustainable poverty reduction capacity (SPRC) evaluation index system. Subsequently, the study employed a backpropagation artificial neural network to assess the SPRC of each village in Lushui City, thereby revealing its spatiotemporal evolution characteristics. By analyzing the lag characteristics of SPRC across various dimensions, the study further categorized the lag types of different villages. Finally, the random forest and multi-scale geographically weighted regression models were utilized to investigate the dominant factors influencing SPRC in Lushui City across different stages and the spatial heterogeneity of their impacts. The findings indicated that: (1) Throughout the study period, Lushui City encountered substantial challenges in achieving sustainable poverty reduction, although implementing poverty reduction initiatives had bolstered its economic sustainable poverty reduction capacity and social sustainable poverty reduction capacity. (2) Some villages in Lushui City exhibited multidimensional lag in their SPRC, necessitating comprehensive measures to achieve regional sustainable poverty reduction. (3) In 2000 and 2010, the primary factors influencing SPRC in Lushui City were environmental (soil erosion amount and precipitation) and social (distance to the nature reserve). However, with the advancement of regional poverty reduction efforts, the main influencing factors in 2019 shifted to economic (land-use mixed degree, density of tourist spots) and social (village agglomeration degree), thereby mitigating the adverse effects of environmental factors on regional SPRC. (4) Most environmental and economic factors exerted a nearly universal impact on SPRC. In contrast, social factors (distance to the main road) exhibited considerable spatial heterogeneity and a limited impact range, with their influence diminishing rapidly beyond a certain threshold. Therefore, enhancing the relevance of social assistance measures and broadening their implementation scope was

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essential. The recommendations derived from these findings help to provide successful experiences from China for poverty reduction in other alpine-gorge regions.

Keywords Sustainable poverty reduction capacity · Influencing factors · Backpropagation artificial neural network · Random forest · Multi-scale geographically weighted regression · Alpine-gorge region

1 Introduction

To achieve global sustainable development, the United Nations proposed 17 sustainable development goals (SDGs) in 2015 (United Nations, 2015). In recent years, emergencies such as extreme climate change, earthquakes, droughts, and the COVID-19 pandemic have significantly impacted regional economies (Arslan et al., 2021; Cetin et al., 2024; Varol et al., 2023), thereby hindering the overall progress toward sustainability (Yin et al., 2023). As the primary objective of the SDGs, poverty eradication has faced severe setbacks; the outbreak of the COVID-19 pandemic has forced over 90 million people into extreme poverty, marking the first increase in the global poverty rate in decades (Leal Filho et al., 2023) and drawing considerable scholarly attention (Bukari et al., 2022; Burlina & Rodriguez-Pose, 2024; Luo et al., 2020). From the perspective of regional development conditions, the predominant cause of regional poverty is the prolonged constraints imposed by multiple chronic pressures, resulting in insufficient endogenous development momentum (Zhou & Liu, 2022). For instance, alpine-gorge regions have long endured chronic stresses, such as ecological fragility and inadequate geographical capital, and have been identified as high-incidence poverty zones with a significant risk of reverting to poverty (Chen et al., 2023). Consequently, under the dual challenges of external uncertainty shocks and internal chronic stress, the sustainable development of impoverished areas remains a considerable global challenge, necessitating sustainable poverty reduction models to address poverty issues and achieve regional sustainable development effectively (Ge et al., 2023).

China was once one of the countries with the most prominent poverty problem in the world. As of 2020, it successfully eradicated absolute poverty, significantly contributing to global poverty reduction efforts (Li et al., 2019). This achievement can be attributed to the government's strong commitment and strategic policy guidance (Gao et al., 2019). The "eight-seven" Poverty Reduction Plan, launched in 1994, marked China's first initiative with explicit objectives and timelines, aiming to address the basic needs of 80 million impoverished individuals within seven years. During this phase, credit support facilitated low-interest loans to enterprises and households in impoverished regions, thereby stimulating production activities. Concurrently, government fiscal appropriations funded the construction of agricultural and transportation infrastructure, with residents comprising the primary labor force, enhancing production capabilities and creating employment opportunities (Meng, 2013). After 2000, China transitioned into a development-oriented poverty reduction phase, focusing primarily on improving the living standards of the impoverished. As poverty levels declined, the number and percentage of impoverished individuals in rural counties fell sharply, leading to a shift in the fundamental unit of poverty reduction efforts from counties to villages (Guo et al., 2022). In response to the evolving economic structure, the government implemented a labor transfer training strategy designed to elevate the skill levels of the labor force in impoverished areas, facilitating their transition to other economic sectors. Additionally, measures such as the reduction and exemption of agricultural

taxes, as well as incentives for enterprises to establish operations in these regions, were enacted to bolster agricultural market development (Fang & Zhang, 2021). To enhance the targeting of poverty reduction initiatives, in 2011, the Chinese government identified 14 contiguous impoverished areas characterized by harsh natural environments, fragile ecologies, complex terrains, and substantial poverty reduction challenges (Yin et al., 2022). Subsequently, in 2013, a targeted poverty reduction strategy was introduced at the macro policy level, which shifted the focus from villages to households, implementing five core measures: industrial poverty reduction, relocation and resettlement, ecological compensation, educational support, and the enhancement of the social security system (Zhou et al., 2018). In light of the declining absolute poverty population and to further reinforce the sustainability of development in impoverished areas, the Chinese government introduced a rural revitalization strategy in 2018 (Cai et al., 2024). Unlike the objectives of the previous poverty reduction phase, this strategy emphasizes the promotion of regional industrial, cultural, and talent development to invigorate the growth potential of underdeveloped rural areas and establish a long-term framework to mitigate relative poverty (Liu et al., 2020). Currently, China is transitioning from poverty reduction to comprehensive rural revitalization, with the focus shifting from eradicating absolute poverty to alleviating relative poverty. However, due to the multifaceted nature of poverty-inducing factors and the diminishing effectiveness of poverty reduction measures, there remains a considerable risk of relapsing into poverty in areas that have previously been lifted out of it. Thus, exploring sustainable pathways for poverty reduction and consolidating the achievements of poverty reduction initiatives have emerged as critical challenges in this phase (Liu et al., 2024).

The alpine-gorge region was once characterized by severe poverty during China's poverty reduction phase. Unlike plains, hills, and other topographical areas, it faces significant challenges in transportation development and infrastructure construction. The region is also prone to geological disasters, has limited arable land, and is geographically remote (Gu et al., 2023). These factors have hindered the development of livelihood resources, exacerbated labor outflow, and led to population hollowing. As a result, the region's capacity for self-development has been weakened (Pan et al., 2018). Furthermore, the alpine-gorge region faces a dichotomy between ecological protection and food security. Implementing a large-scale vegetation restoration plan has resulted in substantial losses of arable land resources (Zeng et al., 2022). The Chinese government has proposed two main strategies to address these challenges: relocation and ecological compensation. The relocation initiative aims to concentrate the impoverished population in nearby areas with better living conditions while also enhancing the infrastructure of the resettlement areas and transforming the livelihoods of relocated households to facilitate regional poverty reduction (Feng et al., 2024). On the other hand, ecological compensation provides cash payments to residents as the primary compensation for rights and interests sacrificed due to ecological protection efforts (Ju et al., 2022). However, the compensation amounts are limited and may not adequately cover residents' opportunity costs, constraining the region's sustainable development potential (Le & Leshan, 2020). Additionally, the low educational attainment of residents hampers their ability to effectively utilize compensation funds, exacerbating the limitations of this measure. In summary, the alpine-gorge region highly depends on external support in its poverty reduction efforts, rendering its regional poverty dynamics particularly unstable. This instability is further compounded by increasing risks from external disturbances. For instance, the risks associated with COVID-19 primarily arise from its direct impact on residents' health and indirect effects resulting from isolation, supply chain disruptions, and other factors (Ge et al., 2022). Insufficient medical services and a limited industrial structure contribute to the fragility of the economic system in the alpine-gorge region (Cui et al., 2023). Indirect effects such as regional isolation and supply chain

interruptions may expose residents to multiple risks, including food shortages and disrupted economic support (Liu et al., 2021a; Zeng et al., 2022). Therefore, exploring sustainable pathways for poverty reduction in alpine-gorge regions is crucial for consolidating the results of poverty reduction initiatives.

In conclusion, achieving the global goal of poverty eradication poses a significant challenge under the dual influences of external uncertainty shocks and internal chronic pressures. Although China has successfully eradicated absolute poverty, poverty reduction efforts in the alpine-gorge region remain overly reliant on external support. The region's challenging terrain and inadequate infrastructure have further hindered endogenous development momentum, resulting in unstable poverty reduction outcomes. Furthermore, as development goals shift and external risks increase, existing poverty reduction measures are inadequate to meet the region's sustainable development needs. Consequently, exploring sustainable poverty reduction pathways and formulating new development strategies have become pressing issues necessitating immediate attention. This study focuses on Lushui City, a representative alpine-gorge region in southwest China, to examine the changing characteristics of the main factors influencing its regional SPRC at three critical time points: 2000, 2010, and 2019. The specific research objectives are as follows: (1) Developing a multidimensional indicator system for evaluating SPRC in alpine-gorge regions. (2) Classifying the SPRC lag types of different administrative villages. (3) Exploring the main factors influencing SPRC at the village level in Lushui City at different stages. (4) Analyzing the spatial heterogeneity of the effects of the main influencing factors on SPRC.

To achieve the above research objectives, this study combined various advanced methods to improve the accuracy and reliability of the analysis. First, we introduced the BPANN to evaluate the SPRC, addressing the nonlinear relationships between indicators often overlooked in traditional evaluation methods. This approach ensures a more accurate evaluation of the regional SPRC by considering these complexities. Secondly, in exploring the main influencing factors of SPRC, we introduced the RF model to identify the main factors with more significant influence. This method performs better than other machine learning methods in identifying the importance of factors. It can also consider the nonlinear effects between variables, making up for the defect that the BPANN cannot reflect the specific impact of a certain indicator on the output results simply by relying on the weights in the network. In addition, based on identifying the main influencing factors, we introduced the MGWR model to explore the local effects of the main influencing factors in space to more accurately guide the allocation of poverty reduction resources. Compared with traditional local regression models such as geographically weighted regression (GWR), this method eliminates the limitation of the same bandwidth, allows the relationship between the dependent and independent variables to change at different scales, and can more accurately reflect the local impact effects of different influencing factors at different spatial scales.

Overall, this research provides scientific insights for China to explore sustainable poverty reduction paths in mountainous and canyon areas in the post-poverty era and offers valuable information for poverty reduction efforts in other alpine-gorge regions worldwide.

2 Literature review

Poverty has consistently posed a significant challenge to the advancement of human society. Initially, it was conceptualized as an economic phenomenon, defined by the inability of individuals or families to meet their basic needs due to insufficient income (Zhou & Liu,

2022). At this stage, the income-based poverty line was the primary method for identifying poverty, prompting extensive scholarly discussions regarding its standards and validity (Ayala et al., 2014; Kakwani & Son, 2016; Sarkar & Pal, 2018). With the deepening of research, scholars recognized that the concept of poverty must encompass not only economic deprivation but also social exclusion, limited opportunities, and inadequate public services (Liu & Xu, 2016). Consequently, poverty identification has evolved from a singular economic perspective to a multidimensional framework that includes income, education, health, environmental conditions, and geographical context. The primary approach involves selecting indicators from these various dimensions to calculate a comprehensive multidimensional poverty index (Alkire & Foster, 2011). However, the challenge of obtaining household and village-level data has led existing research to focus predominantly on larger spatial units, such as states, provinces, and cities. For instance, Dhongde and Haveman (2022) examined the spatiotemporal evolution of multidimensional poverty in states in the United States from 2008 to 2019, finding that implementing health insurance and higher education policies contributed to poverty reduction. Qi et al. (2022) computed the multidimensional poverty index across six dimensions, including education, income, and healthcare, revealing the dynamic evolution of multidimensional poverty disparities among provinces in China. However, studies conducted at large spatial scales have, to some extent, masked the spatial heterogeneity of poverty characteristics within regions. Kim et al. (2016) demonstrated in their analysis of poverty in India that both village and state scales are critical for accurately depicting the geographical patterns of poverty distribution, with village-level analyses better reflecting intra-state heterogeneity and the effects of poverty reduction programs. Therefore, to reduce poverty and promote balanced regional development, it remains essential to focus more on micro-spatial scales, such as communities and villages.

To enhance the relevance of poverty governance, several scholars have employed methodologies such as spatial superposition (Zhou et al., 2020), multi-objective spatial decision-making (Dou et al., 2022), and K-means clustering (Wu et al., 2022) to comprehensively analyze the multidimensional characteristics of poverty in different regions and categorize various types of poverty, thereby informing the formulation of differentiated poverty reduction policies. Furthermore, to identify the primary factors constraining the development of various types of poverty-stricken areas, recent studies have employed least squares regression models (Zhang et al., 2023), multilevel logistic regression models (Tran et al., 2022), and geographic detectors (Liang et al., 2022). Recognizing the spatial heterogeneity of these factors, some researchers have further introduced the GWR model to examine the localized impact characteristics of different influences (Zhu et al., 2022). For instance, Wang et al. (2021) selected potential factors affecting poverty in Yanbian Korean Autonomous Prefecture, Jilin Province, from natural environment, facility accessibility, and other factors, using geographic detectors and GWR models to analyze both the impact of these factors and their spatial heterogeneity. However, the geographically weighted regression model operates under the assumption that the influence of all variables is consistent across the same spatial scale (Brunsdon et al., 1996), which may result in distorted findings in the analysis of spatial heterogeneity across multiple factors, as different influencing factors exhibit varying ranges of impact in regional poverty governance and existing research on regional poverty has yet to adequately focus this issue.

As poverty reduction efforts progress, certain regions have successfully eradicated absolute poverty. However, the escalating risk of external disturbances has exacerbated the vulnerability of impoverished areas (Liu et al., 2024). To consolidate the achievements of poverty reduction and prevent widespread relapse, there has been an increasing number of

studies focused on measuring poverty relapse risk (Ge et al., 2022; Wang et al., 2023) and identifying the influencing factors contributing to poverty relapse (Chen et al., 2023; Cui et al., 2024). It is important to note that the human-land relationship within these regions is dynamic. With the evolving nature of the human-land conflict in impoverished areas and the diminishing effectiveness of previously implemented poverty reduction measures, these regions may encounter new risks of returning to poverty. Therefore, enhancing the SPRC and decreasing reliance on external support has become crucial for achieving sustainable development in poverty-stricken areas (Guo & Liu, 2022; Liu et al., 2024). Currently, research on sustainable poverty reduction emphasizes the capacity building for individuals emerging from poverty (Zhai et al., 2022), the enhancement of sustainable livelihood resilience (Sun et al., 2023), and the evaluation of poverty reduction strategies in promoting sustainable practices (Ipinnaiye & Olaniyan, 2023; Lan et al., 2024). Nonetheless, a gap remains in considering regional characteristics within sustainable poverty reduction research. Given that poverty is a regional phenomenon exhibiting pronounced spatial heterogeneity, insufficient attention to regional characteristics has been shown to negatively impact decision-making processes related to poverty reduction (Bernini et al., 2023).

In summary, relative to existing studies, this research contributes in two aspects: (1) Utilizing a geographical regional perspective, this study examines Lushui City, a representative high alpine-gorge region, to identify the primary factors influencing the SPRC at the village level. This approach addresses the limitations of current studies on sustainable poverty reduction that inadequately consider regional characteristics, thereby providing valuable insights for understanding SPRC from a regional context. (2) The integration of MGWR into sustainable poverty reduction research enhances the optimization of spatial bandwidth configurations for influencing factors when analyzing the spatial heterogeneity of influencing factors to more accurately reveal the differences in their local effects.

3 Materials and methods

3.1 Study area

Lushui City, situated in Nujiang Prefecture's southern part of Yunnan Province, China, at 98°34′~99°08′E,25°33′~26°32′N (Fig. 1). It encompasses 3203.04 km^2 of land, consisting of six towns, three townships, and 71 villages. The city exhibits alpine-gorge landforms with towering mountains, steep valleys, and the Nujiang River cutting through them. Biluo Snow Mountain and Gaoligong Mountain are located within its territory. The city has scarce flat land, and most cultivated land has a slope exceeding 25°. Most of its land belongs to the core area of the "Three Parallel Rivers" World Natural Heritage and the Gaoligong Mountain National Nature Reserve. It has a high forest coverage rate of 67.7% and rich biological, mineral, and tourism resources. The Lisu ethnic group predominates the city's population, accounting for 55.6%.

Due to its challenging terrain, Lushui City experiences significant difficulties in infrastructure development and resource utilization, resulting in severe poverty. Since 1994, it has been designated a national poverty-stricken county, and in 2011, it was recognized as one of China's 14 contiguous impoverished areas. Before implementing the targeted poverty reduction strategy in 2013, the city's inadequate food self-sufficiency and insufficient road infrastructure severely limited material exchange with surrounding regions. During this period, Lushui primarily relied on government funding to address residents' basic

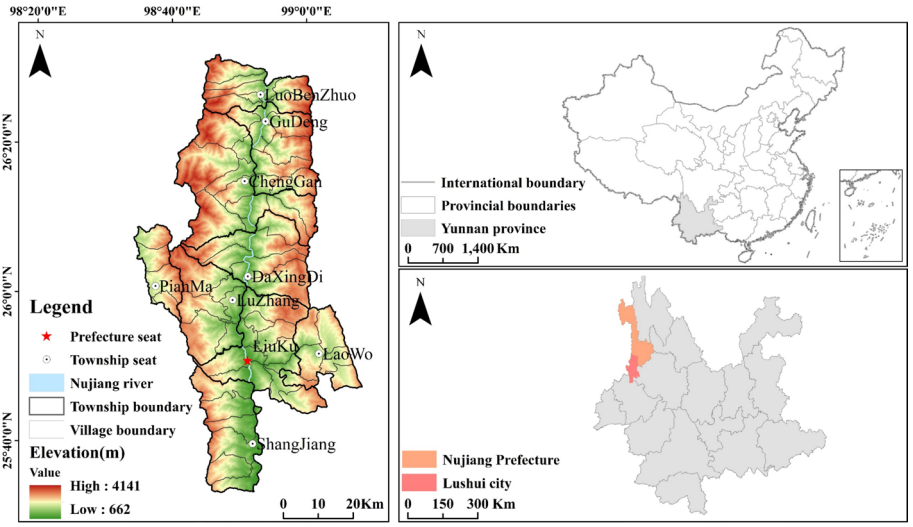


Fig. 1 The study area

needs, including food, clothing, and road construction. By the end of 2012, the poverty incidence rate remained high at 39.2%, significantly exceeding the national average of 10.2% for the same period. After 2013, the implementation of the relocation strategy enabled the relocation of nearly 30,000 impoverished residents to resettlement sites with improved living conditions, thereby significantly contributing to the city's poverty reduction efforts. By 2019, the poverty incidence rate had decreased to 11.97%. However, the outbreak of COVID-19 led to challenges such as limited employment opportunities for impoverished households, difficulties in transporting agricultural products, a decline in tourist numbers, and the suspension of poverty reduction projects, all of which adversely affected progress in poverty reduction. In response, the Chinese government prioritized allocating poverty reduction funds to ensure the effective implementation of major projects, such as relocation and ecological compensation, while addressing agricultural production needs. Ultimately, Lushui City achieved complete poverty reduction in October 2020. Given the instability of poverty reduction outcomes, the Chinese government has proposed household-based monitoring requirements for potential relapse in these areas (Zhang et al., 2022) and emphasized the importance of enhancing the self-development capacity of impoverished regions to promote sustainable development (Xue & Huang, 2021). In summary, Lushui City exemplifies typical alpine-gorge region characteristics and confronts the imperative to consolidate its poverty reduction achievements. Therefore, examining Lushui City is an appropriate case study for exploring the key factors influencing its SPRC.

3.2 Data collection

All geographic data were uniformly referenced to the WGS_1984_UTM_Zone_47N projection coordinate system to ensure consistency in spatial processing. The data correspond to three key research time points, namely 2000, 2010, and 2019. Exceptions include the digital elevation model (DEM) data, soil data, and village boundary data, which exhibit longer timeframes for change. As a result, it is challenging to obtain data that fully aligns

with the specified research nodes. Nevertheless, using existing data can still effectively reflect the long-term characteristics of the region. The data sources and related information are presented in Table 1. The processing methods for major datasets are outlined as follows:

Normalized difference vegetation index (NDVI) data assessed regional vegetation coverage. DEM data extracted regional elevation, slope, and terrain relief information. Soil data was analyzed to evaluate the extent of regional soil erosion. Land use data served two purposes: it enabled the calculation of the degree of land use mix and, with the assistance of attribute extraction tools in ArcGIS, facilitated the separate extraction of farmland and village residential land, which was used to calculate per capita cultivated land area and village agglomeration. Geohazard and tourist point data were subjected to kernel density analysis in ArcGIS to illustrate the spatial density of regional geological disasters and tourism resources. Road data was used to compute regional road network density and to provide essential information for assessing the distances from village residential areas to main roads and nature reserves. Relevant distance indicators were calculated primarily through network analysis in ArcGIS. Before formal calculations, a topological check of the road data was conducted in ArcGIS to remove invalid nodes, including isolated and pseudo nodes. Finally, the values of relevant raster indicators were aggregated using ArcGIS regional statistics tools, with villages as the smallest unit of analysis.

3.3 Methods

This study investigates the key factors influencing SPRC in Lushui City, a typical alpine-gorge region in China. The relationship between the research methods and content is illustrated in Fig. 2. SPRC evaluation serves as the foundation of this study. We constructed an indicator system from three dimensions, environment, economy, and society, and evaluated it using a BPANN. Before the formal evaluation, criteria were established, and a training set was created based on the data characteristics. Following the SPRC evaluation, we classified the lag types of SPRC in different villages and identified the primary dimensions

Table 1 Data types and descriptions

Data	Sources	Resolution	Data format
Road data	http://www.openstreetmap.org	–	Shp
Village boundary data	https://www.resdc.cn	–	Shp
Soil data	https://www.fao.org/soils-portal/soil-survey	–	Shp
Tourist point data	Culture and Tourism Administration of Lushui City	–	Shp
Geohazard data	https://geocloud.cgs.gov.cn	–	Shp
Nature reserve data	https://www.zrbhq.cn	–	Shp
DEM data	http://www.gscloud.cn	30 m	Tiff
NDVI data	http://www.resdc.cn	1 km	Tiff
Precipitation data	http://www.geodata.cn	1 km	Tiff
Temperature data	http://www.geodata.cn	1 km	Tiff
Land use data	https://zenodo.org/record/5210928#.Y2dDTctByUk	30 m	Tiff
Gross domestic product (GDP) raster data	http://www.resdc.cn	1 km	Tiff
Population raster data	http://www.resdc.cn	1 km	Tiff

contributing to poor SPRC in the region. Subsequently, the RF model was employed to identify the key influencing factors, and their spatial heterogeneity was examined using MGWR.

3.3.1 The construction of indicator system of SPRC

Assessing regional SPRC is critical to consolidating poverty reduction gains and promoting regional sustainable development. Currently, the focus of sustainable development has shifted from capital to capabilities, emphasizing the regional ability to cope with external changes. Improving regional resilience can help promote regional sustainable development (Reyers et al., 2022). According to some scholars, poverty reduction

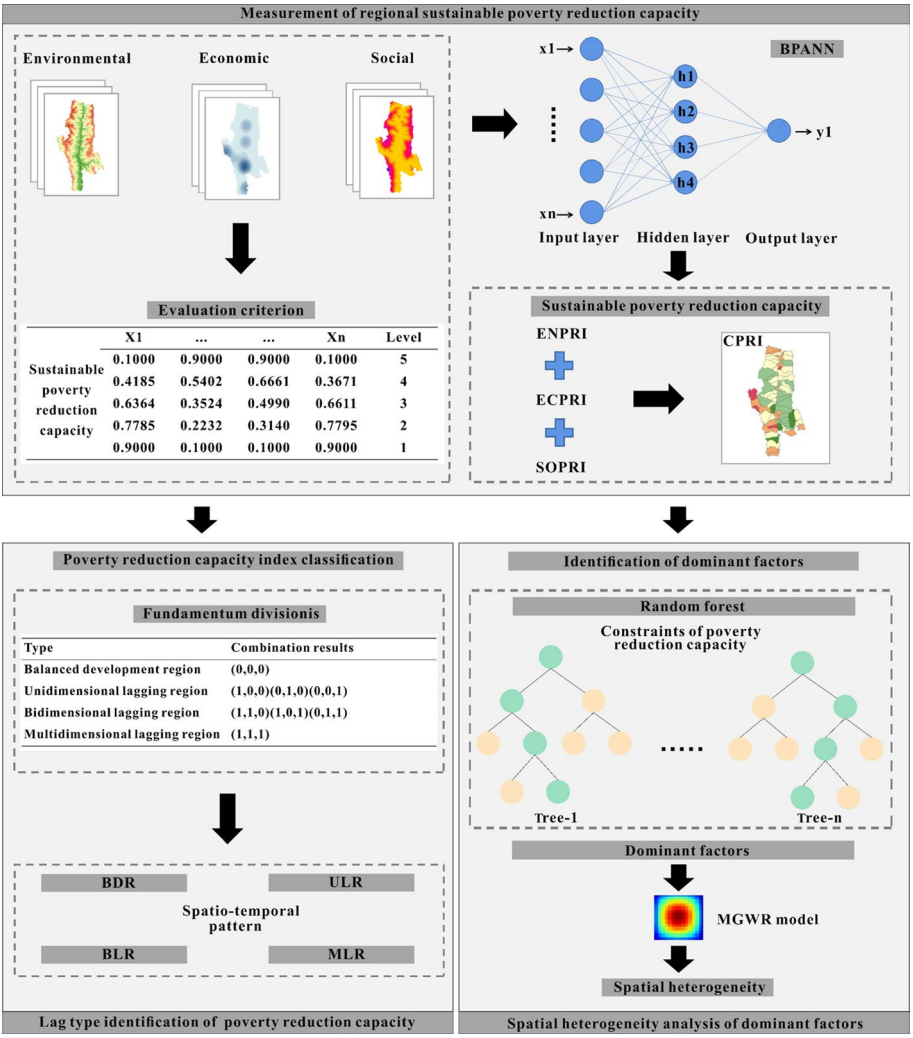


Fig. 2 Research framework

resilience at the individual level refers to the ability to maintain stability and avoid the recurrence of poverty under external shocks. At the regional level, it refers to the ability to provide individuals with better living conditions, which is a prerequisite for individuals to maintain poverty reduction status (Li et al., 2021). Regions with higher economic, social, and environmental capacity tend to show greater resilience (Robinson & Carson, 2016).

We adopt the concepts of multidimensional poverty (Alkire & Foster, 2011) and poverty reduction resilience (Lade et al., 2017) to develop an SPRC evaluation index system based on three dimensions: environment, economy, and society (Fig. 3). We believe that environmental, economic and social systems jointly contribute to absorbing and adapting to external shocks, preserving regional poverty reduction outcomes, and advancing regional sustainable development. The system's development level determines its resilience to external shocks and capacity for sustainable regional poverty reduction. Lagging subsystem development reduces the region's SPRC. The more subsystems lag, the lower the SPRC. We selected 16 indicators from relevant research and field surveys to establish the SPRC evaluation system (Table 2). Environmental indicators assess the effects of alpine-gorge landscapes on regional SPRC, as well as the livability and safety of human settlements. Economic indicators gauge the region's capacity to generate wealth and the diversity of livelihood activities. Social indicators reveal the region's internal and external communication abilities and the influence of policy conditions on the SPRC.

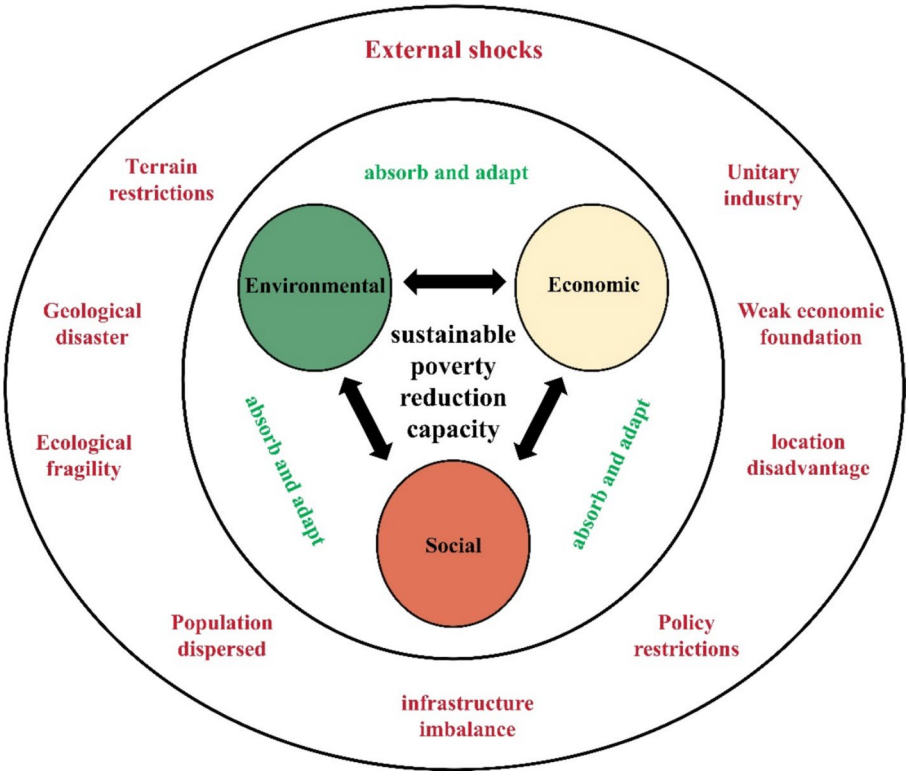


Fig. 3 Conceptual model for SPRC

We selected eight indicators for the environmental dimension. The study area mostly falls within the World Natural Heritage core area and the Gaoligong Mountain National Nature Reserve. These reserves overlap with areas of high vegetation coverage. Based on our field interviews and relevant research, most residents think that the development ban in the reserve restricts their livelihood diversification (Cheng et al., 2023). It hinders regional industrial diversification and lowers the regional SPRC. The complex terrain of the alpine-gorge region has constrained residents' communication with the outside world, resulting in information isolation and limited production capacity, which in turn hampers regional development and construction (Xue & Huang, 2021). As such, elevation, slope, and terrain relief were selected as indicators to reflect their influence on SPRC. Additionally, the region's steep terrain is highly prone to ecological degradation and geological disasters. Ecological degradation, particularly soil erosion, reduces soil fertility and land productivity, negatively impacting residents' income and livelihoods and contributing to poverty. Prolonged poverty further exacerbates the lack of financial resources and ecological protection capacity, entrenching a vicious cycle between ecological degradation and poverty (Zhou et al., 2020). Geological disasters such as landslides and mudslides also impose significant negative effects, including casualties and destruction of housing and infrastructure. These disasters directly degrade residents' quality of life and necessitate substantial financial and labor investments for post-disaster recovery, significantly hindering the region's sustainable poverty reduction efforts (Zhang et al., 2024). Additionally, residents living near protected areas in Lushui City primarily rely on cultivating and harvesting forest-based cash crops for their livelihood. Consequently, favorable water and thermal conditions contribute, to a certain extent, to sustainable poverty reduction in the region. Sufficient precipitation enhances plant functional diversity and ecosystem productivity (Gherardi & Sala, 2015) and alleviates the water supply challenges in the alpine-gorge region, thus

Table 2 SPRC indicator system

Primary indicators	Secondary indicators	Unit	Anticipated impact
Environmental indicator	Vegetation coverage (X1)	–	−
	Elevation (X2)	m	−
	Slope (X3)	°	−
	Terrain relief (X4)	m	−
	Soil erosion amount (X5)	$t/(hm^2 \cdot a)$	−
	Precipitation (X6)	mm	+
	Temperature (X7)	℃	+
	Density of geological disasters (X8)	number/km^2	−
Economic indicator	Farmland areas per person (X9)	hm^2/per	+
	GDP per capita (X10)	yuan/per	+
	Land-use mixed degree (X11)	–	+
	Density of tourist spots (X12)	number/km^2	+
Social indicator	Road network density (X13)	km/km^2	+
	Distance to the main road (X14)	m	−
	Distance to the nature reserve (X15)	m	+
	Village agglomeration degree (X16)	–	+

"+" is a positive indicator, and "−" is a negative indicator

ensuring the basic survival needs of residents. Furthermore, the primary forest-based cash crops and cultivated crops in Lushui City, such as tsaoko amomum fruit, walnuts, and rice, thrive in warm and humid conditions. Higher temperatures promote the healthy growth of these crops, thereby fostering regional economic development and ensuring residents' livelihoods.

We selected four indicators for the economic dimension. Farmland is a critical production resource in alpine-gorge regions, directly influencing residents' income and poverty levels. Studies have shown that escalating food security risks significantly contribute to the intensification of regional poverty (Sullivan et al., 2023). Regions with higher per capita farmland possess greater food self-sufficiency, enhancing residents' resilience to risks (Zeng et al., 2022). Furthermore, these areas are more conducive to implementing poverty reduction strategies such as land consolidation and soil improvement, which further enhance cultivated land quality, facilitate agricultural structural adjustments, and provide a robust material and economic foundation for sustainable poverty reduction in the region (Zhou et al., 2019). The GDP per capita indicates the region's per capita production capacity. Therefore, a higher GDP per capita implies a more assertive regional economic foundation. A robust economic foundation helps to enhance the resilience of the local economy and reduce the negative impact of external shocks (Cui et al., 2023). Diverse land use patterns reflect the diversity of a regional industrial structure, and a diverse industrial structure helps spread risks in response to external disturbances (Zhu et al., 2017). Tourism has also played a significant role in poverty reduction in remote and impoverished areas. It can enhance residents' income, stimulate the growth of related service industries, diversify the regional industrial structure, and foster improvements in regional infrastructure (Zhu et al., 2024).

We selected four indicators for the social dimension. The farther a location is from the nature reserve, the less it is affected by reserve policies, which makes it more favorable for residents to engage in diversified livelihood activities, thereby enhancing their ability to cope with risks. The alpine-gorge region suffers from limited connectivity to the outside world. Improvements in infrastructure, particularly road networks, have been shown to have a sustained positive impact on impoverished areas by reducing spatial isolation, lowering transaction costs, increasing market opportunities, and improving resource accessibility. Over time, these improvements have led to more significant poverty reduction effects (Kucukpehlivan et al., 2023; Tian et al., 2024). Therefore, this study selected two indicators, road network density and distance to the main road, to assess how regional road infrastructure and accessibility contribute to SPRC in the area. Additionally, from a regional perspective, a more concentrated settlement distribution is more conducive to strengthening socio-economic ties, promoting efficient use of public service facilities, and leveraging agglomeration effects to collectively manage risks compared to isolated communities (Hu et al., 2022).

3.3.2 Evaluation model of SPRC

Traditional weighting methods, such as entropy and hierarchical analysis, have notable limitations. On the one hand, they assume a linear relationship between each indicator and the composite evaluation value. On the other hand, these methods are highly dependent on data characteristics and are susceptible to subjective human biases in the weight calculation process (Jiao et al., 2023; Liang et al., 2024). SPRC is influenced by multiple dimensions, and traditional weighting methods cannot adequately capture its

inherent complexity. Therefore, this study used BPANN to evaluate the SPRC of villages in Lushui City, comprehensively considering the nonlinear relationship between different indicators to enhance the accuracy and reliability of the evaluation results.

BPANN is a widely used feedforward neural network consisting of an input layer, one or more hidden layers, and an output layer. Its primary advantage lies in its robust nonlinear modeling capabilities (Li et al., 2024). During the network's operation, input signals are transmitted from the input layer to the hidden layer, which undergoes successive layer-wise processing before reaching the output layer, generating the final output. When a discrepancy exists between the actual and target outputs, the network adjusts the inter-layer weights using the backpropagation algorithm, progressively reducing the error until it falls within an acceptable predefined range (Liu et al., 2023a). The effectiveness of BPANN in multi-objective evaluation studies has been demonstrated in various fields, including urban vulnerability (Duan et al., 2024), urban resilience (Lu et al., 2022), and green space landscape planning (Li & Fan, 2022). Based on R 4.2.1 (https://www.r-project.org/), a BPANN model was constructed to measure regional SPRC. The model mainly consisted of three components:

(1) Construction of training set

The training samples were constructed based on the principle that a higher positive index value and a lower negative index value indicated a stronger SPRC. The data were first standardized to eliminate the influence of varying index units. The standardization formula is as follows:

Positive indicators:

$$X_i^* = \frac{0.8\left(X_i - X_{min}\right)}{\left(X_{max} - X_{min}\right)} + 0.1 \tag{1}$$

Negative indicators:

$$X_i^* = \frac{0.8\left(X_{max} - X_i\right)}{\left(X_{max} - X_{min}\right)} + 0.1 \tag{2}$$

where X_i^* is the data after standardization of each index, X_i is the data before standardization of each index, X_{max} is the maximum value of each index, and X_{min} is the minimum value of each index.

After data standardization, using positive indicators as an example, the quartile division method was applied to categorize each indicator into five ranges, corresponding to the minimum value, lower quartile, median, upper quartile, and maximum value. These ranges were assigned scores from 1 to 5 (negative indicators were the opposite). A higher score indicated a greater positive contribution to the SPRC. When the scores of each indicator fell between 1 and 2, it corresponded to the IV level of poverty reduction difficulty, indicating a weaker regional SPRC. Similarly, when the scores ranged from 4 to 5, they corresponded to the I level of poverty reduction difficulty, representing the stronger regional SPRC. Finally, the training standard shown in Table 3 was derived. Based on this standard, the training set was generated using evenly distributed interpolation, with 80% of the samples used for training and 20% reserved for validation. The formula for the evenly distributed interpolation is as follows:

$$XX_t(l) = X_{td} + \frac{(X_{th} - X_{td})}{(M+1)} \times l \tag{3}$$

where $XX_t(l)$ is the *l-th* interpolation in interval t, M is the total amount of data interpolated into the interval, and X_{td} and X_{th} are the lower and upper limits of interval t, respectively.

(2) Construction of BPANN

Robert demonstrated that a single-hidden-layer BPANN could map any m-dimensional to n-dimensional space (Hecht-Nielsen, 1989). Therefore, this study built a three-layer network with input, hidden, and output layers. The input layer had as many neurons as the indicators in each dimension. The output layer had one neuron that produced the SPRC for each dimension. The hidden layer's neuron number followed the formula (4). Ultimately, we used 11, 8, and 8 neurons in the hidden layer to compute the ENSPRC, ECSPRC, and SOSPRC. The maximum training iterations was set to 1000, with an error threshold of 0.01.

$$N = \sqrt{n^i + n^0} + a \tag{4}$$

where N is the number of nodes in the hidden layer, n^i is the number of nodes in the output layer, n^0 is the number of nodes in the output layer, and a is a constant between 1 and 10.

The calculation formulas for the output of the hidden layer and the output layer are as follows:

$$H_j = X^*_{iv}\left(\sum_{i=1}^{n} w_{ij} X^*_{iv} - a_j\right) \quad j = 1, 2, ..., m; v = 1, 2, ..., k \tag{5}$$

$$O = \sum_{j=1}^{m} H_j w_j - b \tag{6}$$

where H_j is the output value of the hidden layer neuron j, X^*_{iv} is the standardized data of the *i-th* indicator of village v, w_{ij} is the weight between the input layer and the hidden layer, a_j is the threshold of the hidden layer, O is the output result of the output layer, w_j is the weight between the hidden layer and the output layer, and b is the threshold of the output layer. The weight and threshold updates are performed using the Rprop algorithm (Igel & Hüsken, 2003). This method effectively mitigates the vanishing gradient problem encountered in traditional BPANN, eliminating the need for a set learning rate and enhancing the robustness and stability of the model.

In addition, this study used the root mean square error (RMSE) to evaluate the training effect. The smaller the RMSE value, the smaller the error and the better the training effect. The iteration stops when the error value becomes smaller than the set error threshold. The calculation formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{v}\sum_{i=1}^{v} (Y - O)^2} \tag{7}$$

Table 3 Evaluation criteria for SPRC

	X1	X2	X3	X4	Level	Difficulty of poverty reduction
Environmental Sustainable Poverty Reduction Capacity (ENSPRC)	0.1000	0.1000	0.1000	0.1000	5	
						Ⅰ
	0.2469	0.2466	0.2414	0.3163	4	
						Ⅱ
	0.4476	0.4481	0.3719	0.4534	3	
						Ⅲ
	0.6215	0.6812	0.6434	0.6912	2	
						Ⅳ
	0.9000	0.9000	0.9000	0.9000	1	
	X5	X6	X7	X8	Level	Difficulty of poverty reduction
	0.1000	0.9000	0.9000	0.1000	5	
						Ⅰ
	0.4185	0.5402	0.6661	0.3671	4	
						Ⅱ
	0.6364	0.3524	0.4990	0.6611	3	
						Ⅲ
	0.7785	0.2232	0.3140	0.7795	2	
						Ⅳ
	0.9000	0.1000	0.1000	0.9000	1	
	X9	X10	X11	X12	Level	Difficulty of poverty reduction
	0.9000	0.9000	0.9000	0.9000	5	
						Ⅰ
Economic Sustainable Poverty Reduction Capacity (ECSPRC)	0.5558	0.8960	0.6124	0.5396	4	
						Ⅱ
	0.3545	0.2386	0.4415	0.3155	3	
						Ⅲ
	0.2183	0.1162	0.2836	0.1949	2	
						Ⅳ
	0.1000	0.1000	0.1000	0.1000	1	
	X13	X14	X15	X16	Level	Difficulty of poverty reduction
	0.9000	0.1000	0.9000	0.9000	5	
						Ⅰ
Social Sustainable Poverty Reduction Capacity (SOSPRC)	0.5005	0.4542	0.5967	0.5481	4	
						Ⅱ
	0.3173	0.6963	0.3939	0.3880	3	
						Ⅲ
	0.1872	0.8438	0.2373	0.2409	2	
						Ⅳ
	0.1000	0.9000	0.1000	0.1000	1	

Table 4 The classification criteria of CSPRC

Grading criteria	Type
CSPRC < − 1.5std	Low value region
− 1.5std ≤ CSPRC < − 0.5std	Medium–Low value region
− 0.5std ≤ CSPRC < 0.5std	Medium value region
0.5std ≤ CSPRC < 1.5 std	Medium–High value region
CSPRC ≥ 1.5std	High value region

Table 5 The classification results of SPRC lagging types

Primary type	Secondary type (ENSPRC,ECSPRC,SOSPRC)
Balanced development region	(0,0,0)
Unidimensional lagging region	(1,0,0)(0,1,0)(0,0,1)
Bidimensional lagging region	(1,1,0)(1,0,1)(0,1,1)
Multidimensional lagging region	(1,1,1)

where v is the total number of samples and Y is the expected output value obtained by interpolation.

(3) Evaluation of SPRC

We fed the normalized indicators of each year into a trained BPANN to obtain the ENSPRC, ECSPRC, and SOSPRC for each village. Then, we computed the comprehensive sustainable poverty reduction capacity (CSPRC) by summing the three dimension indexes.

3.3.3 Identification method of lagging types of SPRC

We employed the standard deviation method, using the mean as the reference point and one standard deviation (std) as the interval, to categorize the SPRC of different dimensions into five levels. This approach facilitates analyzing spatiotemporal variations in the SPRC across dimensions, identifying regions with underlying issues. Taking CSPRC as an example, the division rules are shown in Table 4.

Drawing on the concept of relative poverty classification, when the SPRC of a specific dimension in a village fell below the mean by 0.5 std, it was considered to be in a lagging state for that dimension. Marking the lagging dimensions as one and the non-lagging dimensions as zero generated various marking combinations. Four primary and eight secondary types were obtained (Table 5). This approach helped to identify the key dimensions contributing to the weaker SPRC in different villages. For instance, the combination (1, 1, 0) indicated that the village's SPRC fell into the two-dimensional lagging category, with its weaker SPRC primarily attributed to the poor development of ENSPRC and ECSPRC. Due to the large number of secondary types involved, this study focused on analyzing the spatiotemporal variations of the primary type. The SPRC lagging types for different villages under the secondary types are presented in Table S1.

3.3.4 RF model

Although BPANN was employed to evaluate the SPRC of different dimensions in villages of Lushui City, the weights between the layers underwent multiple transformations via nonlinear activation functions during the evaluation process. As a result, the relationship between each indicator and the final output is subject to complex variations. Relying solely on the weights in BPANN does not adequately capture the specific impact of individual indicators on the output. Therefore, further analysis is required to assess the importance of these indicators and identify the key factors influencing SPRC.

RF is a decision tree-based integrated machine learning algorithm proposed by Leo Breiman (Breiman, 2001), which is often used to perform tasks such as classification, regression, and judging the importance of factors. As a non-parametric model, it can better capture the nonlinearity relationship among variables and performs better than other machine learning methods in judging the importance of variables (Grömping, 2015). Therefore, this study applied the random forest model to determine the dominant factors influencing the regional SPRC. When assessing variable importance, this method randomly permutes the value of a given variable while keeping other variables fixed. Subsequently, a new set of decision trees is constructed, and the accuracy corresponding to the modified out-of-bag (OOB) data is calculated (OOB data refers to samples not selected for training the tree). The resulting accuracy is then compared to the accuracy of the original OOB data, which includes all variables, and the difference between these two values is computed. A larger absolute difference indicates greater importance of the variable (Wang et al., 2020). The reduction in mean square error (MSE) due to permutations is the most widely used measure of variable importance in RF (Liu et al., 2021b). This study also adopted this metric for assessing variable importance. The formula for its calculation is as follows (Janitza et al., 2016):

$$\Delta MSE_j = \frac{1}{m}\sum_{t=1}^{m}\left(MSE_{OOB}(t) - MSE^{p}_{OOB,j}(t)\right) \tag{8}$$

where ΔMSE_j is the importance score of variable j, with a higher score indicating a more significant variable, m is the number of trees in the random forest, $MSE_{OOB}(t)$ is the original MSE of the *t-th* tree on the OOB data, and $MSE^{p}_{OOB,j}(t)$ is the MSE of the *t-th* tree on the OOB data after permuting variable j.

$$MSE_{OOB}(t) = \frac{1}{n_{OOB}}\sum_{i=1}^{n_{OOB}}\left(y_i - \hat{y}_i(t)\right)^2 \tag{9}$$

where n_{OOB} is the number of samples of OOB data, y_i is the true value, and $\hat{y}_i(t)$ is the predicted value of the *t-th* tree.

$$MSE^{P}_{OOB,j}(t) = \frac{1}{n_{OOB}}\sum_{i=1}^{n_{OOB}}\left(y_i - \hat{y}^{p}_i(t)\right)^2 \tag{10}$$

where $\hat{y}^{p}_i(t)$ is the predicted value of the t-th tree after variable j is replaced.

3.3.5 MGWR model

While the RF model enabled the identification of the main global factors influencing regional SPRC, the presence of spatial heterogeneity suggests that the relationship between

explanatory variables and the dependent variable may be both global and local (Wang et al., 2024). Analyzing the local effects of the main factors on SPRC is crucial for implementing more targeted interventions.

The GWR, as a classical local regression model, has been widely applied to examine the local effects of influencing factors. However, a significant limitation of GWR is its assumption that each explanatory variable affects the dependent variable at the same spatial scale (Zhou et al., 2023). This assumption has faced considerable criticism, as in most cases, different influencing factors may have varying impacts at different spatial scales (Fotheringham et al., 2019). The MGWR, an extension of GWR, addresses the limitation of a uniform bandwidth, allowing the relationship between the dependent and independent variables to vary across different spatial scales, thus enhancing performance in the analysis of local effects (Fotheringham et al., 2017). Therefore, this study employed the MGWR2.2 software (https://sgsup.asu.edu/SPARC) developed by the Spatial Analysis Research Center of Arizona State University to analyze the spatial heterogeneity of different influencing factors on SPRC used formula (11).

$$y_i = \beta_{bw0}(u_i, v_i) + \sum_{j=1}^{k} \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i \tag{11}$$

where (u_i, v_i) is the coordinates of the center point of village i, y_i is the value of the dependent variable at position i, x_{ij} is the value of independent variable j at position i, $\beta_{bw0}(u_i, v_i)$ is the estimated intercept coefficient of position (u_i, v_i), and bwj is the best value for independent variable j Bandwidth, β_{bwj} represents the coefficient of the j independent variable with bandwidth bw, and ε_i is the random error term.

4 Results

4.1 Spatio-temporal pattern of SPRC

(1) Time change

Regions with poor SPRC encountered greater challenges in achieving sustainable poverty reduction. Specifically, Lushui City had long faced significant challenges in comprehensive sustainable poverty reduction, with most villages consistently classified at level III in terms of difficulty (Fig. 4j–l). The difficulty of sustainable poverty reduction in the environmental dimension was consistent with the overall challenges observed in comprehensive poverty reduction (Fig. 4a–c), which could mainly be attributed to the limitations imposed by immutable natural factors such as alpine-gorge terrain and climate.

Nevertheless, poverty reduction efforts strengthened the ECSPRC and SOSPRC in Lushui City. From 2000 to 2010, ECSPRC demonstrated an upward trend, as evidenced by a reduction in the number of villages facing level IV difficulties and an increase in those classified at level II (Fig. 4d, e). In contrast, SOSPRC exhibited a downward trend, with a significant increase in the number of villages facing level IV social sustainability poverty reduction difficulties (Fig. 4g, h). However, this did not imply a weakening of SOSPRC. The discrepancy could have stemmed from the distinction between social support (such as infrastructure development) and direct economic assistance. Social assistance could not

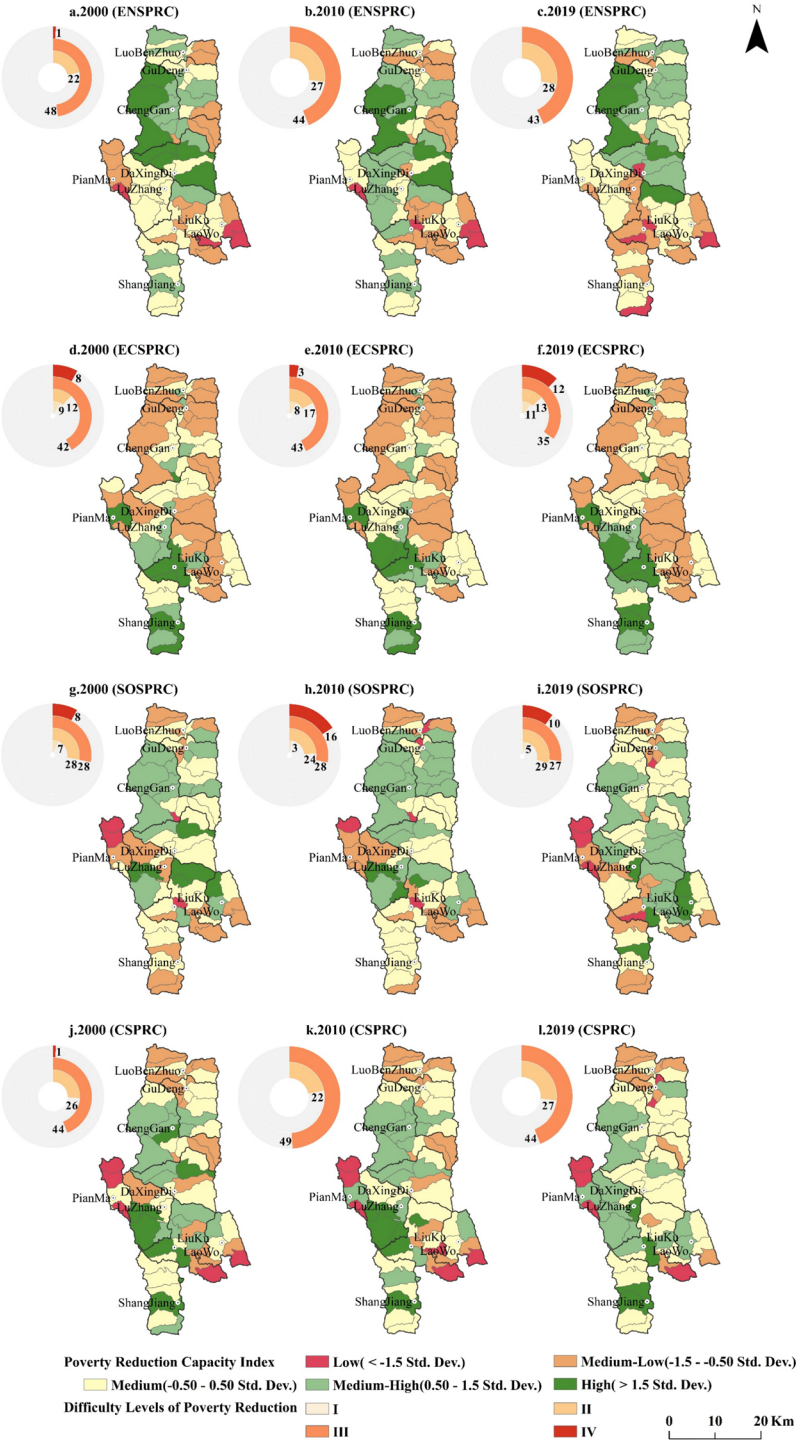


Fig. 4 Spatio-temporal pattern of SPRC. The donut chart illustrates the frequency of villages in different difficulty level of sustainable poverty reduction, according to different dimensions and time nodes

simultaneously address the needs of all villages. Consequently, SOSPRC increased rapidly in villages receiving prioritized assistance, widening the gap between these villages and others.

Between 2010 and 2019, the number of villages facing economically sustainable poverty reduction difficulties at levels I and IV increased (Fig. 4f), likely due to changes in poverty reduction strategies. While implementing the targeted poverty reduction strategy, the government emphasized region-specific assistance measures tailored to local resource endowments. Due to variations in resource conditions and developmental challenges across villages, those with more favorable conditions experienced a faster improvement in ECSPRC. In contrast, villages with less favorable development conditions were classified as facing more significant economic poverty reduction difficulties due to slower improvements in ECSPRC. Concurrently, with the widespread implementation of social assistance measures, SOSPRC continued to rise during this period, leading to a gradual decrease in the number of villages facing social sustainability poverty reduction difficulties at levels III and IV (Fig. 4i).

(2) Spatial change

Dividing the SPRC levels across different dimensions and years based on standard deviation further highlighted the spatial disparities in SPRC among villages in Lushui City. Specifically, the ENSPRC presented a spatial pattern of strong in the north and weak in the south (Fig. 4a–c). Between 2000 and 2019, villages with low ENSPRC were mainly located around Liuku and Laowo Townships. Villages in Luobenzhuo Township, the northern section of Gudeng Township, and the southeastern section of Chenggan Township significantly improved their ENSPRC. Notably, the ENSPRC in Shangjiang Township in the southern region gradually weakened, likely due to intensified human activities that increasingly disrupted the regional ecosystem, as this area served as the core of Lushui City's economic and social development.

The ECSPRC presented a spatial pattern of strong in the south and weak in the north. Villages with strong ECSPRC were concentrated around Shangjiang, Luzhang, and Liuku Townships, while those with weak ECSPRC were mainly distributed in Lushui City's northern sides and Laowo Township. Overall, the spatial pattern of EOSPRC remained stable (Fig. 4d–f).

The spatial pattern of SOSPRC exhibited a gradual shift in high-value areas from the northern region to the southeast (Fig. 4g–i). This trend was likely due to the favorable conditions in Liuku Township, located southeast of Lushui City, where relatively flat terrain and river proximity facilitated development and access to water resources. These advantages supported regional infrastructure and public services improvements, resulting in a marked enhancement of SOSPRC in this area.

Finally, from the perspective of CSPRC spatial distribution, the CSPRC in Pianma Town, Damikou Village in Liuku Town, and Ronghua Village in Laowo Town remained relatively low over the past two decades (Fig. 4j–l), indicating the need for focused efforts to improve SPRC in these areas in the future.

4.2 Spatio-temporal pattern of lagging types of SPRC

According to the changes in quantity (Fig. 5), the most prevalent types in 2000 were the balanced development type (35.21%) and the unidimensional lagging type (33.80%).

The bidimensional and multidimensional lagging types constituted 26.76% and 4.23% of the total, respectively. The proportions of each type in 2010 were similar to those in 2000. In 2019, the bidimensional and multidimensional lagging types decreased to 23.94% and 2.82%, respectively. These results indicate a transformation trend from bidimensional and multidimensional lags to unidimensional lags in the SPRC from 2000 to 2019.

From the perspective of the spatial pattern (Fig. 5), the villages with balanced development in 2000 and 2010 were mainly distributed in Shangjiang Township, Luzhang Township, the northern part of Daxingdi Township, the central part of Chenggan Township, and the southern part of Gudeng Township. Unidimensional lagging villages were mainly located on the northwest and southeast sides of Lushui City. Bidimensional and multidimensional lagging villages were concentrated in Lobenzhuo, Pianma, and Liuku and the southeast part of Laowo Townships, with little change in their spatial patterns. In 2019, the villages in the eastern part of Luobenzhuo Township significantly improved their SPRC, developing from bidimensional to unidimensional lagging types. Villages in the northern part of Shangjiang Township and the southwestern part of Liuku Township deteriorated, changing from balanced development to bidimensional lagging types. Villages in Pianma Township, the northern part of Luobenzhuo Township, and the southeastern part of Laowo Township had long suffered from two-dimensional and multidimensional lagging, with low SPRC.

From the perspective of type transitions (Fig. 6), the transformation between lag types was more frequent from 2010 to 2019 compared to 2000 to 2010. The main direction of transformations from 2000 to 2010 was from the unidimensional lagging type to the balanced development type. However, a few villages in the balanced development type also changed to the unidimensional and bidimensional lagging types. Overall, there was no significant change in the lagging types during this period. Between 2010 and 2019, there was a noticeable shift in the lagging types, with most of the villages in the bidimensional lagging type being upgraded to either the unidimensional lagging type or the balanced development type. However, some of the villages still faced challenges with the unbalanced development of SPRC.

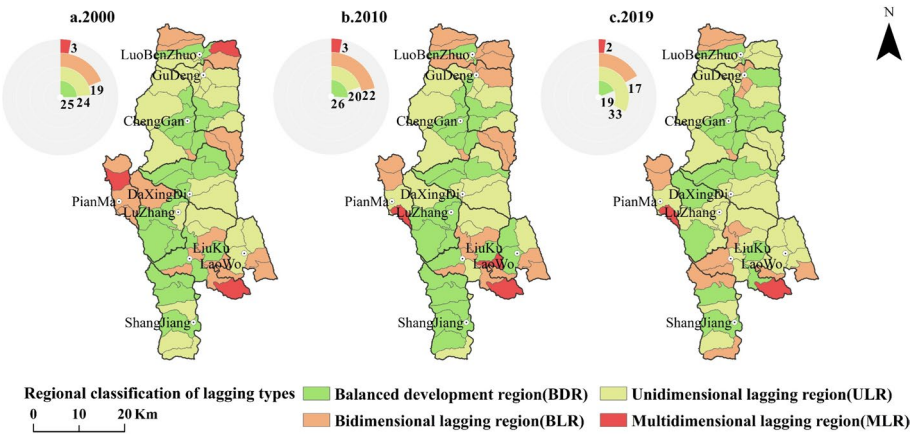


Fig. 5 Spatio-temporal pattern of lagging types of SPRC. The donut chart illustrates the frequency of villages in different lagging types, according to different time nodes

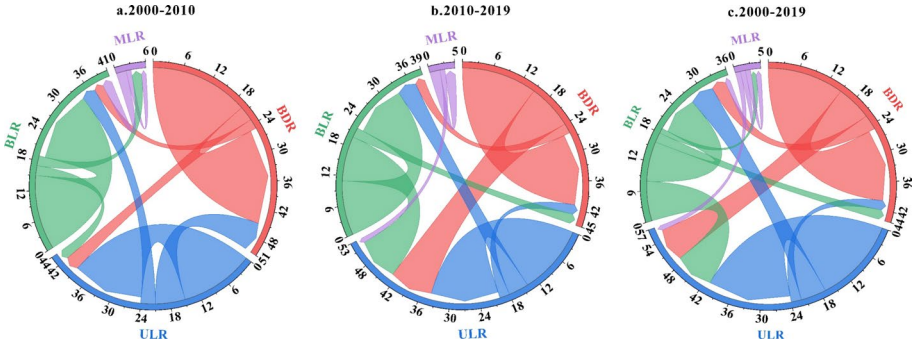


Fig. 6 Transformation diagram of SPRC lagging types

4.3 Influencing factors on SPRC

We applied the RF model to identify the dominant factors influencing SPRC in 2000, 2010, and 2019, excluding factors that did not meet the significance level of $p < 0.05$.

In 2000, the five most influential factors were density of tourist spots (X12), precipitation (X6), distance to the nature reserve (X15), soil erosion amount (X5), and village agglomeration degree (X16) (Fig. 7a). In 2010, they were the density of tourist spots (X12), precipitation (X6), village agglomeration degree (X16), distance to the nature reserve (X15), and soil erosion amount (X5) (Fig. 7b). In 2019, they were village agglomeration degree (X16), density of tourist spots (X12), distance to the main road (X14), precipitation (X6), and land-use mixed degree (X11) (Fig. 7c).

In 2000 and 2010, environmental and social factors were the primary influences on SPRC (Fig. 7a, b). During this time, Lushui City's strong dependence on the primary sector meant that natural environmental conditions (such as precipitation and soil erosion) significantly affected economic development and the sustainability of residents' livelihoods. Meanwhile, the nature reserve policy restricted residents from engaging in understory crop harvesting and hunting, leading to limited livelihood options. The relatively concentrated settlement distribution facilitated resource exchange and cooperation among residents, reducing livelihood vulnerability. This factor's influence on Lushui City's SPRC further improved in 2010. Moreover, as one of the few channels for livelihood diversification in the alpine-gorge region, tourism development substantially impacted Lushui City's SPRC throughout this decade.

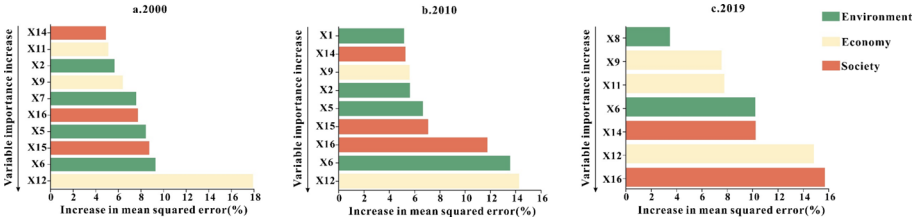


Fig. 7 Ranking chart of relative importance of impact factors

From 2010 to 2019, the primary influencing factors transitioned to economic and social aspects, with the effects of regional land-use mixed degree, distance to the main road, and village agglomeration degree on the SPRC of villages in Lushui City progressively intensifying (Fig. 7b, c). Notably, village agglomeration emerged as the most impactful factor in 2019. This shift indicates that internal regional connectivity and land use diversification are increasingly critical in advancing sustainable poverty reduction as economic and social conditions improve. The improvement of village agglomeration has further strengthened the improvement of SPRC, especially by enhancing resource sharing and social collaboration.

4.4 Spatial heterogeneity of the dominant factors of SPRC

The impact of dominant factors on SPRC varies spatially. We designated the CSPRC of each village as the dependent variable and selected the top five most important factors as the dominant ones. MGWR was then applied to reveal the spatial heterogeneity of these dominant factors. Table 6 and Fig. 8 displayed the spatial distribution of goodness of fit and regression coefficients for different dominant factors in 2000, 2010, and 2019.

The R2 values of the MGWR model exceeded 0.8 across different years, indicating strong explanatory power for SPRC in Lushui City (Table 6). Spatial heterogeneity among the influencing factors was revealed by combining bandwidth and the regression coefficients' standard deviation. At the village level in Lushui City, most factors had a bandwidth of 70, suggesting that their impact on SPRC across villages was nearly global. However, the smaller bandwidth observed for certain factors indicated relatively significant spatial heterogeneity.

Table 6 MGWR regression results

Year	Index	R^2	AICc	Residual sum of squares		
2000		0.851	107.925	10.926		
	Factor	X5	X6	X12	X15	X16
	Mean	−0.589	1.268	3.406	1.021	2.419
	Std	0.141	0.017	0.087	0.092	0.014
	Bandwidth	60	70	70	60	70
	$p<0.05$	100%	100%	100%	100%	100%
2010		0.891	74.634	5.785		
	Factor	X5	X6	X12	X15	X16
	Mean	−0.251	0.074	0.462	0.254	0.487
	Std	0.007	0.018	0.012	0.007	0.110
	Bandwidth	70	70	70	70	46
	$p<0.05$	100%	100%	100%	100%	100%
2019		0.942	41.696	4.993	0.942	
	Factor	X6	X11	X12	X14	X16
	Mean	1.030	1.951	3.479	−2.049	2.801
	Std	0.028	0.010	0.037	0.148	0.021
	Bandwidth	70	70	70	52	70
	$p<0.05$	100%	100%	100%	100%	100%

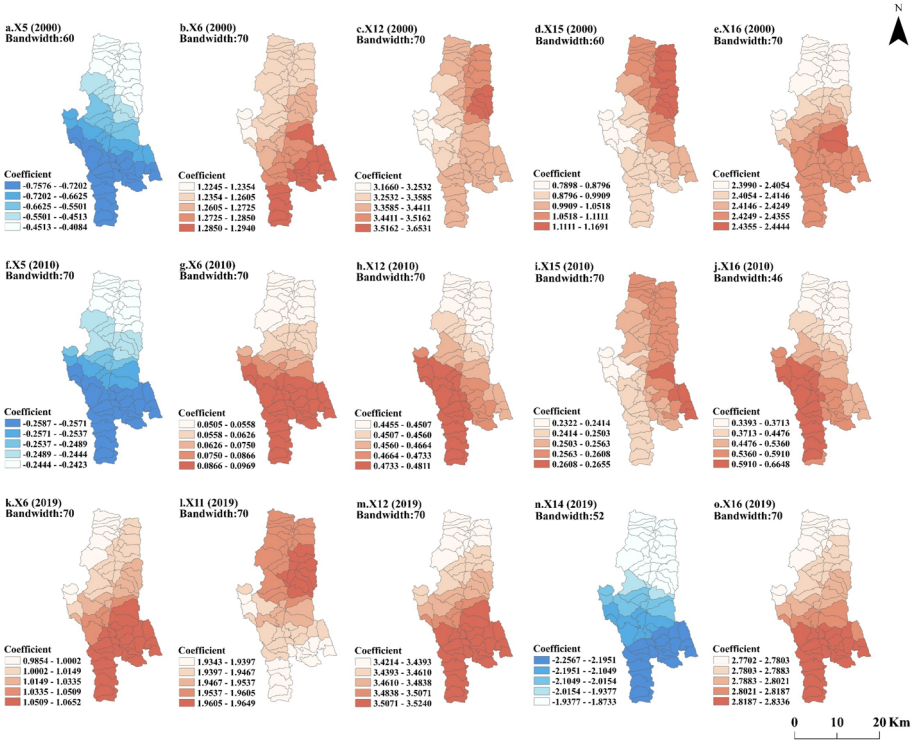


Fig. 8 Spatial distribution of regression coefficients for dominant factors

Specifically, in 2000, the factors with the highest standard deviation of regression coefficients were soil erosion amount (X5) and distance to the nature reserve (X15), each with a bandwidth of 60. By contrast, village agglomeration degree (X16) had the smallest standard deviation of the regression coefficient, with a bandwidth of 70. These results indicate that soil erosion and distance from the protected area exhibited substantial spatial variation in their impacts, while the effect of village agglomeration remained relatively consistent across regions. By 2010, the standard deviation of the regression coefficient for village agglomeration degree (X16) had increased significantly, and its bandwidth had decreased from 70 to 46. Meanwhile, the standard deviation of the regression coefficients for other factors generally declined, except for precipitation (X6). This shift may be attributed to the relocation policy implemented by Lushui City at the time, which initially targeted pilot areas, resulting in a notable increase in village agglomeration levels. This change may be related to the relocation policy implemented by Lushui City at that time. The policy was first implemented in the pilot areas, resulting in a significant increase in the level of village agglomeration in these areas, showing obvious local heterogeneity and changing the local socioeconomic pattern. This shift weakened the spatial heterogeneity of other variables to a certain extent. For instance, after residents in the pilot areas moved away from areas with severe soil erosion, the local influence of soil erosion on SPRC weakened. By 2019, following the completion of the relocation initiatives, Lushui City had established a more stable socioeconomic structure. During this period, the spatial heterogeneity of village agglomeration diminished, and its bandwidth returned to 70. However, distance to the

main road (X14) continued to exhibit pronounced spatial heterogeneity, with a bandwidth of 52 and showed the largest standard deviation of regression coefficients in this period. This suggests that despite the comprehensive implementation of relocation policies, disparities in road infrastructure across different regions in Lushui City remained significant.

The natural breakpoint method was employed to categorize the local regression coefficients of different dominant factors into levels, facilitating a spatial pattern analysis of the spatial heterogeneity of these factors (Fig. 8). From 2000 to 2010, the influence of soil erosion amount (X5) and precipitation (X6) on SPRC in Lushui City exhibited a spatial pattern of "strong in the south and weak in the north." The density of tourist spots (X12) and village agglomeration degree (X16) showed a highly consistent trend, with high-impact areas shifting gradually from eastern Lushui City to Shangjiang and Luzhang Townships in the southwest. This phenomenon may indicate a close association between village agglomeration and tourism development, where increased agglomeration reinforces the clustering effect and promotes regional tourism resource development. Moreover, tourism growth has stimulated the regional economy and attracted population inflows, further increasing village agglomeration. Additionally, with the expansion of the nature reserve in northern Lushui City, the high-impact area for distance to the nature reserve (X15) shifted from the northeast to the southeast. From 2010 to 2019, the spatial influence of precipitation (X6) on villages remained stable. High-impact areas for the density of tourist spots (X12) and village agglomeration degree (X16) shifted from the southwest to the south and southeast. Land-use mixed degree (X11) strongly impacted the SPRC of northeastern villages in Lushui City. At the same time, the high-impact areas for distance to the main road (X14) were concentrated in the south, creating clear spatial differentiation from northern villages. This indicated that disparities in road infrastructure and development levels in Lushui City were concentrated between northern and southern villages. Enhancing road construction in the northern villages and promoting diversified land use would improve SPRC.

5 Discussion

5.1 Enlightenment on achieving sustainable poverty reduction in alpine-gorge regions

The harsh geographical environment is regarded as one of the primary factors that have led the region into a prolonged spatial poverty trap (Zhou & Liu, 2022). The spatiotemporal evolution of SPRC in Lushui City indicates that the region has consistently faced considerable obstacles in achieving sustainable poverty reduction over the past two decades. Notably, the environmental dimension of sustainable poverty reduction difficulty aligns closely with the comprehensive difficulty. This finding underscored the enduring limitations imposed by unchangeable natural environmental factors, such as the alpine-gorge terrain and climate, on SPRC. Furthermore, our classification of SPRC lag types across different villages reveals that many villages face simultaneous restrictions from multidimensional factors, including environmental, economic, and social aspects. To effectively enhance sustainable poverty reduction in the region, adopting a holistic approach that considers the synergistic effects across multiple dimensions and their long-term impacts when designing assistance measures is essential.

From 2000 to 2010, the primary factors influencing SPRC in Lushui City remained largely unchanged, with environmental and social factors such as precipitation, soil erosion,

and distance from protected areas continuing to play dominant roles. Considering the poverty reduction measures implemented by the Chinese government during this period, it is evident that policies focused on labor transfer and agricultural market development primarily promoted regional poverty reduction by increasing employment opportunities and enhancing agricultural income (Fang & Zhang, 2021; Pan et al., 2018). These measures had positive effects mainly in the economic dimension, yet they were insufficient in addressing negative impacts on environmental and social dimensions. From 2010 to 2019, the influence of village agglomeration, proximity to roads, and land use diversity increased significantly, reflecting the effectiveness of the Chinese government's relocation strategy in alpine-gorge regions. Encouraging residents to move to areas with better development potential for centralized resettlement helped overcome the long-standing constraints imposed by alpine-gorge terrain, thereby substantially enhancing village agglomeration. At the same time, the policy reduced residents' reliance on natural resource exploitation and promoted the conservation of regional ecosystems (Arslan et al., 2022a). Additionally, during the resettlement process, the government prioritized constructing livelihood-support facilities and created a range of public welfare jobs, which fostered improvements in regional road infrastructure and the diversified development of residents' livelihoods (Liu et al., 2023b). Overall, the relocation policy has contributed positively to SPRC across the alpine-gorge region's environmental, economic, and social dimensions. As a successful intervention, it holds potential for application in other areas. However, because residents in alpine-gorge areas have lived in relatively isolated environments for prolonged periods, they often face challenges adapting to new living conditions (Qu et al., 2023). Therefore, future efforts should emphasize strengthened social integration support for relocated households to further advance sustainable poverty reduction in alpine-gorge areas.

In addition, over the past 20 years, tourism resources have played a significant role in enhancing the SPRC of Lushui City. Specifically, Lushui City possesses abundant natural landscapes, and its tourism development model focuses on ecotourism. This development model based on environmental protection has been proven to stimulate residents to voluntarily protect the environment to maintain long-term economic growth and ultimately achieve a mutually beneficial outcome for economic development and environmental protection (Zhou et al., 2021). However, as tourism continues to expand, disturbances from human activity are expected to intensify, posing increasing risks to the regional ecosystem. To address these challenges, the legal disclosure of environmental information is crucial. This measure allows stakeholders to promptly monitor the environmental impacts of ecotourism, thereby supporting necessary adjustments to regional development strategies (Arslan et al., 2022b).

This study also found significant spatial heterogeneity in the impact of different dominant factors on SPRC in Lushui City. Environmental factors, such as precipitation and soil erosion amount, demonstrated a broad bandwidth, indicating an almost global impact on SPRC. This is primarily due to the continuity of natural characteristics, like topography and climate, across Lushui City. Similarly, Ma et al. (2018) in examining regional poverty in Liupanshan District, Gansu Province, observed that natural conditions' effects on poverty incidence were less constrained by the research scale, with spatial heterogeneity emerging only at larger spatial scales. In contrast, social factors like village agglomeration degree and distance to the main road exhibited smaller bandwidths, reflecting relatively stronger local heterogeneity. This suggests that the influence of poverty reduction measures on SPRC has limited spatial reach; beyond a certain distance, the impact of these measures diminishes considerably. Therefore, enhancing the precision and expanding the reach of assistance measures is essential. For instance, studies indicate that increasing the

construction of low-grade roads yields a significantly higher return than solely building high-grade roads (Fan & Chan-Kang, 2008). Recognizing spatial heterogeneity allows for a comparative analysis of the variation in dominant indicators across regions during different poverty reduction stages, facilitating a more effective evaluation of assistance measures and providing a scientific basis for policy refinement and optimization.

5.2 The applicability of Lushui City's successful experience

The Hindu Kush-Himalayas region is a quintessential mountainous and severely impoverished area encompassing eight countries: Afghanistan, Bangladesh, Bhutan, China, India, Nepal, Myanmar, and Pakistan (Gerlitz et al., 2015). Taking Nepal and Myanmar as examples, they are predominantly agricultural economies where residents' livelihoods are significantly influenced by natural environmental factors such as topography and climate (Adhikari et al., 2021; Vicol et al., 2018). Additionally, both countries face critical challenges, including underdeveloped infrastructure, limited resource accessibility, and high disaster-related expenditures (Mohanty et al., 2017). Regarding poverty reduction strategies, Nepal has primarily focused on establishing dedicated poverty reduction funds, promoting cross-border employment opportunities for impoverished groups, enhancing infrastructure, and cultivating high-value crops (Kafle et al., 2022; Zhang et al., 2018). Some of these measures align with China's poverty reduction strategies in the early twenty-first century, such as labor transfer training and agricultural market development. In contrast, Myanmar has pursued poverty reduction by transitioning to a market-oriented open economic system (Mohanty et al., 2018). Since China's reform and opening up in 1978, it has progressively shifted from a planned economy to a market economy. Similarly, Vietnam exemplifies a region where terrain-related constraints exacerbate poverty, with ethnic minority groups being the most affected. These groups have long remained in relatively isolated conditions, characterized by low educational attainment and high livelihood vulnerability (Nguyen et al., 2023). Their primary livelihood relies on producing non-timber forest products; however, increasing human disturbance has resulted in persistently high deforestation and forest degradation rates (Vuong et al., 2021). To some extent, these conditions closely resemble the poverty characteristics observed in Lushui City.

In conclusion, poverty eradication is a shared objective of global development. Despite substantial differences in cultural contexts, development stages, and other factors among countries, the constraints encountered in alpine-gorge regions and the poverty reduction strategies adopted exhibit significant similarities. Accordingly, Lushui City's successful poverty reduction practices provide valuable insights for other nations seeking to address poverty in comparable alpine-gorge settings. To further strengthen SPRC in alpine-gorge regions that have been lifted out of poverty and to facilitate the dissemination of China's experience, we proposed the following recommendations:

First, regional poverty reduction requires strategic long-term planning and sustained investment to ensure the continuity and sustainability of poverty reduction efforts across different stages. For instance, road improvement and livelihood security projects often necessitate extended construction periods before their poverty reduction effects become evident. This phenomenon is reflected in the dynamic evolution of SOSPRC in Lushui City. Second, effective regional poverty reduction strategies should incorporate diversified intervention measures that address income growth, ecological restoration, and social security enhancement. For example, ecotourism simultaneously enhances regional environmental protection and stimulates economic benefits, achieving dual

objectives. Third, improving the specificity of assistance measures is crucial, and pilot initiatives should precede the large-scale implementation of new poverty alleviation measures to mitigate potential risks. Monitoring the spatial heterogeneity of poverty reduction effects in real time can provide a scientific foundation for designing more targeted and effective intervention strategies. Fourth, increased attention should be devoted to promoting social integration and capacity building among residents in areas that have already been lifted out of poverty. For instance, advancing the digital transformation of alpine-gorge regions through digital rural construction could enhance residents' ability to access information and improve the efficiency of regional smart management (Mijwil et al., 2022). Furthermore, the development of digital technologies is widely regarded as a key driver of deep regional transformation, ultimately contributing to regional sustainable development (Alamoodi et al., 2024). Finally, international organizations play an indispensable role in the global poverty reduction process, and cooperation between international organizations and governments should be further strengthened. On the one hand, international organizations such as the World Bank and the World Food Program can promote regional poverty reduction by providing direct economic support and material assistance. On the other hand, international organizations such as the United Nations Development Program can integrate various regions' successful poverty reduction experiences, advocate counterpart assistance, and build bridges between deeply impoverished and developed areas. Based on a global perspective, this kind of cooperation will help formulate more applicable poverty reduction strategies for poor areas.

5.3 Limitations

This study investigated the evolution of SPRC and its key influencing factors in Lushui City, a representative alpine-gorge region in China, over the past two decades to offer insights into poverty reduction for other similar regions worldwide. However, certain limitations remain. First, due to the restricted scope of the field survey, this study focused solely on Lushui City as a case study, needing more horizontal comparisons across a broader range of alpine-gorge regions. This limitation may affect the generalizability of the findings. Second, the absence of comprehensive village-level data resulted in the exclusion of indicators that could provide a more holistic understanding of regional SPRC. For instance, understory cash crop cultivation, a vital livelihood strategy for Lushui City residents, was not included due to the lack of effective quantitative methods to characterize this indicator. Third, the analysis of SPRC influencing factors primarily emphasized spatial heterogeneity without delving into the bidirectional causal relationships between SPRC and these factors. This gap may hinder a deeper understanding of the internal mechanisms driving the dynamic evolution of regional SPRC.

Future research will aim to expand and refine the current study to address these limitations. On the one hand, we plan to expand the scope of research further, compare the evolution differences of SPRC in different alpine-gorge regions, and build a more complete evaluation system based on technical means such as questionnaire surveys and remote sensing. On the other hand, we plan to introduce methods such as structural equation modeling (SEM) and cross-lagged regression analysis (CLRA) to reveal the causal relationship between influencing factors and regional SPRC. This approach will facilitate a more systematic understanding of SPRC's dynamic evolution mechanisms and provide robust scientific support for developing more adaptive and effective poverty reduction strategies.

6 Conclusions

From a regional perspective, this study constructed an evaluation system for SPRC in alpine valley areas and combined BPANN, RF, and MGWR models to explore the dominant factors affecting SPRC in Lushui City, a typical alpine-gorge area in China, at different key time points (2000, 2010, and 2019) during China's poverty reduction process. The following main conclusions were obtained:

1. The difficulty of poverty reduction in the environmental dimension closely mirrored the trends observed in the comprehensive poverty reduction challenges in Lushui City, highlighting the constraints imposed by environmental factors on enhancing SPRC in alpine-gorge regions. Although poverty reduction initiatives have partially improved SPRC in the economic and social dimensions, the effects of social assistance require a longer timeframe to manifest fully.
2. Certain villages exhibited lagging performance across multiple SPRC dimensions. The shift in dominant factors influencing SPRC in Lushui City can be attributed to multidimensional poverty reduction measures, such as relocation programs and ecotourism development, which have effectively mitigated the long-standing limitations imposed by environmental factors.
3. Environmental and economic factors at the village scale demonstrated relatively uniform spatial impacts in Lushui City, whereas social factors exhibited pronounced spatial heterogeneity. Therefore, paying attention to the differentiated effectiveness of assistance measures in different regions is significant for achieving sustainable poverty reduction in alpine-gorge areas.

Based on these conclusions, this study distilled key insights from Lushui City's successful poverty reduction practices and proposed recommendations for further development, offering Chinese experiences for poverty reduction initiatives in other alpine-gorge regions. In the future, related research should expand the scope of the study to compare the evolution of SPRC across different alpine-gorge regions and further refine the evaluation system. Additionally, methods such as SEM and CLRA should be introduced to explore the causal relationships between SPRC and its influencing factors. This approach will provide a more systematic understanding of the dynamic evolution of regional SPRC and offer robust scientific support for developing more adaptive and effective poverty reduction strategies.

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Data availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Consent to participate All authors of this manuscript have agreed to participate in the writing of the manuscript.

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