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Original Research

Spatially Informed Quality of Rural Life Model for Land Use Suitability in Mountainous Regions of Wumeng

Xiongbin Zhu[1,2], Sucharita Srirangam[2]*, Tamilsalvi Mari[2], Hong Wu[3], Siyou Xiao[1]

[1]Liupanshui Normal University, No. 19, Minghu Road, Liupanshui City, Guizhou, China
[2]Taylor's University, 1, Jalan Taylors, 47500 Subang Jaya, Selangor Darul Ehsan, Malaysia
[3]The Pennsylvania State University, 201 Old Main, University Park, Pennsylvania, USA

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Abstract

Rising industrialization, urbanization, and population growth have impacted rural and mountainous spatial paradigms, leading to fragmented village layouts and ecological degradation, profoundly affecting the Quality of Rural Life (QRL). Although the Chinese government has issued many policies and regulations, most do not target the improvement of QRL, resulting in implementation challenges and social controversy. This study develops a QRL model that quantitatively links external spatial factors to QRL outcomes at the village scale. Using the Shuicheng District in the Wumeng mountainous region in China as a case study, we employed a positivist quantitative approach, combining structured resident surveys, geospatial data collection, and regression analysis to identify key spatial determinants of QRL. Results indicate that the proportion of arable land and distance to nearest town are the most significant spatial predictors of QRL, while factors such as distance to cities and irrigation water sources showed limited influence. The model offers a practical decision-support tool for improving village site selection and layout planning, helping to mitigate the issues of the low rural living quality caused by irrational land layout. This research contributes to rural revitalization efforts and supports more sustainable, QRL-centered development strategies in mountainous regions.

Keywords: mountainous regions, quality of rural life, external spatial factors, construction land suitability assessment, Wumeng mountains

Introduction

Mountainous regions, home to over one billion people and covering approximately one-quarter of the Earth's surface, play a vital role in sustaining global ecosystems [1]. Mountainous communities contribute significantly to food security, cultural diversity, and traditional land-use practices that sustain biodiversity and landscape stability [2]. Yet, in many parts of the world, rural mountainous communities, particularly those heavily reliant on traditional agriculture, have historically experienced Low Quality of Life (QOL) due to limited infrastructure, public services, and economic

*e-mail: asucharita.srirangam@taylors.edu.my
Tel.: +60-175265374

opportunities [3]. QOL, broadly defined as the overall well-being of individuals or communities, encompasses physical health, psychological state, independence, social relationships, personal beliefs, and relationship with the environment [4]. Effective large-scale settlement planning in mountainous areas is essential not only for maintaining ecological integrity but also for enhancing the Quality of Rural Life (QRL).

While urbanization and industrialization have improved rural living in some respects, they have also introduced new challenges. In China, for example, these forces have disrupted traditional rural spatial structures, resulting in unplanned village layouts and overexploitation of natural resources, which in turn have exacerbated natural disasters like landslides [5]. Since 1978, rapid rural economic development has further escalated housing demand [6]. However, longstanding dispersed settlement patterns – shaped by terrain, history, and customs – necessitate substantial investment in environmental management, infrastructure, and public services [7], making in-place expansion increasingly unsustainable. Additionally, large-scale infrastructure projects, such as reservoirs, power stations, and industrial parks, often compel the relocation of entire villages [8]. In these cases, the careful selection of new village sites – whether for relocation or expansion – is crucial to improving QRL and ensuring long-term sustainability.

Despite two decades of rural revitalization efforts – including poverty alleviation relocations, centralized resettlement, and spatial optimization – the lack of scientific tools for assessing construction land suitability has left site selection heavily reliant on subjective judgments by governmental officials and planners, often sparking social controversy [9]. This underscores the pressing need for a Construction Land Suitability Assessment (CLSA) model [10] suitable for rural mountainous regions. Existing CLSA approaches are either overly simplistic or excessively complex. Simplified models typically focus narrowly on basic land classification and ecological suitability, overemphasizing the natural attributes of land while neglecting the profound relationship between village siting and QRL [10]. In contrast, the complex models often borrow from urban-oriented systems that are too data-intensive and contextually inappropriate for rural areas [11]. A more balanced, QRL-oriented approach is needed to guide sustainable and context-sensitive village planning.

Furthermore, there is a clear need for the CLSA model to explicitly link spatial factors to QRL. External spatial factors – such as terrain, availability of natural resources, and accessibility of public services – play a foundational role in shaping everyday life in rural communities [11]. These factors determine not only the village's development potential but also influence access to health care, education, markets, and mobility, all of which are key dimensions of QRL [12, 13]. While existing research has made notable progress in exploring how spatial factors relate to QOL – for example, in county towns in Gansu Province, China [14], across 31 cities in Germany [15], and through the study of green space and well-being in 51 European cities [16] – these studies primarily address urban or large-scale regional contexts, leaving a critical gap in understanding how external spatial factors affect QRL at the village scale.

Besides the gap in incorporating QRL into CLSA models, a clear gap also remains in the quantification of QRL, particularly in ways that are spatially explicit, context-sensitive, and actionable for planning and policymaking. While urban QOL has been extensively studied and quantified using standardized indices [17], rural mountainous contexts lack equivalent, widely accepted frameworks [18]. Existing QRL assessments tend to focus narrowly on socioeconomic indicators such as income, education, or healthcare access, often neglecting equally vital spatial and environmental factors as mentioned above [10]. Furthermore, most existing studies are either qualitative or descriptive, offering limited utility for predictive modeling or decision-making [11]. This absence of a multi-dimensional and geospatially informed QRL assessment system hinders evidence-based strategies for sustainable rural development.

To fill the gaps in both CLSA modeling and QRL quantification, this study integrates QRL into the core framework of CLSA and establishes a quantitative relationship between QRL and external spatial factors of villages. The Wumeng Mountain region in Guizhou Province, China, characterized by complex topography and significant sociocultural diversity, was selected as the study area.

The central research question is: *How do external spatial factors relate to QRL regarding land use suitability for mountainous regions?* Two sub-questions further structure the investigation: (a) What indicators are appropriate for measuring QRL in the study area? (b) Which external spatial factors most strongly influence QRL? Accordingly, the research sets out the following objectives: (1) to construct a QRL indicator system tailored to Wumeng's mountainous villages; (2) to evaluate current QRL levels based on the indicator system; (3) to identify relevant external spatial factors and develop a QRL model based on these factors to support future village site selections.

The significance of this research is threefold. It advances the geospatial and quantitative study of QRL at the village scale by developing one of the first evaluation systems tailored to rural settlements. It addresses a critical gap in CLSA studies by introducing a data-driven model that integrates QRL as a core criterion. Furthermore, it promotes a shift in rural revitalization from a narrow focus on spatial form optimization to a more holistic emphasis on quality-of-life enhancement. This approach enables policymakers and planners to more effectively address substandard living conditions caused by fragmented planning and inefficient spatial layouts, helping to balance population growth with land

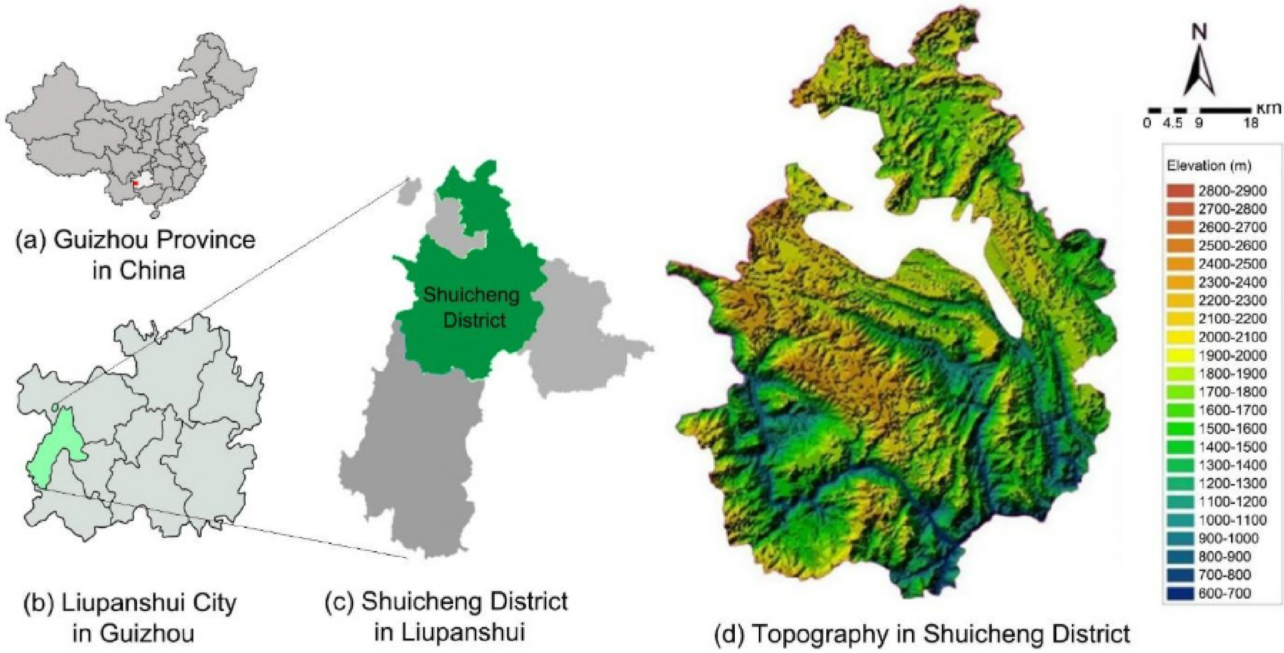

Fig. 1. Location and topography of the Shuicheng District.

constraints and align ecological protection with human well-being.

Materials and Methods

Study Area Overview

The study focuses on the Shuicheng District of Liupanshui City, Guizhou Province, in the Wumeng Mountains in Southwestern China (Fig. 1). This region, located between longitudes 103°10′–103°30′ E and latitudes 25°20′–27°45′ N, has an average elevation of about 2500 m [19]. Covering a total area of 107,000 km^2 and home to about 23 million people, the Wumeng region features diverse landforms and significant variations in climate, geography, and agricultural resources [20]. Liupanshui is one of the four major cities in this region, with a permanent urban population of approximately 750,000. The city sits at an elevation of 1760–1820 m and lies within the upper reaches of the Yangtze and Pearl River watersheds [21].

The Shuicheng District covers an area of 3054.92 km^2 and includes 80 administrative villages (Fig. 2). The district has a population of 746,407 and is characterized by its low latitude, high altitude, steep terrain, and vertical zonation. Situated in the plateau monsoon climatic zone of the mid-subtropical monsoon region, Shuicheng experiences cold winters, with average annual temperatures ranging from 12.3°C to 16.8°C. The area receives approximately 1553.1 hours of sunshine and experiences an average of 215 rainy days annually [22]. This climate is conducive to the cultivation of various subtropical and temperate plant species, including around 900 species of alpine plants and over 390 species of wild medicinal plants. Due to the diversity in climate, landforms, and human infrastructure, the QRL across villages in Shuicheng varies significantly, making the district a natural laboratory for studying QRL (Fig. 2).

We selected eight villages from Shuicheng for QRL modeling based on geographic distribution, population size, and historical continuity. Recognizing the potential significant economic influence of Liupanshui City may diminish with distance [23], the study area was stratified into four zones (0-20 km, 20-40 km, 40-60 km, and 60-80 km) from Liupanshui. Two villages per zone were selected using the following criteria: (1) a history of over 100 years to ensure long-term development and social stability; (2) more than 50 households to meet sample size requirement; and (3) at least 5 km between the two villages within the same zone or township to ensure variability in economic conditions and public service levels.

The selected villages – Fashao, Maliuwan, Xiagou, Miluo, Yina, Minzhu, Maocaodi, and Huaga (Fig. 2) – span different townships, totaling 451 households and 1,867 people. Household sizes range from 54 to 68, with populations between 240 and 342. While most residents are Han, minority groups such as Miao, Yi, Bouyei, Hui, Shui, and Gelao are also present. Agricultural activities are diverse, including staple crops (rice, corn, wheat, potatoes, sweet potatoes), vegetables (broccoli, amaranth, green beans), legumes, fruits (papayas, cherries, bayberries, loquats, thorn pears, plums), and specialty crops like tea and konjac.

Selection of QRL Evaluative Metrics

To evaluate the villages' QRL, we systematically selected evaluative metrics through an extensive

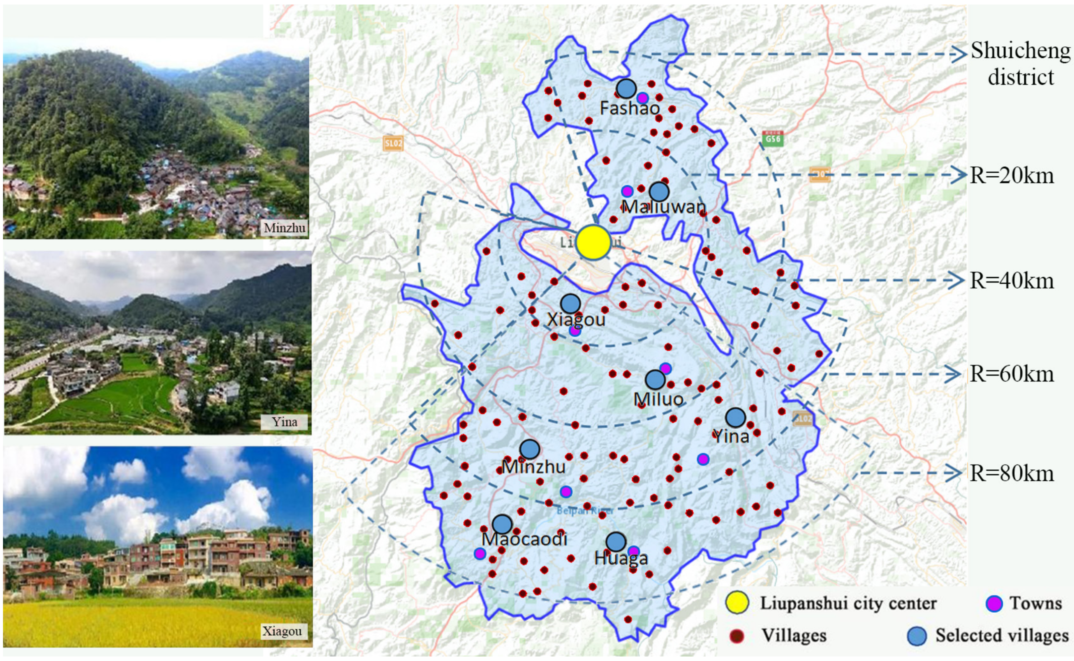

Fig. 2. Locations of selected villages and representative photographs.

review of literature, synthesizing findings from interdisciplinary sources such as urban planning, public health, environmental studies, and social sciences. Using thematic analysis, we identified seven core themes for QRL evaluation, including public services, infrastructure, economic conditions, buildings and amenities, landscape, environmental quality, and experience, each comprising a range of indicators that reflect both objective conditions and subjective perceptions of well-being. A total of 94 commonly referenced indicators were screened across these themes. To ensure contextual relevance, the screened metrics were then adaptively refined considering the unique geographical and cultural characteristics of the Wumeng Mountain region, resulting in the final selection of 26 QRL evaluation indicators (Table 1) tailored to the study area (see detailed rationale in Appendix A, Supplemental Materials).

Selection of Spatial Factors Affecting QRL

Similarly, to identify potential external spatial factors influencing QRL, we conducted an extensive literature review across six categories—topography and terrain, ecological environment, natural resources, location, transportation conditions, and geological conditions, ultimately screening 20 commonly cited factors. These metrics were also refined based on local context, resulting in a final selection of 10 spatial factors (Table 2).

First, elevation, slope, and sunshine duration were selected as key spatial variables because they directly influence agricultural productivity, infrastructure feasibility, and microclimatic conditions in mountainous terrain. Second, forest coverage was chosen for its role in ecological stability, water conservation, microclimate regulation, natural resource availability, and wildfire risk. A 5-km radius around each village was used to reflect the typical spatial extent of villagers' daily activities. Third, distance to the nearest river, reservoir, or lake was chosen to represent access to irrigation, a potentially critical constraint due to terrain and resource limitations despite resolved drinking water issues. Fourth, distance to the nearest natural resource development zone (areas designated for resource-based economic activities such as natural scenic tourism, mineral resource exploitation, or hydropower generation) was included to account for both the economic benefits (e.g., employment) and potential environmental or social disruptions (e.g., pollution, community tensions) associated with proximity to such zones. Fifth, distance to the nearest city and town was chosen due to its impact on access to essential services, employment opportunities, infrastructure, education, healthcare, and markets, where greater distances can lead to resource scarcity, social inequality, and economic stagnation, especially in dispersed settlements of mountainous regions. Sixth, distance to county roads was chosen for its effect on mobility, agricultural transport, infrastructure development, and service accessibility in regions where rugged terrain limits connectivity. Seventh, cultivation condition – measured as the proportion of arable land within a 5-km radius – was included to capture variation in farming potential in the poor soils of the karst region, where agriculture remains vital to rural livelihoods.

Lastly, some commonly cited factors were excluded due to limited variability, redundancy, or diminished relevance in the study context. For example, precipitation and accumulated temperature were excluded because

Table 1. QRL indicators applicable to the study area.

Theme	Indicator	Definition	Reference	Data sources
Public services	M_1 Average life expectancy (years)	Average number of years a newborn is expected to live, given current age-specific mortality rates of the village	[24]	Government statistics
	M_2 Quality of educational facilities (points)	Villagers' rating of basic education services	[25]	Questionnaire survey
	M_3 Access to cultural activity facilities (points)	Villagers' rating of cultural facility accessibility	[26]	Questionnaire survey
	M_4 Market accessibility (points)	Villagers' rating of market accessibility	[27]	Questionnaire survey
	M_5 Access to government assistance programs (points)	Villagers' rating of accessibility to aid programs (e.g., poverty relief, housing grants)	[28]	Questionnaire survey
Infrastructure	M_6 Tap water coverage (%)	Proportion of households with tap water access	[29]	Field survey
	M_7 Sewage pipeline coverage (%)	Proportion of households connected to sewage systems	[30]	Field survey
	M_8 Paved road coverage (%)	Proportion of village roads that are paved	[31]	Field survey
	M_9 Bus accessibility (points)	Villagers' rating of bus accessibility	[32]	Questionnaire survey
	M_{10} Mobile phone service quality (points)	Villagers' rating of mobile phone service quality	[33]	Questionnaire survey
Economic conditions	M_{11} Job accessibility (points)	Villagers' rating of job accessibility	[34]	Questionnaire survey
	M_{12} Average income (RMB)	Annual average income per capita	[35]	Government statistics
	M_{13} Monthly average household electricity consumption (KW•h)	Average monthly electricity consumption per household	[36]	Government statistics
	M_{14} Proportion of food expenditure (%)	Share of food expenses in total household consumption (Engel's Coefficient)	[37]	Government statistics
Buildings and amenities	M_{15} Proportion of concrete buildings (%)	Proportion of concrete building area in total building area	[38]	Field survey
	M_{16} Adequacy of amenities (points)	Villagers' rating of fitness, recreational, and commercial facilities	[39]	Questionnaire survey
Landscape	M_{17} Green space coverage (%)	Proportion of green space in village land	[40]	Government statistics
	M_{18} Public activity space per capita (m^2)	Average communal social/recreational area per person	[41]	Government statistics
	M_{19} Outdoor space comfort (points)	Villagers' rating of outdoor spaces comfort	[42].	Questionnaire survey
	M_{20} Village visual appeal (points)	Villagers' rating of village's visual appeal	[43]	Questionnaire survey
Environmental quality	M_{21} Trash can coverage (%)	Proportion of area covered by trash cans with a 70m service radius	[44]	Field survey
	M_{22} Proportion of households with fecal treatment tanks (%)	Proportion of households with fecal treatment tanks	[45].	Field survey
	M_{23} Noise perception (points)	Villagers' rating of noise interference	[46]	Questionnaire survey
	M_{24} Air quality index (μg/m^3)	Composite air pollutant concentrations ($PM_{2.5}$, PM_{10}, ozone, etc.)	[47]	Government statistics
Experience	M_{25} Community Friendliness (points)	Villagers' rating of village's friendly atmosphere	[48]	Questionnaire survey
	M_{26} Life satisfaction (points)	Villagers' rating of overall life satisfaction	[49]	Questionnaire survey

Table 2. Potential external spatial factors influencing QRL in the study area.

Theme	Indicator	Definition	Reference	Data sources
Topography	N_1 Elevation (m)	The height of the village center above sea level	[50]	Field survey
	N_2 Slope (º)	Mountain slope angle at the village location	[51]	Field survey
	N_3 Sunshine duration (hours)	Actual sunshine hours in an open field on a clear day in December	[52]	Field survey
Ecological environment	N_4 Forest coverage (%)	Forest coverage within a 5 km radius of the village	[53]	Field survey
Natural resources	N_5 Distance to irrigation water sources (km)	Distance to nearest river, reservoir, or lake	[54]	Field survey
	N_6 Distance to resource development zone (km)	Distance to nearest natural resource development zone	[55].	Field survey
Location	N_7 Distance to city (km)	Distance to nearest city	[56]	Field survey
	N_8 Distance to town (km)	Distance to nearest town	[57]	Field survey
Transportation condition	N_9 Distance to county roads (km)	Distance to nearest county road	[58]	Field survey
Geological conditions	N_{10} Cultivation conditions (%)	Proportion of arable land within a 5 km radius of the village	[59]	Field survey

they are relatively uniform across the region and their effects are largely captured by the selected topographic factors. Geological conditions were also excluded, as government-led hazard assessments and relocation policies have already designated high-risk areas as no-build zones [60]. Population density was not assessed directly, as it is largely reflected in proximity to cities, towns, development zones, and county roads, given that it is primarily shaped by transportation access and regulated limits on construction land (100-150 m² per capita) and residential area (80-120 m² per household) [61].

Data Collection

This study integrates three complementary data sources: primary objective data from field investigations, secondary data from government statistical departments, and primary subjective data from questionnaire surveys (Tables 1 and 2). The data source for each metric was selected based on source suitability and availability. This mixed-method approach allows for data triangulation and cross-validation, enhancing data robustness, minimizing single-source biases, and ensuring a comprehensive and reliable QRL assessment.

First, objective data were collected via field surveys, using professional geospatial tools such as GPS receivers and drones to capture accurate spatial details in complex terrain. All 10 spatial factors and another six QRL evaluative metrics were measured. The latter included tap water coverage (M_6), sewage pipeline coverage (M_7), paved roads coverage (M_8), proportion of concrete buildings (M_{15}), trash can coverage (M_{21}), and proportion of households with fecal treatment tanks (M_{22}), all of which reflect the physical infrastructure and environmental conditions of the villages.

Second, secondary data from government statistics provided authoritative and time-efficient information for seven socio-economic metrics that assess broader living conditions. These included average life expectancy (M_1), average income (M_{12}), monthly average household electricity consumption (M_{13}), proportion of food expenditure (M_{14}), green space coverage (M_{17}), public activity space per capita (M_{18}), and air quality index (M_{24}).

Third, primary data were collected via structured, anonymous questionnaires to capture villagers' subjective perceptions of QOL. This method allowed villagers to express their opinions directly, providing comprehensive insights into their needs and expectations. Thirteen indicators were assessed: quality of educational facilities (M_2), access to cultural activity facilities (M_3), market accessibility (M_4), access to government assistance programs (M_5), bus accessibility (M_9), mobile phone service quality (M_{10}), job accessibility (M_{11}), adequacy of amenities (M_{16}), outdoor space comfort (M_{19}), village visual appeal (M_{20}), noise perception (M_{23}), community friendliness (M_{25}), and life satisfaction (M_{26}).

Survey Design and Sampling Method

The questionnaire was designed to measure the 13 subjective indicators described above, using standardized and validated question items where possible, referring to existing literature, to ensure clarity and consistency. The instrument (see Appendix B, Supplemental Materials) was pre-tested with a small group of villagers and refined before distribution to ensure the clarity, neutrality, and cultural appropriateness of the questions. The final questionnaire comprised 59 questions: 50 measuring the indicators and 9 capturing demographic information, such as age, gender, and occupation. Each indicator was assessed through respondents' agreement with 3 to 6 statements, using a 5-point Likert scale (1 = strongly disagree; 5 = strongly agree).

To ensure a sufficient and statistically valid sample size, the G*Power software [62] was used to calculate the minimum number of respondents needed for regression analysis. The maximum effect size was set at 0.8, and the significance level at 0.05 [63]. With eight villages and an actual statistical power of 0.95, a minimum of 600 respondents is recommended to ensure reliable parameter estimates [64]. Therefore, each village was required to contribute at least 75 valid responses.

The survey targeted all residents aged 18 and above, and was administered online via WeChat, a widely used messaging and social media platform in China. WeChat's asynchronous data collection capability helped eliminate interviewer influence and streamline the data-gathering process. The initial survey was launched in December 2023 with the assistance of village chiefs, who helped distribute the electronic questionnaire through WeChat village groups. A preliminary review in May 2024 revealed limited participation from older adults aged 60 and above, and no responses from those over 90. As a result, a supplementary in-person survey was conducted in July 2024, where trained researchers read the questions aloud to senior residents aged 60 and above and recorded their answers on their behalf, ensuring inclusive representation across age groups.

Data Analyses

All data were analyzed using SPSS version 17. We first standardized the QRL indicators and validated data consistency across the three data sources through triangulation and Pearson correlation. QRL was quantified using the Coefficient of Variation to weight indicators by variability. A regression-based model was then developed to identify key spatial factors influencing QRL. Lastly, external validation was conducted in four villages from another district to assess the model's robustness across varied contexts.

Data Processing and Validation

To ensure comparability across indicators with different dimensions and ranges, the study adopted Min-Max normalization, which scales all data to the [0, 1] range and eliminates dimensional inconsistencies, making it suitable for integrated comparative analysis [65, 66].

The reliability and validity of the survey data were assessed using standard statistical methods, including Cronbach's Alpha for internal consistency and the Kaiser-Meyer-Olkin (KMO) measure and factor explanatory power for validity.

Given the study's integration of three data sources – questionnaire surveys, government statistical reports, and field investigations – triangulation was employed to assess data consistency and reliability. While each source captures different aspects of QRL, prior studies indicate correlations among them [67, 68]. The Mean Value Method was used to calculate the average scores of indicators within each data source: 7 statistical indicators (M_1, M_{12}-M_{14}, M_{17}, M_{18}, and M_{24}) from government reports, 6 spatial indicators (M_6-M_8, M_{15}, M_{21}, and M_{22}) from field surveys, and 13 subjective indicators (M_2-M_5, M_9-M_{11}, M_{16}, M_{19}, M_{20}, M_{23}, M_{25}, and M_{26}) from questionnaire data. These means were then compared using Pearson correlation analysis to evaluate inter-source consistency and confirm data reliability.

Quantification of QRL

Once the consistency and reliability of the three data sources were confirmed, the study employed the Coefficient of Variation (CV) method [69] to evaluate the QRL of the eight villages by assigning weights to the 26 QRL indicators. CV, calculated as the ratio of an indicator's standard deviation to its mean, reflects its relative volatility – the degree of variation across villages. Indicators with higher volatility, and thus greater impact on QRL differences, received higher weights. This method captures the relative importance of each indicator and avoids biases of subjective weighting methods [70]. The final QRL values for each village were calculated by applying the weights to the normalized indicators and summing the resulting weighted scores.

QRL Model Development and Validation

SPSS was used to develop a predictive model of QRL, treating the ten selected external spatial factors as independent variables and QRL scores of villages as dependent variables. Prior to analysis, a Shapiro-Wilk test confirmed that all 11 variables met the assumption of normality. To avoid multicollinearity and ensure analytical validity, autocorrelation analysis was performed among the 10 spatial factors to reduce the number of independent variables and identify factors significantly related to QRL. Given the relatively large number of independent variables compared to the sample size, stepwise regression was adopted to avoid overfitting. This method identifies the most influential predictors by sequentially analyzing each variable's contribution [71, 72].

To test the model's generalizability, external validation was conducted in Zhongshan District, geographically independent from the original research area. The same sampling and evaluation methods were applied to a new set of villages to test the model's performance under different geographic and socio-environmental contexts [73, 74]. Four villages were selected to ensure diversity in both location and land use: Mingsheng and Wangjiazhai (remote villages with significantly different arable land proportions), and Daqiao and Songlinjiao (town-adjacent villages with

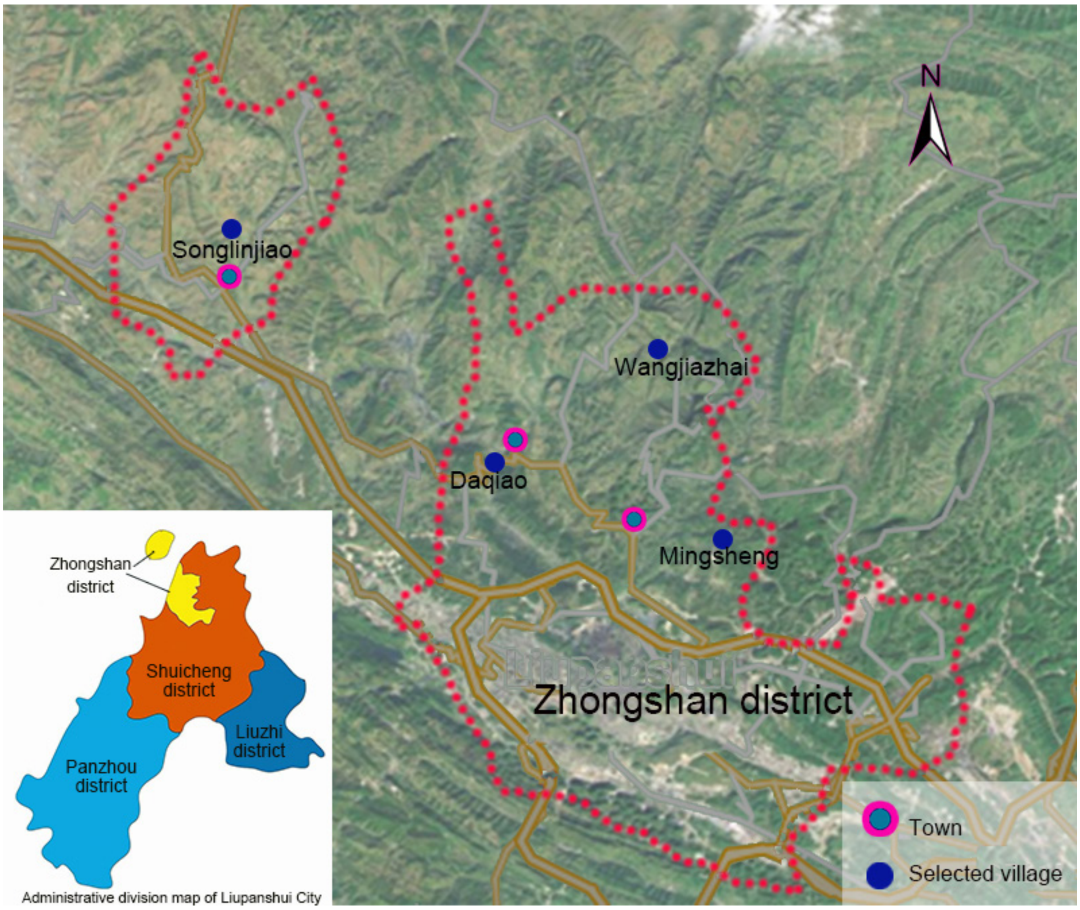

Fig. 3. Locations of the four villages for model validation in Zhongshan District.

similar arable land variation) (Fig. 3). Another sample size analysis using G*Power software indicated that at least 300 valid responses were required from these four villages.

Results

Survey Results

The study received a total of 1,231 valid responses (Table 3). Respondents were slightly more likely to be female (53.5%) than male (46.5%). The majority were farmers (81.2%) or farmers with off-farm employment (10.9%). Most fell within the 40-59 age group (40.3%). Nearly half had completed high school (49.6%), while only 5.4% had attended college.

Reliability and validity tests conducted on the survey data [75] show that all Cronbach's Alpha values exceeded 0.8, indicating high internal consistency. KMO values ranged from 0.7 to 0.8, supporting the data's suitability for factor analysis. Additionally, the explanatory power of extracted factors surpassed 74% of the variance in each village, confirming strong content validity. These results demonstrate that the questionnaire is both reliable and valid in its design and measurement [76].

Analysis of data from three sources revealed consistent trends across the eight villages. Village V_5 (Miluo) consistently scored the highest across all sources, while V_3 (Minzhu) and V_4 (Yina) showed the lowest scores. Fig. 4 shows general agreement among sources despite some variations. Pearson correlation analysis confirmed strong, statistically significant correlations between all data sources (ranging from 0.889 to 0.976, $p<0.01$), demonstrating their consistency and reliability. These results affirm the validity of using integrated data for assessing QRL across different villages.

The data for the 26 QRL indicators (Table 4) show that Village V_5 (Miluo) consistently outperforms others across most indicators, including lifespan, education, infrastructure, income, amenities, and life satisfaction, indicating a high overall QRL. V_7 (Maliuwan) and V_2 (Huaga) also score well in many areas. In contrast, V_3 (Minzhu) and V_4 (Yina) generally have the lowest values across health, infrastructure, income, and service access, suggesting a lower QRL. Other villages (V_1, V_6, and V_8) show moderate performance with mixed strengths and weaknesses across categories.

The eight villages also show significant variation in the ten external spatial factors (Table 5). V_2, V_7, and V_8 have the highest elevations, while V_4 is the lowest. Slopes are steepest in V_3 and V_4, but gentler in V_5 and V_7.

Table 3. Demographic characteristics of respondents.

Demographic Variable		Frequency	Percentage
Gender	Male	572	46.5%
	Female	659	53.5%
Age	18-39 years old	412	34.7%
	40-59 years old	494	40.3%
	60-79 years old	281	23.5%
	80-99 years old	31	2.6%
Occupation	Student	99	7.9%
	Farmer	996	81.2%
	Employed farmer	140	10.9%
	Other	0	0%
Education background	No formal education	139	11.3%
	Primary school	415	33.7%
	High school	611	49.6%
	College	66	5.4%
	Postgraduate or above	0	0.0%
Total		1231	100%

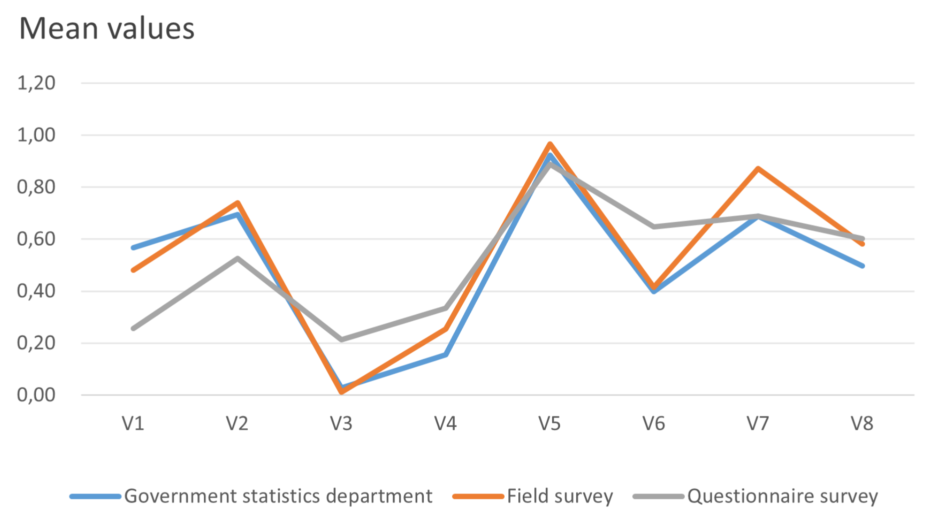

Fig. 4. Mean values of indicators for the eight villages from the three data sources.

Sunshine is most abundant in V_3, V_4, and V_6, and lowest in V_7. V_4 has the highest forest coverage (42.5%), while V_5 has the least (12.2%). Water availability is greatest in V_5 and V_6, but lowest in V_2. In terms of accessibility, V_5, V_7, and V_8 are well-connected to development zones, cities, towns, and county roads, while V_2 and V_3 are more remote. Cultivation suitability is highest in V_5 and V_7, and lowest in V_3 and V_4.

QRL Scores

Table 6 presents the coefficient of variation (CV) and corresponding weight (Wi) for the 26 QRL indicators. Indicators with the highest weights – such as average income (M_{12}), electricity use (M_{13}), air quality (M_{24}), sewage coverage (M_7), and noise perception (M_{23}) – demonstrate greater variability and thus carry more influence in the composite QRL assessment. Conversely, indicators like public activity space (M_{18}), bus accessibility (M_9), and community friendliness (M_{25})

Table 4. The descriptive statistics for QRL indicators.

Indicators and factors	V_1 Maocaodi	V_2 Huaga	V_3 Minzhu	V_4 Yina	V_5 Miluo	V_6 Fashao	V_7 Maliuwan	V_8 Xiagou
M_1	71.8	72.3	68.2	69.1	73.4	69.3	71.5	69.1
M_2	5.4	7.9	4.2	5.7	11.8	6.3	9.6	8.9
M_3	3.2	4.2	1.9	2.7	4.8	4.1	4.2	3.6
M_4	3.3	3.8	2.4	3.41	4.6	4.2	4.2	3.7
M_5	2.6	4.2	1.6	2.2	4.9	4.1	4.3	3.6
M_6	67.2	85.4	68.6	65.3	86.2	82.5	88.7	81.6
M_7	25.4	32.1	22.1	21.5	45.2	39.4	41.2	33.6
M_8	55.7	63.4	46.2	52.3	67.1	58.3	60.2	65.5
M_9	2.7	2.9	1.8	2.0	4.2	3.1	3.6	3.7
M_{10}	2.4	2.5	1.8	2.6	4.0	2.6	3.2	3.5
M_{11}	9.9	9.4	11.9	10.4	11.7	10.8	11.8	13.8
M_{12}	16.5	12.4	18.9	16.4	15.5	19.7	16.2	21.9
M_{13}	162.9	182.7	138.9	142.8	180.5	172.3	172.4	150.3
M_{14}	30.1	32.3	30.4	32.8	35.9	35.3	30.5	30.1
M_{15}	39.2	51.3	36.5	53.4	61.4	55.3	53.5	57.8
M_{16}	2.2	3.3	1.9	2.1	4.5	3.1	3.5	2.8
M_{17}	10.8	15.1	9.3	10.4	26.5	14.2	20.7	18.3
M_{18}	1.5	1.8	1.2	1.3	1.9	1.5	1.6	1.4
M_{19}	4.4	4.2	2.4	1.9	4.3	2.8	3.9	3.6
M_{20}	2.9	4.2	1.9	2.2	4.7	2.7	4.3	3.2
M_{21}	73.4	75.3	70.4	75.9	88.8	85.2	85.3	83.7
M_{22}	75.3	75.6	69.4	73.7	86.5	71.8	84.6	75.3
M_{23}	4.6	4.1	1.5	3.4	4.2	3.7	3.9	2.9
M_{24}	28.6	31.4	42.8	38.5	36.5	39.4	39.6	51.2
M_{25}	2.9	4.1	1.6	2.7	4.5	3.2	3.8	2.1
M_{26}	2.8	4.1	1.9	2.4	4.6	3.5	3.1	2.6

have lower weights, reflecting more consistency across villages. Based on this weighting scheme, the final QRL scores are 0.39, 0.61, 0.11, 0.24, 0.90, 0.51, 0.72, and 0.56, respectively, with 1.0 as the maximum possible score. Village V_5, scoring 0.90, ranks highest, while V_3, scoring only 0.11, ranks the lowest.

QRL Model

The autocorrelation analyses revealed significant relationships among the external spatial factors. Specifically, N_6 and N_8 were strongly positively correlated (p=0.003), while N_2 and N_4 showed significant negative correlations with N_{10} (p=0.01 and 0.016, respectively). To prevent multicollinearity, N_2, N_4, and N_6 were excluded from the regression analysis. If N_8 and N_{10} later show significant correlations with QRL, it may suggest indirect effects from N_2, N_4, and N_6. After excluding the three variables, the remaining seven were included in SPSS for stepwise regression. The analysis showed that only N_8 (distance to nearest town) and N_{10} (proportion of arable land) were significantly correlated with QRL, with low VIF values (<5), confirming no serious multicollinearity issues (Table 7).

The regression equation derived from the model is:

$$QRL = 0.490 - 0.431(N_8) + 0.381(N_{10})$$

where a one-unit increase in N_8 is associated with a 0.431 decrease in QRL, while a one-unit increase in N_{10} corresponds to a 0.381 increase in QRL.

The model validation in four additional villages predicted the QRL of each village using their respective N_8 and N_{10} values, and the results were compared with

Table 5. The 10 external spatial factors for the 8 villages.

Indicators		V_1 Maocaodi	V_2 Huaga	V_3 Minzhu	V_4 Yina	V_5 Miluo	V_6 Fashao	V_7 Maliuwan	V_8 Xiagou
N_1	Elevation	1768	1801	1763	1531	1672	1733	1802	1807
N_2	Slope	7.90	20.30	27.50	32.10	5.40	8.50	6.50	9.40
N_3	Sunshine duration	3.20	5.00	8.40	7.80	5.40	7.80	2.80	6.80
N_4	Forest coverage	16.30	22.20	27.80	42.50	12.20	20.90	13.40	18.20
N_5	Water availability	5.70	2.50	4.90	3.30	23.60	25.40	13.20	8.60
N_6	Distance to development zone	18.60	6.20	25.50	18.30	0.90	12.70	6.50	4.30
N_7	Distance to city	94.20	123.60	82.30	76.50	46.10	65.20	3.60	1.70
N_8	Distance to town	8.90	5.50	23.90	12.60	1.50	6.90	8.80	5.80
N_9	Distance to county roads	12	46	12	5	22	62	2.5	1.9
N_{10}	Cultivation suitability	22.40	16.40	11.30	12.80	32.50	18.10	29.70	20.50

the QRL values measured from the three sources (including a total of 527 responses). The predicted rankings completely matched the measured rankings (Table 8), indicating the model's strong applicability and accuracy for comparing QRL in the mountainous regions of Wumeng.

Discussion

Factors Influencing QRL

The QRL model developed (QRL = 0.490 – 0.431(N8) + 0.381(N10)) highlights two key direct spatial influences: distance to the nearest town (N_8) and the proportion of arable land (N_{10}).

The negative impact of N_8 on QRL is consistent with existing research indicating that towns, as centers of economic, cultural, and social services, provide essential access to transportation, markets, healthcare, and education services – all critical components of QRL [77]. This finding underscores the importance of choosing village relocation and expansion sites closer to towns to maximize service access and economic opportunities. The study also found a positive correlation between N_6 (distance from resource development zones) and N_8, reflecting a typical development pattern in mountainous areas: resource development zones tend to cluster near towns to leverage existing transportation networks, public services, and infrastructure. This finding aligns with both local realities and broader literature highlighting the dependency of mountainous area development on town nodes [78].

Although many studies suggest that proximity to resource development zones – especially extractive or resource-based industries like coal mining and thermal power generation – can bring long-term harm to rural communities by causing environmental degradation, resource depletion, and labor outmigration [79], our findings suggest a more positive outcome in the study area. This can be attributed to several factors. First, although coal development had previously impacted QRL negatively, strict environmental policies and effective management have significantly reduced pollution risks [78]. Second, resource development has spurred infrastructure improvements and increased employment opportunities, contributing to higher QRL. Unlike other regions experiencing significant labor outflow, targeted policy interventions and active economic diversification have helped stabilize the local population [79]. Villages such as Maocaodi (V_1), Huaga (V_2), and Miluo (V_5) have successfully diversified their economies through rural tourism, tea processing, e-commerce-based agricultural sales, and value-added food processing. This diversification has mitigated the social costs typically associated with resource dependence.

Notably, arable land availability (N_{10}) emerged as the second key determinant of QRL, highlighting the centrality of agriculture to rural livelihoods [80]. This finding aligns with prior studies emphasizing that more arable land supports higher household incomes, better food security, and stronger economic resilience [59]. However, arable land availability is not independent of other spatial factors. In particular, steep slopes (N_2) and dense forests (N_4) significantly constrain agricultural

Table 6. Weight calculation for QRL indicators and final QRL scores (Di = standard deviation; Zi = mean; Wi = weight).

Indicator	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	D_i	Z_i	CV	W_i
M_1	0.51	0.85	0.15	0.00	1.00	0.30	0.74	0.41	0.33	0.49	0.66	3.93%
M_2	0.30	0.46	0.27	0.00	1.00	0.81	0.80	0.82	0.33	0.56	0.58	3.49%
M_3	0.00	0.21	0.40	0.48	1.00	0.63	0.49	0.46	0.27	0.46	0.60	3.58%
M_4	0.17	0.35	0.06	0.00	0.63	0.76	0.78	1.00	0.35	0.47	0.75	4.49%
M_5	0.29	0.89	0.00	0.27	1.00	0.28	0.74	0.84	0.35	0.54	0.64	3.83%
M_6	0.27	0.62	0.00	0.07	1.00	0.65	0.99	0.36	0.36	0.49	0.72	4.33%
M_7	0.28	0.37	0.00	0.25	1.00	0.14	0.73	0.28	0.31	0.38	0.80	4.80%
M_8	0.48	0.78	0.00	0.47	1.00	0.58	0.97	0.86	0.31	0.64	0.48	2.89%
M_9	0.52	1.00	0.00	0.93	0.79	0.70	0.94	0.34	0.32	0.65	0.50	2.97%
M_{10}	0.51	0.62	0.30	0.56	1.00	0.58	0.49	0.00	0.27	0.51	0.52	3.13%
M_{11}	0.26	0.81	0.00	0.51	1.00	0.87	0.67	0.58	0.31	0.59	0.53	3.14%
M_{12}	0.38	0.05	0.00	0.16	1.00	0.29	0.66	0.83	0.35	0.42	0.82	4.93%
M_{13}	0.43	0.63	0.00	0.22	1.00	0.63	0.22	0.03	0.32	0.40	0.81	4.87%
M_{14}	0.46	0.87	0.00	0.17	1.00	0.33	0.74	0.68	0.33	0.53	0.61	3.67%
M_{15}	0.35	0.68	0.00	0.09	1.00	0.72	0.68	0.84	0.34	0.54	0.62	3.69%
M_{16}	0.49	0.53	0.12	0.00	1.00	0.74	0.77	0.91	0.34	0.57	0.59	3.53%
M_{17}	0.83	0.67	0.00	0.18	1.00	0.38	0.82	0.39	0.33	0.53	0.62	3.68%
M_{18}	0.57	0.79	0.00	0.36	1.00	0.79	0.86	0.71	0.30	0.63	0.47	2.82%
M_{19}	0.00	0.23	0.34	0.33	1.00	0.35	0.41	0.33	0.26	0.37	0.71	4.24%
M_{20}	0.00	0.14	0.78	0.36	1.00	0.74	0.64	0.34	0.32	0.50	0.64	3.85%
M_{21}	0.72	1.00	0.07	0.00	0.88	0.25	0.91	0.46	0.37	0.54	0.69	4.14%
M_{22}	0.77	1.00	0.00	0.66	0.91	0.15	0.96	0.69	0.35	0.64	0.54	3.25%
M_{23}	0.63	1.00	0.06	0.00	0.22	0.33	0.48	0.39	0.30	0.39	0.78	4.63%
M_{24}	0.79	1.00	0.05	0.00	0.46	0.07	0.79	0.42	0.36	0.45	0.81	4.82%
M_{25}	0.00	0.37	0.44	0.70	1.00	0.89	0.86	0.82	0.32	0.63	0.50	2.97%
M_{26}	0.18	0.22	0.00	0.21	0.91	0.74	0.86	1.00	0.37	0.51	0.73	4.34%
Total												1.00
Final QRL score	0.39	0.61	0.11	0.24	0.90	0.51	0.72	0.56				

Table 7. Regression results for QRL predictors.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity statistics	
		B	SE	Beta			Tolerance	VIF
1	(constant)	.236	.078		3.012	.024		
	N10	.623	.144	.870	4.330	.005	1.000	1.000
2	(constant)	.490	.108		4.534	.006		
	N10	.381	.134	.532	2.845	.036	.559	1.790
	N8	-.431	.159	-.509	-2.720	.042	.559	1.790

Table 8. Comparison table of prediction and survey results of QRL.

Village	N_8	N_{10}	Prediction		Measured	
			QRL	Rank	QRL	Rank
Wangjiazhai	9.3	0.58	0.54	2	0.53	2
Daqiao	3.5	0.51	0.76	1	0.83	1
Mingsheng	8.5	0.25	0.15	4	0.29	4
Songlinjiao	2.1	0.28	0.53	3	0.35	3

expansion, suggesting that future village site selection should prioritize areas with gentle slopes and moderate forest coverage that allows for viable agricultural use. While these natural constraints have historically limited agricultural productivity, technological innovations and land management strategies – such as terracing, agroforestry, and ecological agriculture – offer ways to mitigate these limitations [11]. Nevertheless, strict environmental protection policies, while essential for landscape restoration, may further restrict arable land, posing ongoing challenges for balancing ecological conservation with rural development needs.

Factors with No Impact on QRL

The study found that N_5 (distance to irrigation water sources), N_7 (distance to nearest city), and N_9 (distance to county road) had no significant impact on QRL in the study area, contrasting with broader literature that emphasizes the importance of these factors [81, 82]. This discrepancy can largely be attributed to the study area's natural conditions, infrastructure, and socio-economic model.

For irrigation sources (N_5), the study area benefits from abundant rainfall and has achieved full coverage of rural drinking water safety projects. Soil and water conservation efforts, such as groundwater extraction via wells in mountaintop villages, ensure a stable drinking water supply even during dry seasons. As a result, traditional spatial constraints related to irrigation source locations have become less relevant for QRL. While water availability remains critical, its influence on QRL in this context has been effectively mitigated through infrastructure and natural resource conditions.

Meanwhile, towns, as the core providers of medical care, education, commerce, and other daily services, have significantly reduced villages' dependence on distant city centers. Although urban proximity is often associated with better employment and service access elsewhere [83], the study area's agricultural self-sufficiency model and reliance on local towns mean that daily life rarely requires travel to the city, except in cases of severe illness.

Transportation is often considered a key driver of rural development [82], yet the study found that distance to county roads (N_9) had no significant impact on QRL. Transportation improvements in the area have brought added convenience but have not fundamentally shifted living standards. This challenges the assumption that improved transportation inherently improves rural living. For villages relying on traditional agriculture and self-sufficiency, meaningful improvements in QRL still depend on broader shifts in local economic structure and industrial diversification. Therefore, transportation should be considered in tandem with economic development, ecological protection, and resident lifestyle needs, rather than as an isolated planning priority.

Additionally, the study found no significant correlation between N_1 (elevation) and N_3 (sunshine duration) and QRL, largely due to the geographical environment, technological progress, land-use planning, and agricultural adaptability. First, the spatial variation in elevation and accumulated temperature across villages is relatively small, with most villages concentrated between 1,500 and 2,000 m. Annual average sunshine duration in all villages exceeds 1,400 hours, and accumulated temperature exceeds 5,500°C·day. Even villages on northern slopes, typically expected to face sunlight limitations, receive sufficient sunshine – over 3 hours during the winter solstice – thanks to thoughtful land-use planning and building orientation. Second, technological advances and agricultural adaptation have further reduced environmental constraints. Local farmers have adopted climate-resilient crops, such as corn and potatoes, and implemented modern cultivation techniques like greenhouse farming and water-saving irrigation [84]. These measures have collectively offset the negative impacts traditionally associated with high altitude and limited sunshine exposure. Thus, while elevation and slope orientation often affect QRL elsewhere, in the study area [85, 86], their influence has been significantly diminished by both favorable natural conditions and effective human interventions.

Contributions and Implications for Rural Planning

The study advances research on QRL by quantitatively linking village siting and spatial layout with residents' living conditions. It establishes a novel research framework that correlates 10 external spatial factors with QRL, highlighting how rational land selection and village planning can enhance rural well-being. The research also develops a tailored QRL assessment system specifically for mountainous rural regions, addressing the shortcomings of existing urban-centered models by incorporating 26 indicators across health, income, environment, infrastructure, and social relations. Furthermore, the study proposes a suitability assessment model for village construction sites, offering guidance that integrates ecological, geographical, and social considerations. Together, these contributions provide important theoretical insights and practical tools for optimizing rural revitalization and sustainable development in complex mountain landscapes.

Based on the findings reported, several recommendations can be proposed to guide the sustainable development of rural areas in the Wumeng Mountains. First, when selecting sites for village relocation or new rural construction, priority should be given to areas that are close to towns, have a high proportion of arable land, feature gentle slopes, and contain moderate coverage of forest protection areas. These physical characteristics are more conducive to improving the QRL and support long-term development by providing better access to services, infrastructure, and productive land.

Second, development strategies should focus on concentrating construction land and rural population around towns rather than cities. This helps support coordinated urban-rural development, leverage the driving role of towns, narrow the urban-rural divide, and promote more effective circulation of resources and information.

Finally, due to the significant impact of farmland on QRL, special attention should be paid to farmland protection in rural development and urban expansion processes. This is essential for sustaining the rural economy and ensuring that farmers maintain sufficient arable land to support their livelihoods.

Limitations and Future Research Directions

Despite significant findings and practical implications, we note several limitations of this study. Due to the lack of an established QRL index system in rural China, the study referred to urban QOL evaluation indicators. The adapted system reflects the local geographic and cultural context, but it may have limited applicability in areas with different lifestyles, ethnic compositions, or development levels. As rural living conditions vary widely across regions, future adaptations of the system should account for local cultural and socioeconomic differences. Second, the regression model is based on correlations between external spatial factors and QRL, but these relationships do not imply causation. Therefore, while the model is useful for comparing QRL across villages, it is not suitable for predicting the precise QRL scores of individual villages. Its primary value lies in informing spatial prioritization and guiding village development strategies.

Additionally, the model's geographical specificity poses limitations. It is tailored to the Wumeng Mountains, characterized by ethnic minority demography, dispersed settlements, traditional mountain agriculture, and strong policy regulations such as "rural revitalization" and "ecological protection" [87]. These characteristics influence the weights and relevance of the model's core variables. Given this regional specificity, the model may not be directly applicable to plains or regions with superior natural conditions, better infrastructure, industrial diversity, and a higher degree of urban-rural integration.

To enhance the model's robustness and applicability, several directions for future research are proposed. First, future inquiries should consider incorporating more social and cultural dimensions into the QRL framework. As rural QOL evolves with modernization, factors such as spiritual well-being, cultural engagement, social equity, and governance may become increasingly important and should be reflected in the evaluation system.

Second, including a greater number of villages or survey respondents will strengthen the model's statistical foundation and broaden its applicability. Applying and testing the model across more diverse rural settings will also help refine its structure and identify limitations in transferability.

Lastly, it is important to recognize that rural areas are dynamic and continually evolving. Changes in population structure, land use, technological advancement, economic development, policy shifts, and residents' aspirations will all impact QRL. Therefore, the model should be continuously adjusted to reflect these evolving realities. This may involve expanding the range of spatiotemporal factors considered, recalibrating parameters, or integrating time-series data to track long-term trends. Addressing these limitations and pursuing these research directions will enhance the model's accuracy, relevance, and flexibility, supporting more informed decision-making in the sustainable development of rural areas.

Conclusions

This study comprehensively evaluated the QRL of eight villages in China's Wumeng Mountains, using a framework of 26 indicators (13 subjective and 13 objective) spanning multiple dimensions of rural infrastructure, environment, economy, and social well-being. The regression analysis connecting QRL to 10 external spatial factors of the villages indicated that a higher proportion of arable land significantly improves QRL, while a greater distance from the nearest town has a negative impact. Additionally, 3 factors (slope, forest coverage, and distance from the nearest resource development zone) exert indirect negative impacts on QRL. The remaining 5 factors (elevation, sunshine duration, irrigation source, distance from city, and distance from county roads) showed no significant impact on QRL.

The main contribution of this study lies in simplifying the traditionally complex process of village site selection by introducing a quantitative analysis method based on the correlation between QRL and external spatial factors. This model enables policymakers to more accurately assess land use planning and rural development strategies by fully considering spatial and environmental factors. It not only provides theoretical support for land policies and rural planning but also provides an efficient decision-making tool for promoting sustainable development in mountainous areas.

Overall, this study demonstrates that QRL in mountainous areas is closely linked to agricultural land endowment and spatial accessibility to towns. The findings enrich the growing body of research advocating for the integration of spatial and environmental variables in rural development planning. Furthermore, the study provides a replicable framework for QRL assessment and highlights the need for context-specific models that reflect local geographic, economic, and cultural realities.

Looking ahead, future research should expand the model by incorporating more social and cultural dimensions, increasing sample sizes, and testing across diverse rural contexts to enhance its statistical robustness and generalizability. Additionally, integrating spatiotemporal dynamics and long-term data will help capture evolving rural realities and ensure the model remains relevant and adaptable for guiding sustainable rural development.

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Conflict of Interest

The authors declare no conflict of interest.

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