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Expert Opinion Dimensions of Rural Landscape Quality in Xiangxi, Hunan, China: Principal Component Analysis and Factor Analysis

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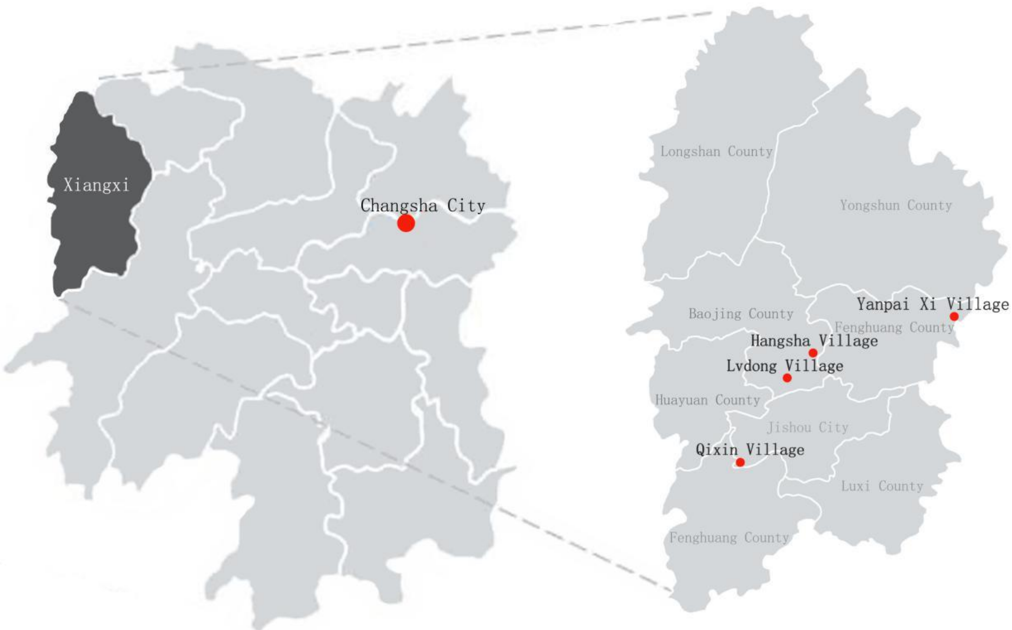
Abstract: Scholars and planning/design professionals are interested in the quantitative, metric properties influencing the quality and assessment of rural landscape space. These metrics are important for guiding rural planning, design, and construction of cultural rural environments. Respondents and metrics from four sampled villages (Qixin, Hangsha, Yanpai Xi, and Lvdong) in the Xiangxi District of Hunan Province in China were examined, employing statistical principal component analysis and factor analysis methods to understand the identifying properties concerning planning and design features of these rural mountain village landscape spaces. The two approaches reveal different aspects from the same variables. Through factor analysis and rotation, four general dimensions were revealed explaining approximately 62% of the variance: a settlement and environmental axis, an intangible culture axis, a productive landscape axis, and a transportation and public space axis, supporting the standing notion that the variables were ordinated across four dimensions in these mountain villages and occupied an elliptical plane that was different than the predicted space occupied by nearby cites. In contrast, principal component analysis revealed that the variables could be grouped into one latent dimension explaining 48% of the variance and revealing an alternative interpretation and spatial plot of the sites.

Keywords: landscape metrics; landscape architecture; cultural geography; physical geography; rural studies; rural planning; cultural sustainability; Asian studies; social science; cultural anthropology

1. Introduction

As an agricultural country with over 5000 years of “farming culture”, China’s agricultural area accounts for nearly 56% of the land area [1]. These rural environments contain agricultural production areas, villages, mountains, rivers, and other natural landscape features reflecting the local history and civilization. Rural landscape evaluation is the core of rural landscape theory expressed by Liu and Wang [2], and also an important means to achieve the protection and development of rural landscape with regional characteristics, directing future planning and development of rural areas. The United States enacted the Wilderness Act (1964) which initiated the evaluation and protection of rural landscape resources; while the United Kingdom began to conduct qualitative analysis of rural landscape quality since the 1980s, emphasizing public participation and sensory evaluation [3,4]. Towards the end of the 20th century, Australia, Netherlands, Russia, Canada, and other countries explored planning and management metrics [5]. In the Netherlands, an expert scoring method to evaluate the quality of rural landscape was employed [6]. To understand the public’s preferences, direct surveys were initiated to achieve a consistent approach to rural landscape quality evaluation [7–27]. In the past, evaluation methods of rural landscape quality have been diversified, mainly including analytic hierarchy process (AHP), questionnaire survey methods, and visual assessments method [28,29]. Recently, there has been an emphasis upon landscape and design metrics to measure and ordinate environments [30–35]. In addition, there have been approaches to employ fractals to understand and replicate spaces modified by humans [36–38]. Although rural landscape evaluation has been an interest of some scholars, the rural landscape multivariate evaluation system has not been extensively examined, investigations are often quantitatively weak, and a somewhat complete comprehensive evaluation system has not been fully explored, yet there is much to learn [10]. Over the last 50 years, investigators have focused upon the perceptions of citizens with the understanding that experts (academics and experienced professionals within China from the planning and design arena) view the environment differently [10]. Few studies have examined the perceptions of experts; Kongjian Yu is one of the few to conduct such studies [39]. Our study examined the evaluation of the rural landscape of the Xiangxi District in Hunan Province, China, by surveying the responses of planning and design experts to gain their perception of the environmental qualities that comprise the characteristics of the setting. Such studies often generate many variables to consider and may rely upon multivariate statistical analysis to clarify the results [40–52].

To provide a more quantitative approach, factor analysis (FA) and principal component analysis (PCA) are two methods of multivariate statistical analysis which have been widely used in soil science, water quality science, climatology, medicine, urban geography, and other fields and have achieved insights into the relationships amongst a larger set of variables [40–52]. These approaches attempt to reduce and group the number of dimensions/variables to glean a clearer understanding of underlying relationships amongst the variables. In this investigation, the team examined spatial variables (24) addressing a somewhat culturally distinct rural environment in the Xiangxi District of Hunan Province in China (Figure 1), generating results from four villages (Qixin, Hangsha, Yanpai Xi, and Lvdong). The team employed both FA and PCA to extract descriptions of the data and to suggest implications for the planning, design, and management of these rural cultural areas.



(**a**) (**b**)

Figure 1. These maps locate the study area in Hunan Province, China: (**a**) the location of Xiangxi and provincial capital in Hunan Province; (**b**) the location of the four villages in Xiangxi.

2. Study Area and Methodology

2.1. Xiangxi Study Area and Photographic Images

Xiangxi Tujia and Miao Autonomous Prefecture of Hunan Province (Xiangxi for short) is located in the Wuling Mountain Area. Due to the unique karst landform and isolated traffic patterns, there are a large number of intact traditional villages with a long history and rich in cultural relics. In order to promote the protection and development of traditional villages, the Ministry of Housing and Urban–Rural Development of China and other departments established a list of traditional Chinese villages according to the evaluation and identification index system of traditional villages, totaling 6799 villages. The study team (including scholars from the College of Landscape Architecture and Art, Hunan Agriculture University, Changsha, Hunan Province, China, and the College of Landscape Architecture, Beijing Forestry University, Beijing, China) chose four of the most representative (village remoteness, traditional buildings, preserved farmland, maintain traditional culture, elevation between 478–750 m, and presence of traditional streets) villages for a more in-depth study: Lvdong, Qixin, Hangsha, and Yanpai Xi, located in the Xiangxi area of Figure 1. The four traditional mountain villages comprised the basis for the questionnaire. The four villages are located in the eastern end of Yunnan–Guizhou plateau and the middle part of the Wuling mountain range with an average elevation of 478–750 m, vegetation coverage, and no large-scale tourism development. Because they are located in remote mountains, they are less disturbed by modern culture, and their historical and cultural values are more evident. Their traditional residential buildings, streets, and farmlands are well preserved. The four traditional villages in this study appeared to have great similarity.

For each village, 8 to 9 photographs were chosen to obtain respondent impressions/opinions (2–3 images for village overall condition and the surrounding environment, two for close distance examples of the settlement and residential environment landscape, one to show the village water, 2–3 images for customs or landmarks) (Figures 2–5). The photographic samples were collected under favorable weather conditions from October 2016 to October 2017, attempting to show the compositional characteristics of each village in a similar manner.

Figure 2. These pictures are of the Lvdong village area (copyright © 2017 Bin Wen all rights reserved, used by permission).

Figure 3. These photographs are of the Qixin village area (copyright © 2017 Bin Wen all rights reserved, used by permission).

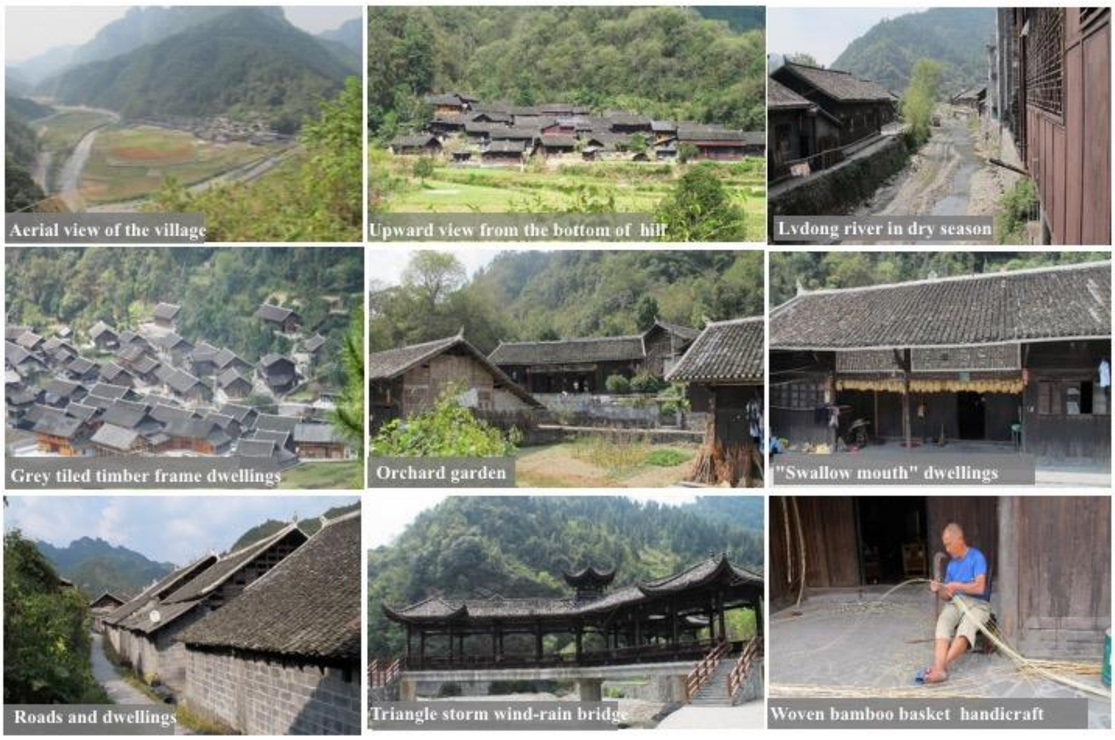


Figure 4. These images are of the Hangsha village area (copyright © 2017 Bin Wen all rights reserved, used by permission).

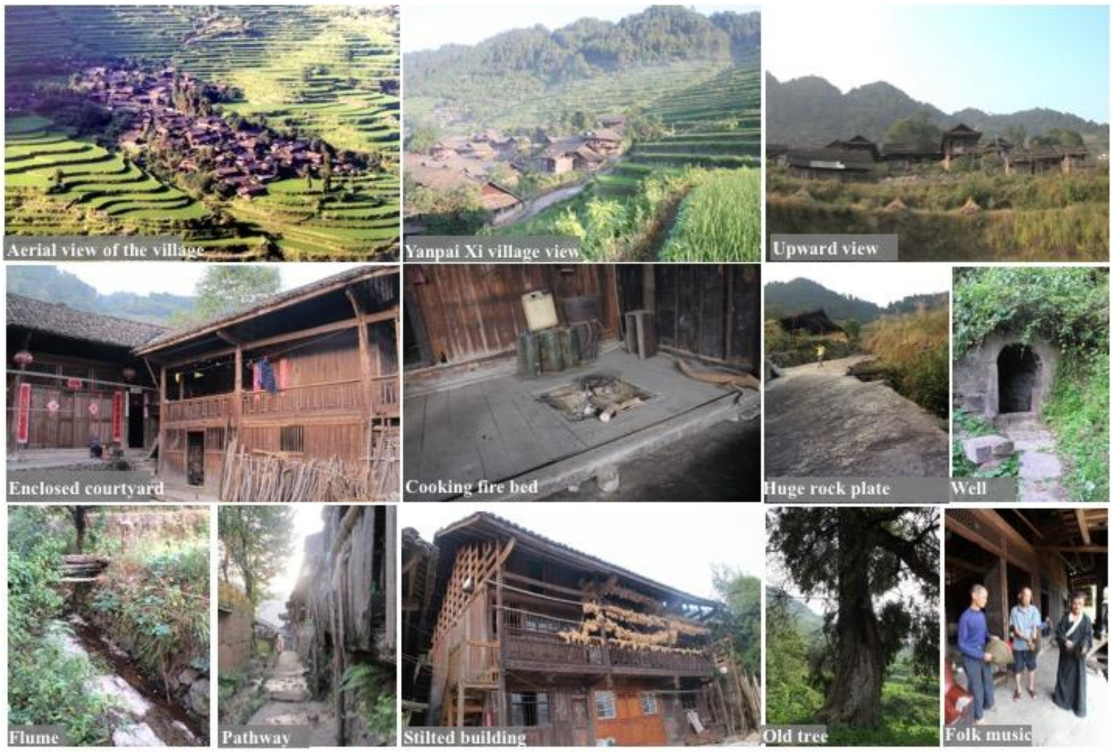


Figure 5. This set of pictures are from the of Yanpai Xi village area (copyright © 2017 Bin Wen all rights reserved, used by permission).

2.2. Methodology

To derive a response instrument from the images, a series of variables needed to be employed in a respondent survey. In determining the variables, 30 graduate students in landscape architecture from Beijing Forestry University, Hunan Agricultural University, and 10 experts on rural tourism, planning, and design were interviewed concerning their opinions about assessment impact variables in rural landscapes. The results identified, potentially, 45 different items. Then, 40 Asian tourists who have experienced rural tourism were asked, "In your opinion, what are the variables affecting rural landscape evaluation?" This approach generated approximately 50 potential variables. In the end, this led to a total of 24 variables (Table 1). The variables were able to be measured in a respondent survey employing the Likert scale, an ordinal data approach (Table A1).

Respondents were selected from individuals who were engaged in or experienced in rural tourism, and the survey was conducted by an on-line network questionnaire. A total of 164 questionnaires were distributed, and 164 effective questionnaires were received, an effective rate of 100%. The entire questionnaire survey process was completed within a continuous period of time, ensuring the randomness and representativeness of data samples. The gender ratio was 52% female and 48% male. The age groups in the respondents ranged from 20 to 39 (51%) and 40 to 59 (29%) with the remaining in other age groups. In terms of education level, respondents mainly received undergraduate and master's degrees (46% and 29%, respectively), and those with doctor's degree or above accounted for 9%. The remaining respondents had no higher education degrees.

Prior to giving responses, the purpose and method of research were told to the respondents. Then, the group of slides for a village were presented. The respondents had 1 min to view the image. The respondent's responses were then assessed with FA and PCA. The data captured were ordinal in nature, and these methods are most suitable to non-parametric statistical approaches; however, for multivariate analysis, a reliable/widely accepted non-parametric approach for FA and PCA have not been widely adopted. Since this study is exploratory in nature, parametric FA and PCA were employed.

Table 1. The list of variables employed in the respondent survey.

ID	Variable
V1	forest vegetation coverage area
V2	farmland coverage area
V3	unique natural scenery
V4	the color and species of farmland/orchard garden/tea garden
V5	water form
V6	farmland texture level
V7	settlement scale
V8	residential building technology level
V9	quantity of remaining historic buildings
V10	integrity of old settlements
V11	types of public gathering spaces
V12	number of landmark structures
V13	the features of construction materials
V14	traffic organization in villages
V15	cleanliness of villages
V16	accessibility of external traffic
V17	visual interference of surrounding environment
V18	isolation from the outside world
V19	landscape vision and orientation
V20	visibility of sights
V21	folk customs
V22	activation and inheritance of folk art
V23	aboriginal reservations
V24	legends and stories

3. Results

The overall reliability of 164 questionnaires was tested with the Cronbach's alpha coefficient which had a value of 0.952, indicating that the questionnaire had high reliability. The Kaiser–Meyer–Olkin measure (KMO) and Bartlett test of sphericity were used in the study. The KMO value was measured to be 0.958 which was much greater than the minimal number of 0.5, indicating that the data samples were robustly sufficient and suitable for factor analysis, and the results of principal component analysis had practicability. At the same time, Bartlett's significance value for the spherical test was 0.000 which was less than an alpha of 0.01, indicating that there was a correlation among the variables and that this data were suitable for factor analysis. The correlation coefficient matrix of 24 variables was obtained. A large proportion, approximately over 90% of the variables, generated correlation coefficients among the variables that were greater than 0.3, meaning there was a substantial linear correlation among many of the variables; in other words, the variables were able to be grouped or associated.

In this study, principal component analysis (PCA) was used to identify the general number of dimensions. Normally in PCA, eigenvalues dropping lower than one are often considered dimensions with low explanatory values. The characteristic root of the first principal component is 11.513 which can explain 47.969% of information across all variables (Table 2). The characteristic root of the second principal component is 1.355, which can explain 5.647% of the information in all variables. The characteristic root of the third principal component is 1.171, which can explain the information of 4.881% in all variables. However, the cumulative contribution rate of the three principal components was only 58.497%. According to the related literature, the principal component should be accumulated to explain 60–70% of the variation of the data; thus, to extract the fourth principal component, the cumulated variance contribution ratio in the first four principal components reached 62.220%, explaining 62.22% of the total variable difference. The PCA suggests, at most, there were up to four meaningful dimensions. According to standard principal component analysis, the dimensions of the principal components are not rotated explaining the maximum amount of variance per orthogonal dimension. The eigenvector of the first dimension contained larger coefficients for the variables ranging from 0.553 to 0.776. Usually, such values are strongly associated with the first dimension [40–52]. In other words, it would be possible to explain 47.969% of the variance in one dimension with all of the variables strongly associated with the first dimension. However, the study team was interested in exploring the results with rotations.

Table 2. The results from the PCA.

Dimension	Eigenvalue	Variance Contribution Rate (%)	Accumulative Variance Contribution Rate (%)
1	11.513	47.969	47.969
2	1.355	5.647	53.616
3	1.171	4.881	58.497
4	0.893	3.723	62.220
5	0.780	3.624	65.843
6	0.779	3.247	69.091
7	0.676	2.815	71.906
8	0.642	2.674	74.579
9	0.587	2.444	77.023
10	0.548	2.281	79.305
11	0.519	2.161	81.465
12	0.498	2.073	83.539
13	0.471	1.962	85.501
14	0.423	1.762	87.263
15	0.396	1.650	88.913
16	0.382	1.592	90.505
17	0.358	1.491	91.995
18	0.336	1.402	93.397
19	0.304	1.268	94.665
20	0.298	1.241	95.906
21	0.276	1.151	97.057
22	0.267	1.113	98.170
23	0.228	0.951	99.121
24	0.211	0.879	100.00

The study team employed the maximum variance method to normalize the rotation with Kaiser and the rotation convergence of eight iterations for factor analysis. The new factor loads of all variables on the four principal components were obtained by rotation. The scale of factor axis composition can be observed from Table 3. The four common factors included the physical load and the main characteristics of 24 evaluation factors. It should be noted that dimension names were heuristically derived by trying to identify a general character of the grouped variables. In addition, six of the variables (listed at the bottom of Table 3) were not associated with any of the latent dimensions.

Table 3. Results after factor analysis rotation. Bold factor loading coefficients indicate strong affiliation.

Rotated-Latent Dimension Name	Variables	Factor Loading			
		1	2	3	4
Settlements and environmental factors	V18 Isolation	**0.742**	0.129	0.126	0.205
	V19 Landscape vision	**0.692**	0.404	0.067	0.255
	V9 Remaining historic buildings	**0.684**	0.264	0.28	0.203
	V20 Air quality/visibility	**0.67**	0.462	0.074	0.231
	V10 Integrity of old settlement	**0.633**	0.271	0.348	0.224
	V8 Technology level of residential building	**0.624**	0.23	0.303	0.256
	V13 Features of construction materials are local	**0.619**	0.207	0.294	0.256
	V17 The visual interference	**0.613**	0.106	0.344	0.175
	V15 The cleanliness of village appearance	**0.508**	0.196	0.479	0.253
Intangible cultural factors	V21 Folk customs apparent	0.329	**0.722**	0.205	0.144
	V22 Activation inheritance folk art	0.308	**0.707**	0.365	0.109
	V23 Aboriginal reservations	0.423	**0.675**	0.267	0.113
Transport and public space factors	V16 External traffic accessibility	0.025	0.247	**0.711**	0.245
	V11 Public gathering space is abundant	0.348	0.16	**0.689**	0.214
	V14 The traffic organization in village	0.376	0.211	**0.644**	0.239
Productive landscape factors	V6 The texture level of farmland	0.276	0.053	0.272	**0.743**
	V2 The coverage area of farmland	0.266	0.06	0.172	**0.706**
	V4 farmland/orchard garden/tea garden is colorful and diverse	0.294	0.267	0.27	**0.652**
	V12 The landmark structures are abundant	0.47	0.354	0.422	0.177
	V3 Unique natural scenery is abundant	0.438	0.428	0.08	0.366
	V24 Legends and stories are rich	0.179	0.523	0.541	0.169
	V5 The form of waters is abundant	0.154	0.475	0.306	0.476
	V1 The coverage area of forest vegetation	0.449	0.251	0.041	0.476
	V7 Settlements are large - small	0.096	0.414	0.277	0.433

In the factor analysis results, the general qualitative characteristics of these villages included a strong sense of isolation from the outside world, a strong orientation towards nature (biospheric, not noospheric), an abundance of traditionally styled Chinese buildings (little modernism and post-modernism), good air quality (not polluted), strong evidence of cultural relics (stone carvings, stelae, etc.), strong evidence of quality traditional construction methods, strong use of local materials (wood and stone), strong absence of modern technology (no highways, little sign of electrical lines, towers, rail lines, no neon lighting), and a strong sense of care in appearance (no rubble, no litter). Other characteristics included: a strong evidence of local traditions/customs, a strong evidence of Miao folk art (silver work, embroidery, batik, etc.), evidence of authentic traditional lifestyles, good external traffic connections, a variety of traditional open spaces (well site, sun drying space, etc.), a strong sense of order in the transportation spaces, strong spatial separation of land uses (clear distinction between farmland, urban space, woodland), an overwhelming abundance of farmland in contrast to urban land, and that the agricultural land is diverse. The PCA results included a similar character but also included the properties of the remaining six variables: abundant landmarks, abundant natural scenery, associated legends and stories for the area, presence of water, the presence of forested lands, and the village size ranges from 500 to 1000 residents.

Often, the concept behind factor analysis is that there is a predetermined or imagined structure (factors) that is suggested or has evolved in the literature and is illustrated in a classic study by Dunn, whereas principle component analysis does not assume a preordained structure [53,54]. The rotations and clusters associated with factor analysis attempt to ascertain the strength of the expected structure. The factor loading coefficients in Table 3 which have values greater than 0.6 represent a strong association with the factor. These values are shown in bold in Table 3. Each of the eighteen variables with a strong association are affiliated with one of the predefined factors. The remaining six variables have only a weak association with the four predetermined factors. The four predetermined factors: settlements and environmental factors; intangible cultural factors; transport and public space factors; and productive landscape factors are orthogonal dimensions (meaning independent) and demonstrate evidence of structural/statistical/numerical existence. In other words, the villages in the study can be defined by the four factors and eighteen variables, explaining 62.220% of the variance (Tables 4, A1 and A2). This means there is still almost 38% of the variance (100 minus 62 leaves 38) that the factor analysis does not explain and is open to further study. A study area can be evaluated with the linear combinations of four equations that can define the characteristics for a village, town, and city as illustrated in Equation (1), for the first factor which generates a numerical score for the first factor. Equations for the other three factors can be similarly constructed. Numerical scores for the PCA dimensions can also be accomplished with coefficients from each eigenvector (see Tables 5 and A2) as illustrated in Equation (2). The plotting of villages and other communities based upon these equations and their application is illustrated in the discussion.

$$\begin{gathered}\text{Settlements and environmental factors} = \\ (\text{V18} \times 0.742 \times \text{mean V18}/(\text{Variance V18})^{**0.5}) + \\ (\text{V19} \times 0.692 \times \text{mean V19}/(\text{Variance V19})^{**0.5}) + \\ (\text{V9} \times 0.684 \times \text{mean V9}/(\text{Variance V9})^{**0.5}) + \\ (\text{V20} \times 0.670 \times \text{mean V20}/(\text{Variance V20}^{**0.5)}) + \\ (\text{V10} \times 0.633 \times \text{mean V10}/(\text{Variance V10})^{**0.5}) + \\ (\text{V8} \times 0.624 \times \text{mean V8}/(\text{Variance V8})^{**0.5}) + \\ (\text{V13} \times 0.619 \times \text{mean V13}/(\text{Variance V13})^{**0.5}) + \\ (\text{V17} \times 0.613 \times \text{mean V17}/(\text{Variance V17})^{**0.5}) + \\ (\text{V15} \times 0.508 \times \text{mean V15}/(\text{Variance V15})^{**0.5})\end{gathered} \tag{1}$$

$$\begin{gathered}\text{PCA Eigenvector 1} = \\ (\text{V10} \times 0.776 \times \text{mean V10}/(\text{Variance V10})^{**0.5}) + \\ (\text{V9} \times 0.766 \times \text{mean V9}/(\text{Variance V9})^{**0.5}) + \\ (\text{V19} \times 0.765 \times \text{mean V19}/(\text{Variance V19})^{**0.5}) + \\ (\text{V23} \times 0.753 \times \text{mean V23}/(\text{Variance V23})^{**0.5}) + \\ (\text{V8} \times 0.745 \times \text{mean V8}/(\text{Variance V8})^{**0.5}) + \\ (\text{V22} \times 0.738 \times \text{mean V22}/(\text{Variance V22})^{**0.5}) + \\ (\text{V15} \times 0.733 \times \text{mean V15}/(\text{Variance V15})^{**0.5}) + \\ (\text{V13} \times 0.727 \times \text{mean V13}/(\text{Variance V13})^{**0.5}) + \\ (\text{V12} \times 0.726 \times \text{mean V12}/(\text{Variance V12})^{**0.5}) + \\ (\text{V14} \times 0.724 \times \text{mean V14}/(\text{Variance V14})^{**0.5}) + \\ (\text{V4} \times 0.710 \times \text{mean V4}/(\text{Variance V4})^{**0.5}) + \\ (\text{V20} \times 0.706 \times \text{mean V20}/(\text{Variance V20})^{**0.5}) + \\ (\text{V21} \times 0.703 \times \text{mean V21}/(\text{Variance V21})^{**0.5}) + \\ (\text{V11} \times 0.692 \times \text{mean V11}/(\text{Variance V11})^{**0.5}) + \\ (\text{V24} \times 0.673 \times \text{mean V24}/(\text{Variance V24})^{**0.5}) + \\ (\text{V18} \times 0.671 \times \text{mean V18}/(\text{Variance V18})^{**0.5}) + \\ (\text{V3} \times 0.670 \text{ mean V3}/(\text{Variance V3})^{**0.5}) + \\ (\text{V17} \times 0.663 \text{ mean V13}/(\text{Variance V13})^{**0.5}) + \\ (\text{V5} \times 0.662 \times \text{mean V5}/(\text{Variance V5})^{**0.5}) + \\ (\text{V6} \times 0.637 \times \text{mean V6}/(\text{Variance V6})^{**0.5}) + \\ (\text{V1} \times 0.623 \times \text{mean V1}/(\text{Variance V1})^{**0.5}) + \\ (\text{V2} \times 0.573 \times \text{mean V2}/(\text{Variance V2})^{**0.5}) + \\ (\text{V7} \times 0.565 \times \text{mean V7}/(\text{Variance V7})^{**0.5}) + \\ (\text{V16} \times 0.553 \times \text{mean V16}/(\text{Variance V16})^{**0.5})\end{gathered} \tag{2}$$

Table 4. The eigenvalues from the factor rotation.

Rotation Sum of Squares and Loads		
Eigenvalues	**Variance Contribution Rate (%)**	**Accumulative Variance Contribution Rate (%)**
5.309	22.120	22.120
3.409	14.205	36.325
3.218	13.410	49.735
2.996	12.484	62.220

Table 5. Coefficient loadings for the first four PCA dimensions. Bold coefficients indicate a strong association with the PCA dimension.

Variable	Coefficient Loading per PCA Dimension			
	1	**2**	**3**	**4**
V10	**0.776**	0.122	0.015	0.163
V9	**0.766**	0.209	0.021	0.160
V19	**0.765**	0.344	0.061	0.060
V23	**0.753**	0.014	0.361	0.143
V8	**0.745**	0.147	0.038	0.144
V22	**0.738**	0.137	0.393	0.150
V15	**0.733**	0.053	0.045	0.218
V13	**0.727**	0.153	0.054	0.151
V12	**0.726**	0.042	0.112	0.116
V14	**0.724**	0.259	0.013	0.256
V4	**0.710**	0.119	0.310	0.205
V20	**0.706**	0.426	0.109	0.168
V21	**0.703**	0.016	0.367	0.255
V11	**0.692**	0.301	0.024	0.312
V24	**0.673**	0.340	0.240	0.022
V18	**0.671**	0.371	0.077	0.175
V3	**0.670**	0.142	0.002	0.214
V17	**0.663**	0.135	0.055	0.273
V5	**0.662**	0.233	0.037	0.276
V6	**0.637**	0.125	0.517	0.128
V1	**0.623**	0.178	0.203	0.179
V2	**0.573**	0.057	0.491	0.173
V7	**0.565**	0.240	0.044	0.259
V16	**0.553**	0.550	0.016	0.138

4. Discussion

Both factor analysis and principal component analysis can be implemented with statistical software to study the relationships amongst variables. The procedures can reveal that there exist weak and non-existent relationships or they may reveal meaningful clusters or groupings of the variables. The results depend upon how the variables relate to each other. When there are many variables, without multivariate analysis, it can be difficult to interpret the collection of the variables. Principle component analysis and factor analysis can reveal the collective relationships of the variables as illustrated in past studies of Indian and Canadian cities across the countries studied [55,56]. These factors and dimensions can be employed to make numerical comparisons of various sites, plots of the dimensions, and study the variations and characteristics amongst the cities. While geographers and urban planners have studied cities at a national level, the study of the special cultural spatial characteristics has yet only been modestly examined.

In this study, the characteristics of the villages can be described by the variables and plotted. The new coefficient loadings for the variables in the factor analysis are obtained by rotation. According to the results of the evaluation of common factor 1 (settlements and environments factor) project, coefficients above 0.508 form a list of nine variables: V18 isolated degree, V19 landscape view toward the environment, V20/V9 historic building air quality/sight visibility villages overall integrity protection, V8 and V10 architectural style and technology level, V13 building material characteristics, V17 surrounding environment visual noise, V15 village cleanliness. The V18 had the highest coefficient value of 0.742. These nine adjectives reflect the surrounding and internal environment of the village, the whole settlement, and the building characteristics of residential buildings.

In the examination of factor/dimension 2, there were three variables with a coefficient load above 0.675: V21 folk customs, V22 activation inheritance of folk art, and V23 settlement function continuity. V21 had the highest value, 0.722. These adjectives reflect the cultural characteristics and authenticity of the village, so they were named as intangible cultural factors.

In the evaluation of common factor 3, there were three variables with factor loading above 0.644: V16 external traffic accessibility, V11 common meeting space type, and traffic organization in V14 village. The V16 had the highest value, 0.711. This group of variables mainly reflect the external and internal traffic organization of the village as well as the nodes of common assembly space. Therefore, they were named traffic and common space factors.

In the examination of dimension 4, there were three variables whose coefficient loading was above 0.652: V6 texture level of farmland, the coverage area of V2 farmland, and color and type of V4 farmland/orchard/vegetable garden/tea garden. The V6 was the highest with a coefficient score of 0.743. This group of adjectives reflects the characteristics of productive landscape in villages, so they were named productive landscape factors.

Principal component analysis and factor analysis obtained new dimensions (clustered vectors of variables). They represent two different views of the same data. The PCA generated dimensions with the largest orthogonal variance possible, and it is possible to lump all variables together in one large dimension which explains 47.969% of the variance (Table 5).

Factor analysis revealed sets of variables in dimensions that seemed to be, in this instance, an understandable set of dimensions: settlements and environmental factors; intangible cultural factors; transport and public space factors; and productive landscape factors. In addition, the seven of the variables were not strongly affiliated with any of the four rotated dimensions. These variables were: indicators of V12, V3, V24, V5, V1, and V7.

For comparison purposes, the first four principal components and the factor analysis dimensions can be employed in linear equations to assess and compare additional villages and environments as illustrated by the multivariate efforts of other investigators [40–52].

A three-dimensional plot can be constructed of the factor analysis and the principal component results (Figure 6). The plots of the four villages can be compared to plots of nearby cities in the area, including: Changsha, Nantong, Wuhan, Guangzhou, Zhuzhou, Yueyang, Jishou, and Chongqing. The plots represent the data with two different perspectives. The factor analysis plot separates the villages from the cities along two primarily parallel planes by factor 3, the transportation and public space factor. The principle component plot separates the villages from the cities with the villages containing an orbit beyond the cluster of the cities in a three-dimensional setting. Both approaches can differentiate the cities from the villages with the same data but present the ordination differently.

The two approaches show that that villages can be differentiated and are indeed spatially different along the variables measured.

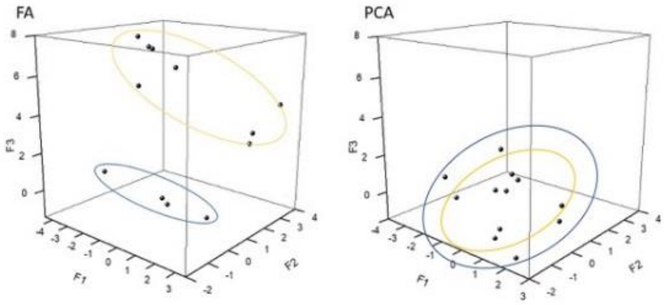


Figure 6. The left side presents the plots of the four villages (surrounded by a blue ellipse) and the cities examined (surrounded by a yellow ellipse) with the scores from factor analysis' first three factors. The right side presents a cluster of the cities (yellow ellipse) surrounded by the plots of the villages surrounded by a blue ellipse from the first three eigenvalues and associated eigenvectors (copyright © 2019 Bin Wen all rights reserved, used by permission).

Once these results have been obtained, illustrating that there are characteristics of the villages that can be quantifiably identified, the next step in the investigatory process is to examine the variables in detail that explain the nuances among the villages and their differences from the cities. This step is being accomplished in a publication by Wen, Li, and Zhou (in publication) [57].

According to different common factors, the quality evaluation of rural landscape space in each village was quantified, and the result was consistent with the actual situation of each village. The research results provide a theoretical basis for the construction of new villages and the protection and development of traditional villages. The subjects of this research questionnaire are experienced tourists who have been or are in the process of traveling. Although the subjects spanned different ages and cultural backgrounds, the main source was still urban residents. Only 8% of the respondents were farmers. Moreover, due to the different cultural background and training of planning/design professions, this expert-based opinion response survey may not reflect the values of the public. Therefore, the findings may be biased.

In addition, the comparison between principal component analysis and factor analysis in statistics is used to understand the differences and similarities. In future studies, this method needs to be further examined for assessment approaches employing ordinal data and data suitable for non-parametric statistical tests.

The study is limited by the selection of villages, variables employed, images chosen, and the experts interviewed in the study. The results presented in the study, while significant, are not definitive. Numerous studies are required to corroborate or refute such findings.

In Figure 6, note that the four villages were not identical and contained differences, but that through FA and PCA, the location of the variables was different than the location of the other towns/cities plotted in the figure. The results illustrate that spatially there is something that is differently expressed across 18 variables in FA and 24 variables in PCA. For planning and design assessment and landscape management, villages in the Xinagxi study area should occupy positions in the general three-dimensional space revealed in this study. Villages with calculated scores that occupy a different region may have drifted away from their historic characteristics or are not part of the set of traditional communities. The equations from FA and PCA can calculate the position of other communities; however, the equations are not the final answer in planning, design, and management but rather information about the general spatial character or an existing community or the impacts of proposed changes. The equations and plots may provide feedback on alternatives and management of these spaces. In addition, villages, towns, and cities can be considered design treatments and compared for statistical difference by employing Friedman's Two-way Analysis of Variance by Ranks, a procedure that compares treatments across all the variables in interest [58].

5. Conclusions

This research investigating the environmental quality of mountain villages is at a formative stage. Much more work and effort can be conducted to refute or corroborate these results. Evaluation and comparison of rural landscape factors with different variables will take time and a series of investigations. This study revealed that the PCA approach can generate a single comprehensive dimension, while the factor analysis approach generated four distinct dimensions. This research demonstrates that the relatively isolated and undisturbed village environment can be quantitatively measured, described, and differentiated from other nearby urban settings. The two methods illustrated different representations/interpretations of the same data. Factor analysis differentiated the villages from nearby cities by separating them into two distinct elliptical planes (Figure 6). Principal component analysis separated the villages on the edges of a three-dimensional elliptical orbit with the cities closer to the center of the three-dimensional plane (Figure 6). These two methods suggest that there is a multivariate statistical difference between the villages and nearby cities. A detailed discourse describing the statistical and physical differences between these villages and cities and their characteristics are discussed in a forthcoming article [57].

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Appendix A

Table A1. List of the variables employed in the study of rural landscape in mountain villages where: 5 = very satisfied, 4 = satisfaction, 3 = in general, 2 = not satisfied, 1 = very dissatisfied, by respondents.

	The Evaluation Factors	Extended Adjective	Criteria	Score (Maximum = 5, Minimum = 1)
V01	The coverage area by forest vegetation	The percentage of forest cover in the total village area (%)	The coverage area of forest vegetation is more - less	
V02	The coverage area of farmland	The percentage of farmland coverage in total village area (%)	The coverage area of farmland is more - less	
V03	Unique natural scenery	Whether there has the unique landform, the scenery of lake and mountain and so on	Unique natural scenery is abundance - lack	
V04	The color, species of farmland/ orchard garden/ tea garden	Whether the colors and species of farmland/orchard garden/tea garden are diversity or not	Farmland/orchard/garden/tea garden in rich colors and varieties–monotonous	
V05	The richness form of waters	Whether there are wells, springs, linear rivers or channels of massive reservoirs	The richness form of waters is abundant–not abundant	
V06	Farmland texture level	Whether there are uneven crisscrossed lines, curved area size and other changes in farmland	The texture level of farmland is clear -fuzzy	

Table A1. *Cont.*

	The Evaluation Factors	Extended Adjective	Criteria	Score (Maximum = 5, Minimum = 1)
V07	Settlement scale	The number of people less than 100 = small village. 100~500 people = medium village. 500~1000 people = large village. Larger than 1000 people = large village	Settlement scale is large–small	
V08	Residential building technology level	Whether there has unique modeling language, fastidious construction, fine work, exquisite craft and so on	Technology level of residential building is good -not	
V09	Quantity of remaining historic buildings	The number of buildings of historical value reflecting historical features and local characteristics	Remaining historic buildings are more–less	
V10	Integrity of old settlement	Protection integrity of village dwellings, cultural relics, historical sites, cliff stone carving, ancestral halls, temples and others	Integrity of old settlement is high - low	
V11	Types of public gathering space	Types of village square, bridge, well, sun dried grain square and other outdoor venues	Types of public gathering space are abundance - lack	
V12	Types of landmark structures	Types of bell tower, drum tower, watchtower, shelter bridge, ancestral hall, waving hand hall and other landmark buildings	The types of landmark structures are abundant - inadequate	
V13	The features of construction material	The characteristic style of wood bamboo, rammed brick, thatched roof, stone and other local materials	Features of construction materials are local -modern	
V14	Transportation organization in village	The roadway in village is orderly or not	The traffic organization in village is orderly–disorderly	
V15	Cleanliness of village	Village is clean or not	The cleanliness of village appearance is good - not	
V16	Accessibility of external transport	The external traffic of township, county, provincial and other is convenience or not	External traffic accessibility is good - bad	
V17	Visual interference of surrounding environment	The intrusive of modern infrastructure across the village such as highway, railway and so on	The visual interference is small - big	
V18	Isolation from the outside world	Distance from the town	Isolation is good - not	
V19	Landscape vision or orientation	Whether the landscape views toward nature is great or not	Landscape vision is beautiful - not	
V20	Visibility of sights	The maximum distance at which the object can be clearly seen	Visibility is good–not	
V21	Folk customs	Whether there have many interesting folk customs.	Folk customs are strong - not	
V22	Activation and inheritance of folk art	The protection and utilization of Miao nationality silver ornaments, batik, embroidery, Miao drum and other folk arts	Activation and inheritance folk art is high - low	
V23	Aboriginal reservations	The continuation and inheritance of traditional production and lifestyle	Aboriginal reservations are high -low	
V24	Legends and stories	Stories and relics of national resistance of Miao King or figures of Anti-Japanese War	Legends and stories are rich -not	

Table A2. Four villages and eight cities scored showing all 24 variables.

	Qixin Village	Lvdong Village	Hangsha Village	Yanpai Xi Village	Changsha City	Wuhan City	Wuchang City	Chongqing City	Guangzhou City	Zhuzhou City	Yueyang City	Jishou City
V01	3.99	4.06	3.96	3.9	2.5	2.3	2.1	3	2.2	2.3	2.4	3.4
V02	3.41	3.63	3.71	4.04	0.1	0.2	0.13	0.13	0.14	0.15	0.04	0.08
V03	4	3.88	3.58	3.68	0.4	0.3	0.3	0.9	0.3	0.5	0.7	1.3
V04	3.48	3.48	3.6	3.71	0.01	0.03	0.03	0.02	0.01	0.02	0.01	0.05
V05	3.58	3.32	3.5	3.57	3.52	4.52	2.56	4.84	4.62	4.22	4.86	3.84
V06	3.52	3.52	3.56	3.84	0.01	0.03	0.03	0.02	0.01	0.02	0.01	0.05
V07	3.49	3.57	3.6	3.59	4.23	4.34	4.43	4.12	4.34	4.43	4.15	4.18
V08	3.82	3.85	3.73	3.59	3	3.54	2.67	4.6	4.1	2.1	3.1	2.15
V09	3.84	3.72	3.73	3.65	1.23	0.23	0.34	0.23	1.45	0.21	0.34	0.12
V10	3.81	3.74	3.83	3.72	0.1	0.12	0.12	0.21	0.05	0.03	0.07	0.08
V11	3.29	3.35	3.6	3.61	4.5	4.3	4.2	4.6	4.8	4.1	4.44	3.51
V12	3.84	3.71	3.77	3.64	3.71	4.15	3.31	3.11	4.31	3.71	4.31	3.82
V13	3.66	3.65	3.53	3.59	1.1	1.34	1.23	1.45	1.11	1.07	1.45	1.43
V14	3.37	3.34	3.49	3.48	4.6	4.43	4.56	4.72	4.83	4.98	4.56	4.67
V15	3.59	3.58	3.71	3.73	4.66	4.73	4.86	4.92	4.68	4.48	4.59	4.77
V16	3.19	3.18	3.49	3.31	4.66	4.73	4.86	4.92	4.86	4.88	4.59	4.87
V17	3.62	3.6	3.63	3.62	1.1	1.4	1.66	1.77	1.34	1.52	1.34	1.67
V18	3.68	3.71	3.62	3.66	0.32	0.11	0.22	0.21	0.12	0.08	0.02	0.12
V19	3.88	3.98	3.78	3.79	0.5	0.65	0.67	0.89	0.23	0.12	0.45	0.76
V20	4.01	3.97	3.94	3.77	0.4	0.87	0.31	0.78	0.32	0.23	0.21	0.53
V21	3.86	3.54	3.71	3.59	1.56	1.78	1.21	1.23	1.45	1.87	1.24	1.56
V22	3.66	3.46	3.73	3.56	0.23	0.21	0.12	0.45	0.21	0.02	0.32	0.12
V23	3.7	3.57	3.72	3.59	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01
V24	3.39	3.34	3.48	3.4	3.4	3.23	3.32	3.33	3.45	3.56	3.76	3.76

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