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UAV remote sensing and deep learning for assessing and optimizing architectural texture in traditional villages

Yang Shi[1,6], Wenke Wang[2,6], Jie Zhang[2,3] ✉, Dong Li[4], Fei Liu[4] & Wensheng Li[2,5]

The architectural texture of traditional villages reflects regional culture and is vital for sustainable conservation and renewal. However, for culturally diverse villages, current methods often lack integration of multi-dimensional evaluation and fusion of traditional and modern techniques, limiting data efficiency and analytical rigor. This study proposes a framework combining UAV remote sensing, deep learning (optimized Mask R-CNN), morphological indices, and statistical analysis. Applied to 27 traditional villages in Beijing, results show: (1) the method enables fast, accurate extraction of architectural texture with minimal manual input; (2) villages show heterogeneity in scale, proportion, and orientation, while patterns and boundaries remain stable; (3) texture features are influenced by geography, culture, history, economy, and construction methods; (4) indicators like settlement size and building proportion correlate strongly with other variables, offering insights for spatial planning. This interdisciplinary approach supports scientific evaluation and offers a digital foundation for preserving and optimizing traditional village environments.

Traditional villages are vital witnesses of human civilization, carrying significant historical, artistic, and scientific value. Over centuries of social and cultural evolution across diverse geographical environments, these settlements have developed unique landscape characteristics—such as architectural styles, spatial patterns, and boundary forms—that reflect local culture and ethnic identity[1,2]. However, rapid global urbanization has triggered widespread threats to vernacular environments, including the expansion of village boundaries, destruction of traditional buildings, disordered spatial layouts, disproportionate architectural scales, and blurred settlement edges. These issues pose serious challenges to the preservation of local cultural heritage[3].

To address this, China's Ministry of Housing and Urban-Rural Development has introduced the Evaluation and Identification Index System for Traditional Villages (Trial)[4], which highlights architectural texture as a key indicator of the overall physical character of village architecture. It plays a crucial role in understanding settlement development patterns and guiding landscape conservation[5]. Therefore, there is an urgent need for a universal and transferable evaluation framework capable of identifying and assessing architectural textures. Such a system would support intelligent analysis, protection, and sustainable development of traditional villages across multicultural contexts.

Since the early geographic analysis of urban layouts by Conzen, quantitative morphological indices have evolved into a cross-culturally applicable method[6]. Based on mathematical and statistical principles of spatial form, these indices offer notable advantages in terms of practicality, flexibility, and operability. They have been widely applied in studies of architectural texture from various perspectives.

For example, several studies have demonstrated the feasibility of using shape indices to analyze spatial disorder, diversity, and complexity[7–9]. Other applications include assessments of settlement boundaries, road network patterns, building orientation indices[10], patch area, fractal dimensions, and settlement scale indices[11], as well as broader morphological features, spatial structures, and integrated building orientation metrics[12]. Some studies further combine morphological indicators with space syntax[13], or utilize indices such as ratio, boundary definition, saturation, and building density[14].

These methods have been employed in diverse contexts, including China[10,13,15], Vietnam[16], and Indonesia[17], contributing to the scientific rigor of traditional village morphology studies and demonstrating the adaptability and universality of morphological index approaches across different regions.

Although morphological index methods have been widely applied, they still fall short in advancing a systematic architectural texture index

[1]Institute of Science and Technology Development, Beijing University of Civil Engineering and Architecture, Beijing, China. [2]School of Architecture and Urban Planning, Beijing University of Civil Engineering and Architecture, Beijing, China. [3]School of Architecture, Tsinghua University, Beijing, China. [4]School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing, China. [5]School of Vocational Education, Shandong Youth University of Political Science, Jinan, China. [6]These authors contributed equally: Yang Shi, Wenke Wang. ✉e-mail: zjzhangjie@mail.tsinghua.edu.cn

framework and revealing deeper underlying mechanisms. The architectural texture of traditional Chinese villages is highly specific, shaped by geographical location, cultural context, and social relationships. Notably, mountain villages account for more than half of the nationally protected traditional villages, exhibiting spatial layouts that are distinctly adapted to topographic conditions, in contrast to those in plains regions[18].

In different regions, building orientation is influenced to varying degrees by the Confucian cosmological worldview, reflecting certain spatial organization patterns and directional logic[19]. Furthermore, the layout and clustering of buildings are often reinforced by kinship ties, resulting in unique courtyard group formations[20]. These complex, multi-dimensional texture features require a more customized and context-sensitive evaluation framework.

Current research tends to focus on a single or limited set of architectural texture dimensions, lacking a comprehensive and systematic exploration of architectural texture indicators. Most studies emphasize either comparative descriptions of texture features[10,12,14] or their relationships with elements such as transportation, natural environment, and local customs[7,8,15], while the latent structural patterns across multiple dimensions remain understudied. This limits the ability to reveal the developmental logic and spatial evolution of traditional village forms.

Therefore, under the premise of high-quality and refined spatial management, future research should emphasize the construction of a multidimensional index system that integrates features such as settlement boundary morphology, building distribution patterns, orientation, settlement scale, and architectural proportions.

It is worth noting that the complex geographical environments of traditional villages often make field surveys time-consuming and labor-intensive. In earlier periods with limited technological capacity, large-scale and rapid investigation or quantitative evaluation of architectural textures in traditional villages was extremely difficult[21]. With the advancement of digitalization, informatization, and artificial intelligence, deep learning and remote sensing technologies have significantly improved the efficiency of data acquisition and processing in heritage conservation, bringing new momentum to the study of traditional village architectural textures[22].

Due to resolution limitations, open-access satellite imagery is mostly suitable for detecting sparsely distributed buildings[17,23,24] or settlement patches that exhibit clear contrast with their surroundings[25]. However, it remains inadequate for extracting detailed texture information from traditional villages, which typically feature multi-type, multi-scale, and multi-temporal architectural forms. In contrast, drone-based remote sensing has been widely adopted in the heritage field for its low cost, high operability, and noninvasive nature[26]. When enhanced with super-resolution reconstruction, UAV imagery can clearly capture the complex built environments of traditional villages[27,28]. Combined with deep learning models such as Mask R-CNN and HRNet, this approach enables high-precision extraction of architectural texture features in Chinese traditional villages, including automated identification of building types, locations, and boundaries[29–31].

While integrated approaches combining remote sensing, Earth observation, and morphological index analysis have been successfully applied in urban studies[32,33], their application to the evaluation of architectural texture in traditional villages remains largely unexplored. Whether these methods can fully leverage their advantages—namely high accuracy, scientific rigor, and efficiency—still requires further investigation.

This study integrates deep learning, UAV remote sensing, and traditional morphological indices to establish a technical framework for evaluating the architectural texture of traditional villages, addressing common challenges in vernacular cultural heritage preservation. First, deep learning models are combined with drone imagery to efficiently extract information on building types, boundaries, and spatial distribution. Based on this, a correlation analysis of multidimensional architectural texture indicators is conducted, demonstrating how culturally meaningful texture metrics can be embedded within a generalized analytical framework. The study further reveals common features, spatial anomalies, and underlying structural relationships in the architectural textures of traditional villages in Beijing. Using traditional villages in Beijing as a case study, the proposed framework proves to be both practical and transferable, offering valuable insights for international heritage conservation efforts facing similar challenges.

Methods

The study aims to provide a scientific, efficient, and comprehensive assessment of the architectural texture of traditional villages. It develops an integrated technical approach that combines deep learning, UAV remote sensing, the morphology index method, and correlation coefficient analysis, as shown in Fig. 1. In data acquisition and processing, drones capture and reconstruct high-resolution images. For deep learning, the enhanced Mask R-CNN model is employed to address the complex features of the built environment in traditional villages. The morphology index method classifies building types and establishes a quantitative evaluation system for architectural texture. In characterizing architectural texture, descriptive statistics, histogram analysis, and correlation coefficient analysis are used to examine the distribution, standard features, and intrinsic correlations of architectural texture. The study also investigates the underlying causes of the architectural texture and proposes recommendations for future optimization and control.

UAV remote sensing

Beijing has a rich cultural heritage of traditional villages. Since the 2012 survey, 26 national-level traditional villages have been identified, each with significant historical and cultural backgrounds, including Red Culture, Great Wall Culture, and Ancient Road Culture. In line with the Beijing Urban Overall Plan (2016–2035), the city has also selected 44 municipal-level traditional villages, with a focus on those that, while not nationally recognized, hold considerable value for preservation. Additionally, Beijing is home to numerous historical villages with deep cultural significance, such as the fortress settlements at the base of the Ming Great Wall in Miyun District. These villages, with their wealth of traditional buildings and well-preserved settlement patterns, offer comparable research value to the existing traditional villages. This study focuses on 27 villages, including 19 national-level traditional villages, 3 municipal-level traditional villages, and 5 historical villages (Fig. 2).

Given the complex traffic conditions and geographic features of traditional villages in Beijing, this study employs the DJI M300RTK UAV to capture low-altitude remote sensing images. To minimize the impact of solar radiation, wind speed, and other environmental factors on data quality, data collection was conducted under sunny and breezy weather conditions. A detailed flight plan was developed, incorporating flight altitude, speed, overlap rate, and return altitude, as outlined in Table 1. The raw image data were then reconstructed with super-resolution using Context Capture software, enabling clear visualization of building morphology, materials, and colors (Fig. 3). This approach offers significant advantages over open-source remote sensing images, effectively overcoming the resolution limitations of traditional high-resolution sources.

Deep learning model

Given the multi-scale, multi-type, and multi-temporal architectural distribution in traditional villages, this study employs an enhanced Mask R-CNN instance segmentation model[29], derived from the original Mask R-CNN[34] with superior architecture and fitting performance. The model replaces the traditional feature pyramid with the path aggregate feature pyramid network (PAFPN)[35], which leverages precise localization signals from the bottom layer, shortening the information path, and enhancing the contextual relationships between multi-layer features. This modification improves the model's ability to handle complex environments. Additionally, the inclusion of the atlas space pyramid pool (ASPP)[36] module captures multi-scale information, further enhancing the model's detection and recognition capabilities in complex settings. To address data scarcity, the study incorporates transfer learning and data augmentation strategies during the pre-training phase.

In practical application, tasks such as building classification, data labeling, training, evaluation, and morphological optimization are carried

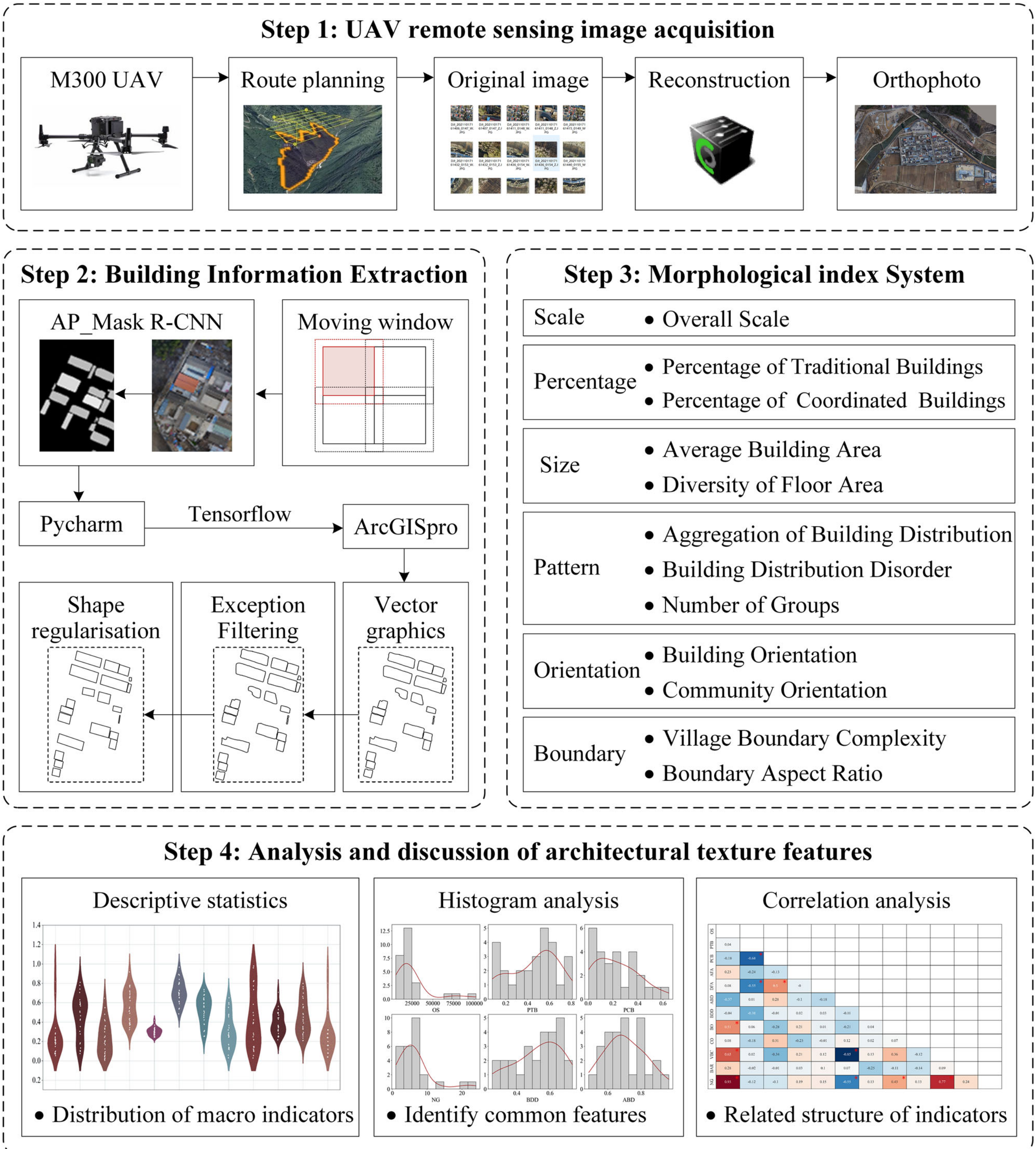

Fig. 1 | Research framework.

out sequentially (Fig. 4). First, the study catalogs the roof forms, materials, and colors of buildings across eight villages, identifying six initial building types, which are categorized into traditional-style, style-coordinated, and other-style buildings based on the traditional village protection and development plan, as shown in Fig. 5. Next, Labelme software is used to annotate buildings in the UAV shadow, constructing the instance segmentation dataset, which is then trained and evaluated under the TensorFlow 2.5 deep learning framework. The model achieves precision scores of 0.91, 0.75, and 0.65 for traditional-style, style-coordinated, and other-style buildings, respectively; recall values of 0.92, 0.86, and 0.75; and F1 scores of 0.91, 0.79, and 0.69, demonstrating a clear improvement over existing models.

To handle large-format UAV images, the study uses a moving window method, ignoring edge pixels[37] and adjusting for the scale of traditional village buildings with a window size of 600 × 600 pixels. This approach effectively mitigates issues with fragmented building recognition caused by large image sizes. Post-processing includes regularization algorithms for building morphology and anomaly filtering[38] to enhance the completeness and smoothness of building contours, resulting in more accurate building vector information. Finally, the recognition results are cross-checked through visual interpretation and refined with minimal manual correction to ensure the accuracy and scientific integrity of the architectural texture analysis.

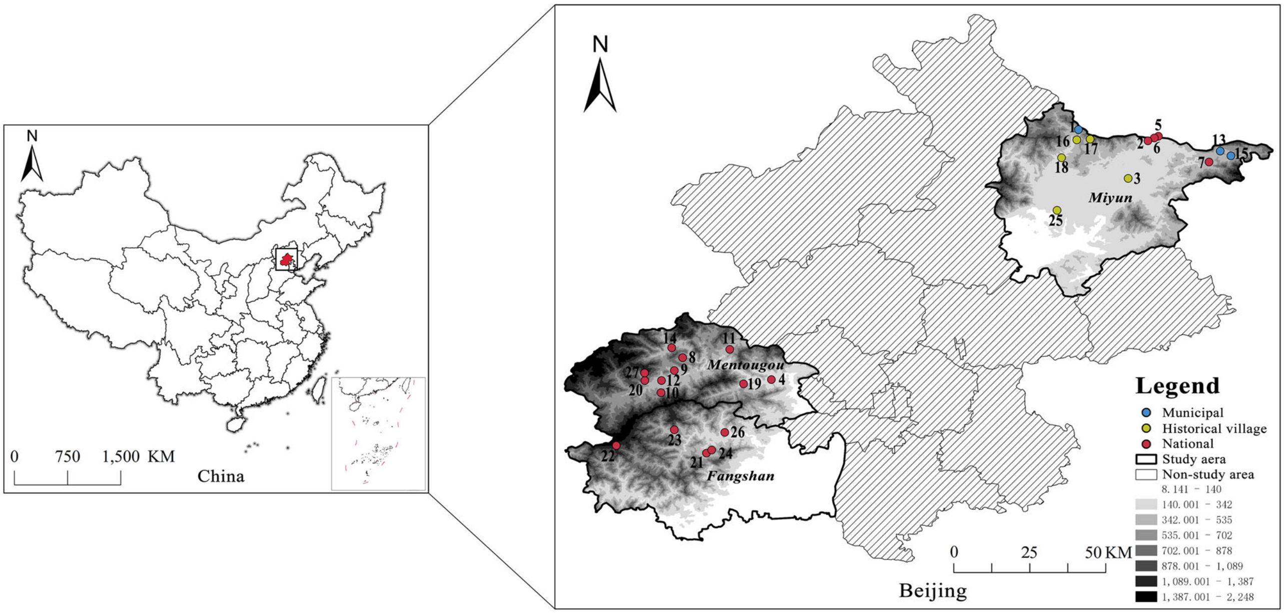

Fig. 2 | Study area, Note: 1. Baimaguan Village; 2. Chaoguan Village; 3. Dongguan Village; 4. Dongshiguyan Village; 5. Gubeikou Village; 6. Heshi Village; 7. Jijiaying Village; 8. Jieshi Village; 9. Lingshui Village; 10. Malan Village; 11. Weizishui Village; 12. Xihulin Village; 13. Xiaokou Village; 14. Yanhecheng Village; 15. Yaoqiaoyu Village; 16. Xiaoying Village; 17. Xituogu Village; 18. Fengjiayu Village; 19. Qianjuntai Village; 20. Huanglingxi Village; 21. Shuiyu Village; 22. Baoshui Village; 23. Liugshui Village; 24. Nanjiao Village; 25. Shangyu Village; 26. Heilongguan Village; 27. Cuandixia Village.

Table 1 | Flight plan parameters

Technical indicators	Parameters
Aviation High	100–150 m
Return altitude	200 m
Flight mode	RTK
Speed	8 m/s
Overlap	75–80%

Morphological index methodology

To assess the multi-dimensional architectural texture of traditional villages, this study adopts the morphology index method for quantitative evaluation. A comprehensive index system covering six dimensions—scale, proportion, size, pattern, orientation, and boundary—is developed, based on the "Indicator System of Evaluation and Recognition of Traditional Villages (for Trial Implementation)"[39] and existing studies[39].

First, in the context of value assessment for traditional Chinese villages, two dimensions, scale and proportion, are used to evaluate the overall building area and the proportion of different building types. Next, within the scale dimension, two indicators—average building area and diversity—are introduced to assess the overall architectural scale characteristics of the villages. In the pattern dimension, three indicators—building distribution aggregation, building distribution disorder, and the number of clusters—are used to evaluate the spatial structure of traditional villages. For the orientation dimension, the ratio of south-facing buildings and the alignment of clusters are incorporated to evaluate the orientation characteristics of buildings and the overall long-axis distribution of the settlement. Finally, in the boundary dimension, two indicators—boundary morphological complexity and boundary aspect ratio—are introduced to characterize the macro features of the settlement. The calculation methods and detailed explanations for all indicators are provided in Table 2.

Correlation analysis methods

Correlation analysis is a standard method for assessing the strength and direction of relationships between variables. Common approaches include Spearman and Pearson correlation coefficient analyses, which are widely used in architectural heritage preservation[8,40], environmental science[41], and ecological conservation[42]. In practice, to ensure the reliability of correlation assumptions and avoid random results, a two-tailed test is typically applied to assess the significance of the correlation coefficient. A value below 0.05 indicates a significant correlation, while values above 0.05 are considered insignificant. However, differences in linearity assumptions, data distribution, and outliers may lead to conflicting results when applying these two methods to the same dataset. In this study, to enhance objectivity and scientific rigor, both Spearman and Pearson correlation analyses are combined to explore the intrinsic correlations between the quantitative indicators of architectural texture.

Results

The data conversion process for architectural information extraction is illustrated in Fig. 6. First, the improved Mask R-CNN model is applied to UAV images of 27 traditional villages, generating a grayscale map where varying grayscale levels represent different architectural types. After minimal manual adjustment and morphological optimization, the final vector map is produced, containing detailed information on building types, scales, and distribution. This completes the architectural data collection for the 27 traditional villages.

Descriptive statistics of the architectural texture of traditional villages

The statistical analysis results of all architectural texture indicators are presented in Table 3 and visualized through violin plots in Fig. 7. OS ranges from 5388 to 102,150 square meters, with a coefficient of variation of 0.91, indicating the highest intrinsic heterogeneity among all indicators. PTB varies between 0.08 and 0.81, with a mean of 0.46 and a coefficient of variation of 0.48, suggesting that the overall integrity of traditional features in Beijing's villages is relatively high and stable. PCB ranges from 0.01 to 0.65, with a coefficient of variation of 0.76, reflecting a greater variability in coordinated architectural features across different villages. AFA and DFA in the scale dimension, as well as ABD and BDD in the pattern dimension, have the lowest coefficients of variation, indicating a more uniform

Fig. 3 | Remote sensing images of Jijiaying village, **a** Google Image; **b** Super-resolution drone image.

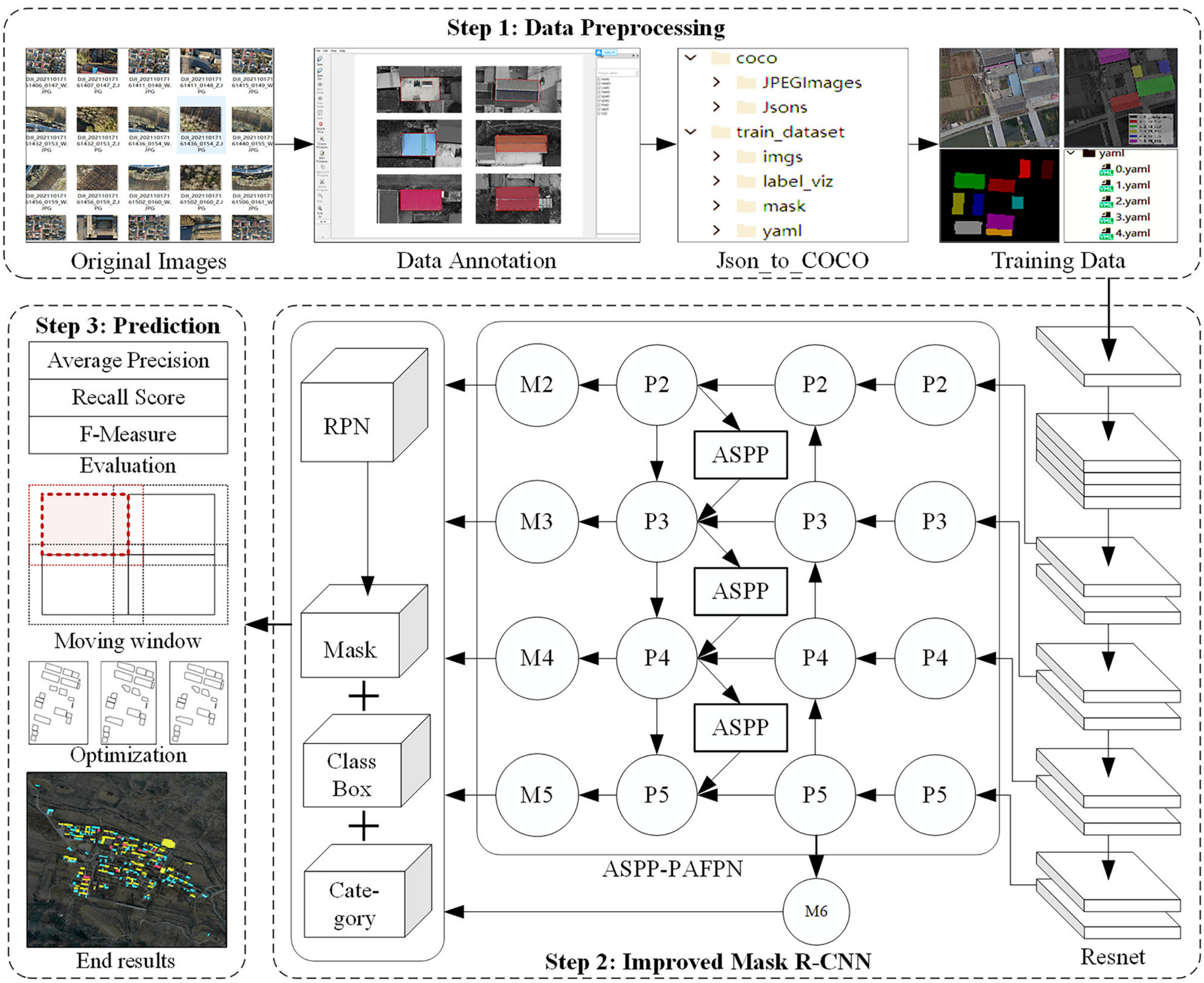

Fig. 4 | Improved Mask R-CNN model architecture and application flow.

architectural scale and distribution pattern. NG, BO, and CO have coefficients of variation greater than 0.5, signaling higher territorial variation in these indicators across villages. In the boundary dimension, the coefficients of variation for VBC and BAR are below 0.5, suggesting that boundary features are less effective in distinguishing architectural texture. In conclusion, the study reveals significant descriptive differences among the architectural texture indicators in Beijing's traditional villages.

Divergent characteristics of the architectural texture of traditional villages

To further explore the distribution characteristics of different indicators, this study uses histograms to visualize the evaluation results of architectural texture across multiple dimensions. As shown in Fig. 8, under the scale dimension, 24 OS values fall within 35,000 square meters. Additionally, the areas of Nanjiao Village, Gubeikou Village, and Hexi Village exceed

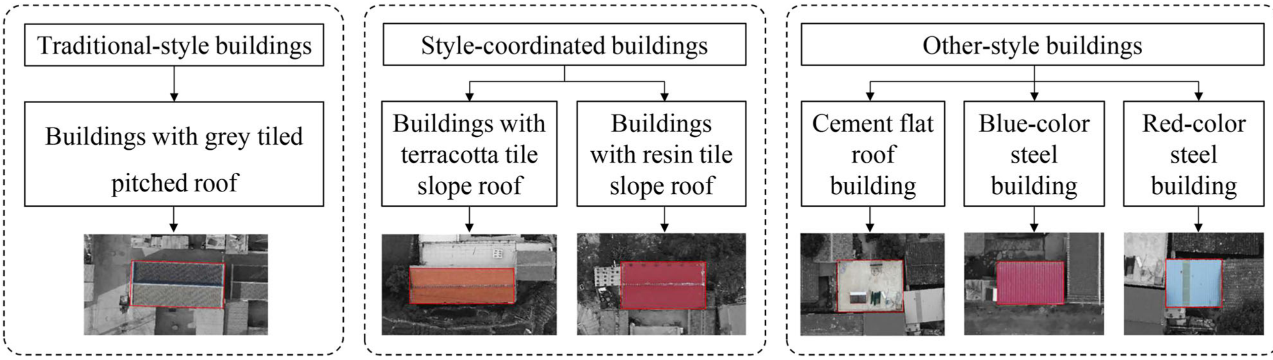

Fig. 5 | Traditional villages' architectural style types summarized.

Table 2 | Quantitative evaluation index system of architectural texture

Dimension	Evaluation index	calculation method	Evaluation content	Reference
Scale	Overall scale(OS)	$BS = \sum_1^n T_n$ (1)	T_n refers to the area of the n th building, and BS represents the total area of a single type of building in a traditional village; $\sum_0^n B_n$ denotes the total area of all buildings, and PB denotes the percentage of each type of building.	11,39,59,60
Proportion	Percentage of traditional buildings(PTB)	$PB = \frac{S}{\sum_1^n B_n}$ (2)		39
	Percentage of coordinated buildings(PCB)			39
Size	Average floor area(AFA)	$AA = \frac{\sum_1^n B_n}{n}$ (3)	AA denotes the average value of floor area (square meters); B_n denotes single building floor area (m^2); DA is non-traditional floor area diversity.	10,11
	Diversity of floor area(DFA)	$DA = \frac{\sum_1^n (B_n - S_b)}{n} / 2S_b$ (4)		10,61
Pattern	Aggregation of building distribution(ABD)	$AD = \frac{\sum_1^n L_n}{n}$ (5)	L_n is the distance between two building units (m), AD is the observed average distance between two building units (m), which is used to characterize the degree of aggregation of building spacing; CD is the degree of disturbance in the distribution of buildings between two building units.	10
	Building Distribution Disorder(BDD)	$CD = \frac{\sum_1^n (L_n - \bar{D}_o)}{n} / 2\bar{D}_o$ (6)		10,59,61
	Number of groups(NG)	Meanshift algorithm (7)	The study used 100 meters as a bandwidth to specify the size of the neighborhood used to calculate density.	23,62
Orientation	building orientation(BO)	$BO = \frac{N_D}{n}$ (8)	N_D is the number of buildings in a traditional village with all buildings facing within 15 degrees of due south, and BO indicates the percentage of buildings with a south-facing orientation.	63
	community orientation(CO)	$CO = \lvert A \rvert$ (9)	A indicates the direction of the long axis of the colony, with values closer to 90 favoring north-south and closer to 0 favoring east-west.	63
Boundary	Village boundary complexity(VBC)	$FD = \frac{P}{\sqrt{CA}} \times 100\%$ (10)	P denotes the perimeter of the village building boundary, CA denotes the area of the boundary of the main body of the village building, and FD denotes the number of fractal dimensions. The larger the value, the more complex the settlement boundary pattern.	9–11,50,54,55,64
	Boundary aspect ratio(BAR)	$BAR = \frac{L}{B}$ (11)	L and B denote the horizontal and vertical lengths of the smallest outer rectangle of the colony boundary, respectively.	9,10,54,55,59,61

70,000 square meters, reflecting the generally small-scale nature of the villages, influenced by their mountainous environment. In the proportion dimension, PTB values are primarily centered around 60%, with 15 villages having more than 50% of traditional buildings. Meanwhile, 81% of villages exhibit less than 40% PCB, with a few villages, such as Yanhecheng Village and Xihulin Village, having higher values. Overall, the traditional villages in Beijing maintain a high level of traditional landscape integrity. In the pattern dimension, 89% of NG values are below 10, 85% of BDD values range from 0.3 to 0.7, and 78% of ABD values lie between 0.5 and 0.8. These values reflect the architectural texture of traditional villages in Beijing, characterized by fewer clusters, moderate aggregation, and higher levels of disorder. Under the scale dimension, 96% of AFA values are between 30 and 80 square meters, contrasting with the more concentrated distribution of DFA values between 0.25 and 0.35. This indicates significant variability in AFA values across villages, although architectural scales within individual villages tend to be more uniform. In the boundary dimension, 89% of VBC values are between 4.3 and 10, with a concentration around 6, all higher than the circular $2\sqrt{\pi}$, suggesting that boundary features are complex and varied. Additionally, 52% of BAR values exceed 2, indicating that settlements primarily follow linear development patterns. Under the orientation dimension, the number of villages with east-west long-axis orientations gradually decreases compared to those with north-south orientations, with 70% of CO values falling within 45 degrees of east-west to north or south, reflecting the dominance of the east-west direction in settlement orientation. The BO values range from 0 to 65%, with 63% of villages having fewer than 30% of south-facing buildings, indicating a diverse range of architectural orientations across the traditional villages of Beijing. The study reveals significant dimensional differences in the architectural texture of Beijing's traditional villages. Overall, the histogram frequency distribution enhances the understanding of these differentiation characteristics, such as distribution density, range, maximum and minimum values, and more.

Correlation analysis of quantitative indicators of architectural texture

Exploring the underlying structure between architectural texture indicators helps to comprehensively understand the formation and evolutionary patterns of traditional village architectural textures, providing effective strategies for the sustainable development of settlement architectural styles. The results

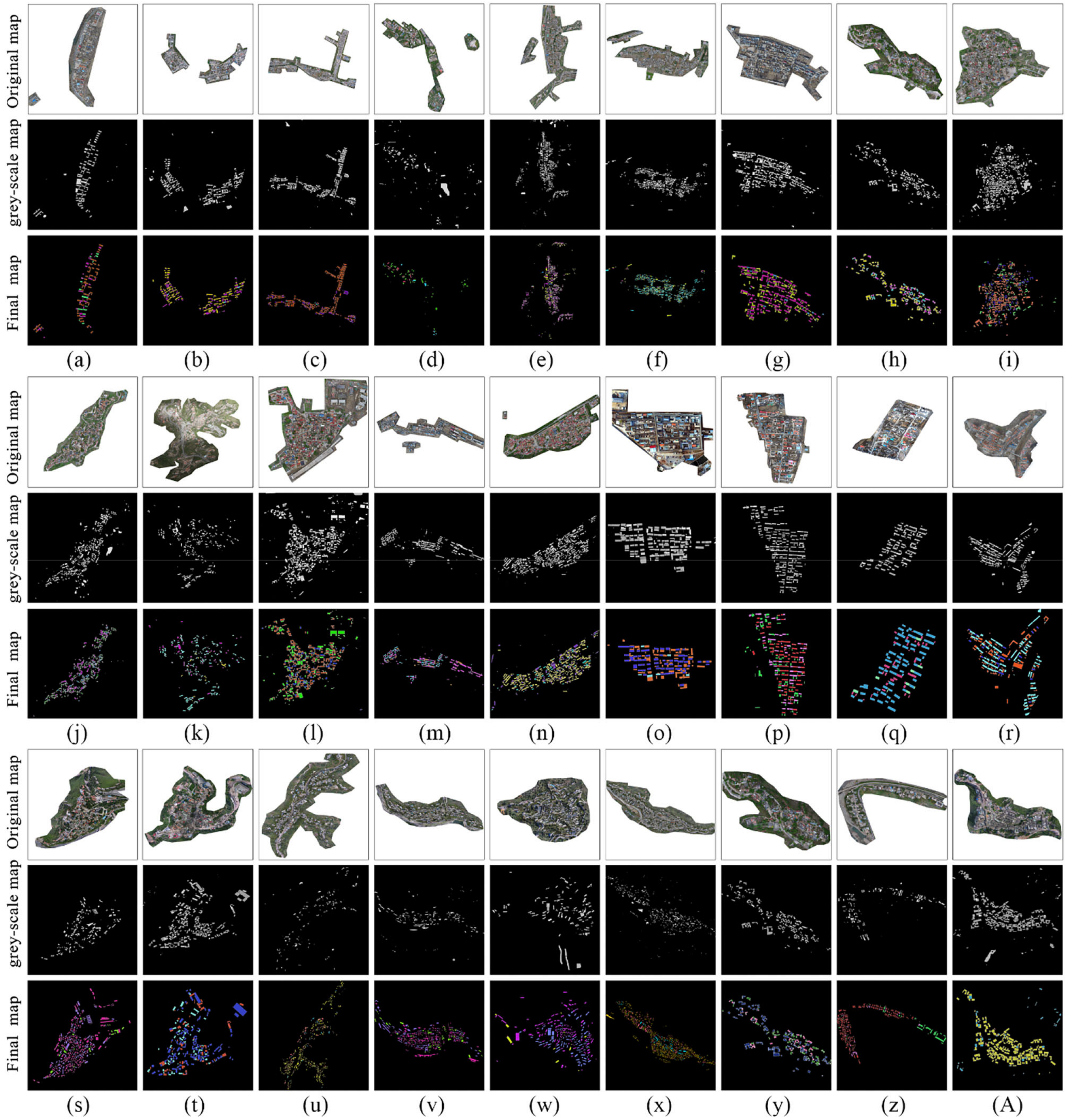

Fig. 6 | Traditional village architecture extraction data conversion process, the labeling order is the same as that in Fig. 1.

of the Pearson and Spearman correlation analyses are presented in Fig. 9. Asterisks (*) in the upper-right corner indicate correlations with a significance level below 0.05. The findings reveal a high degree of consistency between the two correlation methods, both highlighting the significant correlations between several indicators. Eight indicators—OS, PTB, PCB, DFA, ABD, NG, BO, and VBC—showed substantial associations across all six dimensions. Specifically, OS demonstrated a strong positive correlation with NG, VBC, and BO, suggesting that larger clusters tend to have more groups, more complex boundaries, and a greater number of south-facing buildings. In the second group, PTB showed a significant negative correlation with DFA and PCB, while PCB exhibited a positive correlation with DFA. This indicates that villages with more traditional buildings tend to have fewer style-coordinated buildings and lower architectural scale diversity. Conversely, villages with more style-coordinated buildings showed higher architectural scale diversity. In the third group, ABD negatively correlated with NG and VBC, suggesting that villages with higher aggregation levels may have fewer clusters and simpler boundary patterns.

Discussion

In light of the large number of traditional villages, their wide distribution, and complex environments, as well as the inefficiencies of traditional evaluation methods that rely heavily on subjective judgments, this study for the first time constructs a comprehensive methodological system integrating UAV remote sensing, deep learning technology, multi-dimensional morphological indexes, and statistical and correlation analyses. Using 27 traditional villages in Beijing as examples, the study demonstrates the effectiveness and innovation of combining new technology with traditional methodologies, and discusses the multi-dimensional characteristics and

Table 3 | Statistical analysis of quantitative indicators of architectural texture

Dimension	Evaluation index	Sample size	Minimum	Maximum	Mean	Standard deviation	Coefficient of variation
Scale	OS	27.00	5387.63	102,149.64	25,268.63	23,035.11	0.91
Proportion	PTB	27.00	0.08	0.81	0.46	0.22	0.48
	PCB	27.00	0.01	0.65	0.23	0.17	0.76
Size	AFA	27.00	32.31	91.75	55.98	16.46	0.29
	DFA	27.00	0.24	0.42	0.30	0.04	0.14
Pattern	ABD	27.00	0.49	0.97	0.70	0.12	0.17
	BDD	27.00	0.25	0.74	0.53	0.14	0.27
	NG	27.00	1.00	24.00	6.48	5.21	0.80
Orientation	BO	27.00	0.03	0.65	0.30	0.17	0.58
	CO	27.00	2.69	88.12	37.65	27.58	0.73
Boundary	VBC	27.00	4.35	14.16	7.76	2.34	0.30
	BAR	27.00	1.05	4.00	2.24	0.90	0.40

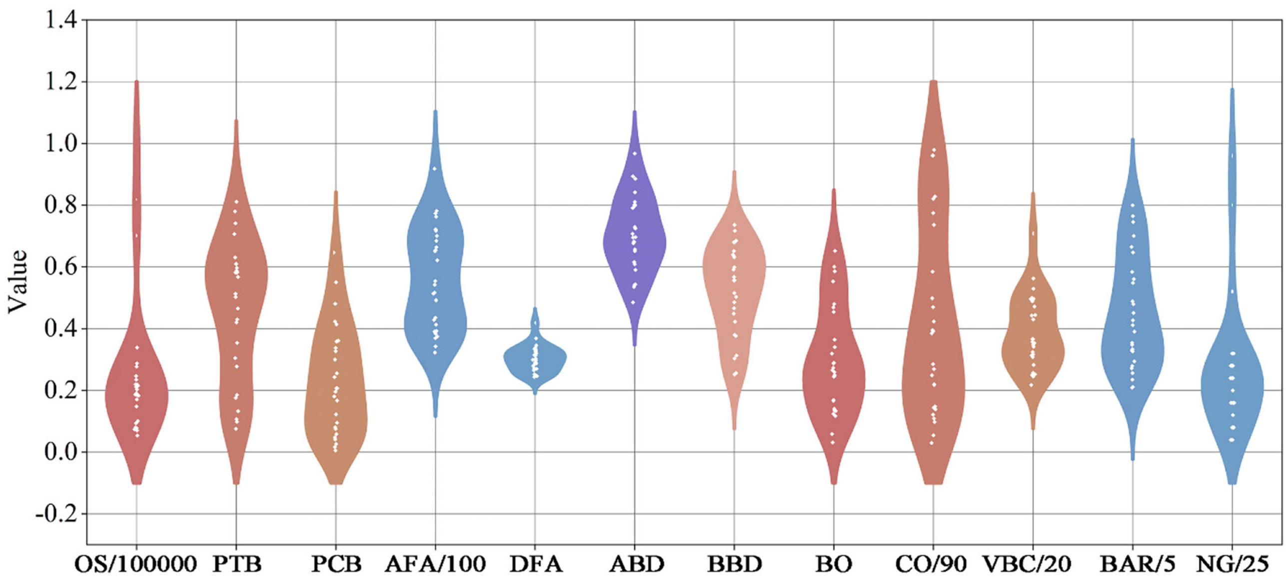

Fig. 7 | Distributional characteristics of architectural texture evaluation results.

internal correlation structure of the building texture, which is of great significance for realizing the digital protection and deep understanding of the traditional village building texture.

First, the integration of UAV remote sensing and deep learning technologies has revolutionized the evaluation of architectural textures in traditional villages, particularly in regions like Beijing, where these villages are numerous and widely distributed. Traditional methods, which often rely on subjective judgments, are increasingly being supplemented by more objective, technology-driven approaches. UAVs facilitate the acquisition of high-precision data in rural areas, especially in traditional villages located in remote mountainous regions. This data plays a crucial role in overcoming the challenges of identifying traditional villages, which are often characterized by target aggregation, small-scale structures, and multiple temporal states. The deep learning model used in this study is instance segmentation, a versatile model that effectively combines the benefits of target detection and semantic segmentation[34]. It allows for the simultaneous extraction of architectural type, boundary, and location information, which lays the foundation for developing a multidimensional architectural texture index system. The Mask R-CNN model optimized with PAFPN and ASPP achieves higher accuracy in extracting architectural details from traditional village buildings. During application, it was observed that building value correlates positively with extraction accuracy. Specifically, traditional-style buildings, which have more uniform forms, tend to yield higher extraction accuracy. In contrast, buildings with coordinated styles, such as double-sloped roofs and diverse materials, as well as buildings of other styles with varied roof forms, exhibit greater heterogeneity, requiring more sophisticated deep learning recognition. This integrated approach, combining UAV imagery, deep learning, and traditional methods, offers significant advantages that have often been overlooked in previous studies[17,23,30], making it highly valuable for evaluating the architectural texture of traditional villages.

Second, as we delve deeper into the architectural texture of Beijing's traditional villages, we observe notable heterogeneity, especially in scale, proportion, and orientation, which highlights the distinct characteristics of different villages. For instance, the village size dimension reveals that the majority of these villages feature small architectural structures that harmonize with the natural environment, creating a distinctive and idyllic landscape. However, larger villages such as Nanjiao Village, Gubeikou Village, and Hexi Village, with areas exceeding 70,000 square meters, often owe their size to special historical functions, resource endowments, or geographical advantages[43]. These larger villages exhibit more complex architectural layouts and spatial planning, reflecting a rich history shaped by cultural, historical, and socio-economic forces.

Moving to the proportion dimension, the overall higher integrity of traditional features indicates that Beijing's traditional villages have

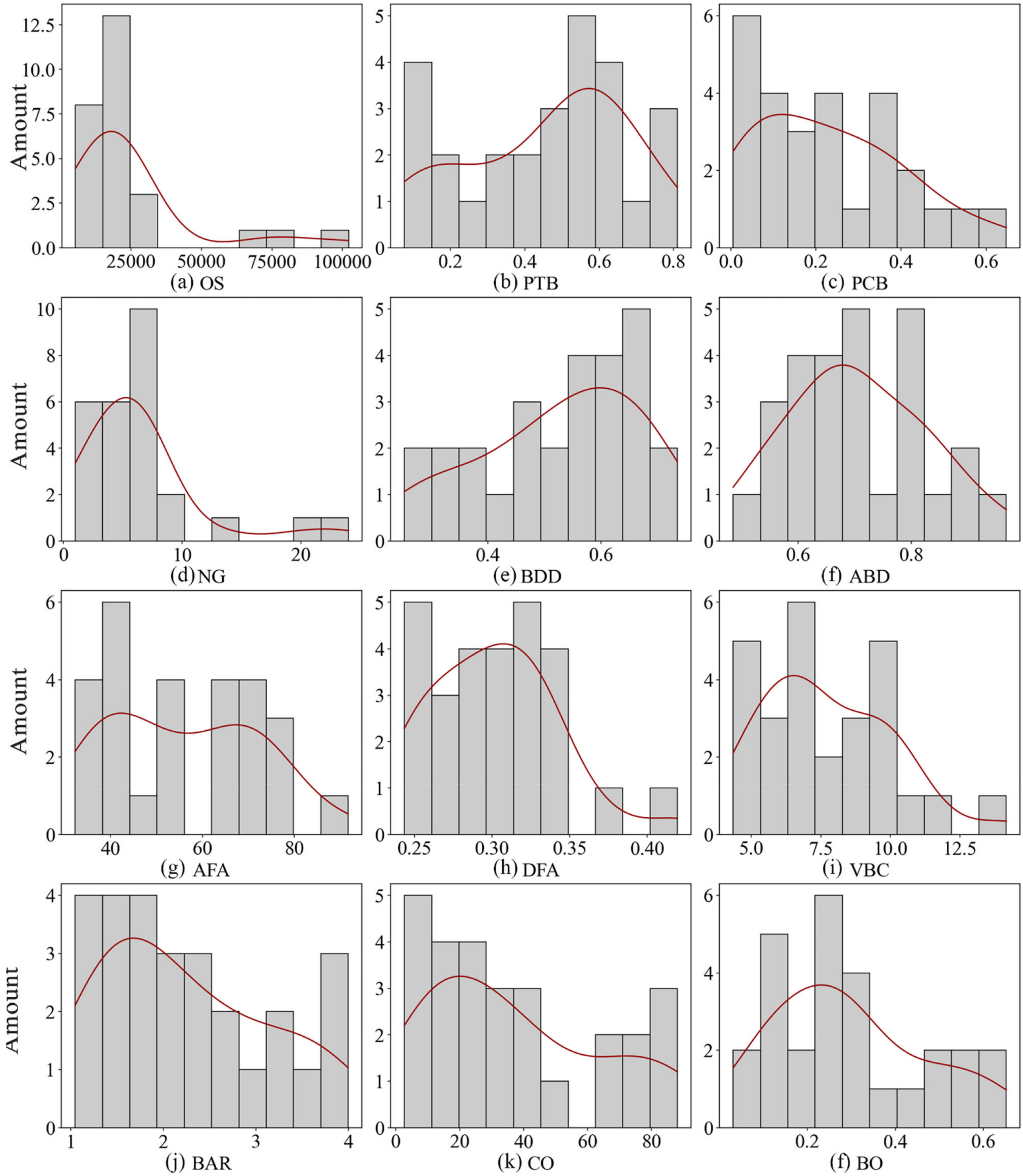

Fig. 8 | Histogram analysis of quantitative indicators of architectural texture.

successfully preserved their historical and cultural essence. However, the high proportion of coordinated buildings in certain towns highlights the challenges posed by urbanization, where old and new structures must be integrated and replaced[44]. Villages with a high degree of traditional integrity should focus on enhancing protection efforts to prevent overdevelopment and irrational transformation[45]. On the other hand, villages with a significant proportion of coordinated buildings should focus on strengthening the unity between traditional and modern architectural styles, promoting awareness of traditional building preservation[46], encouraging the restoration of traditional features, and fostering cultural heritage.

Exploring the building pattern dimension reveals the distinctiveness of Beijing's traditional villages in terms of spatial organization. The small number of clusters may be linked to factors such as village population size, family structures[10], and land distribution. The degree of agglomeration remains stable across villages, which not only ensures close architectural connections but also preserves spatial independence, improving residents' living interactions[47], agricultural production[48], and energy efficiency[47,49]. Greater disorder suggests that the development of these villages does not strictly adhere to plans but has organically evolved due to the influence of natural topography, cultural backgrounds, and environmental factors such

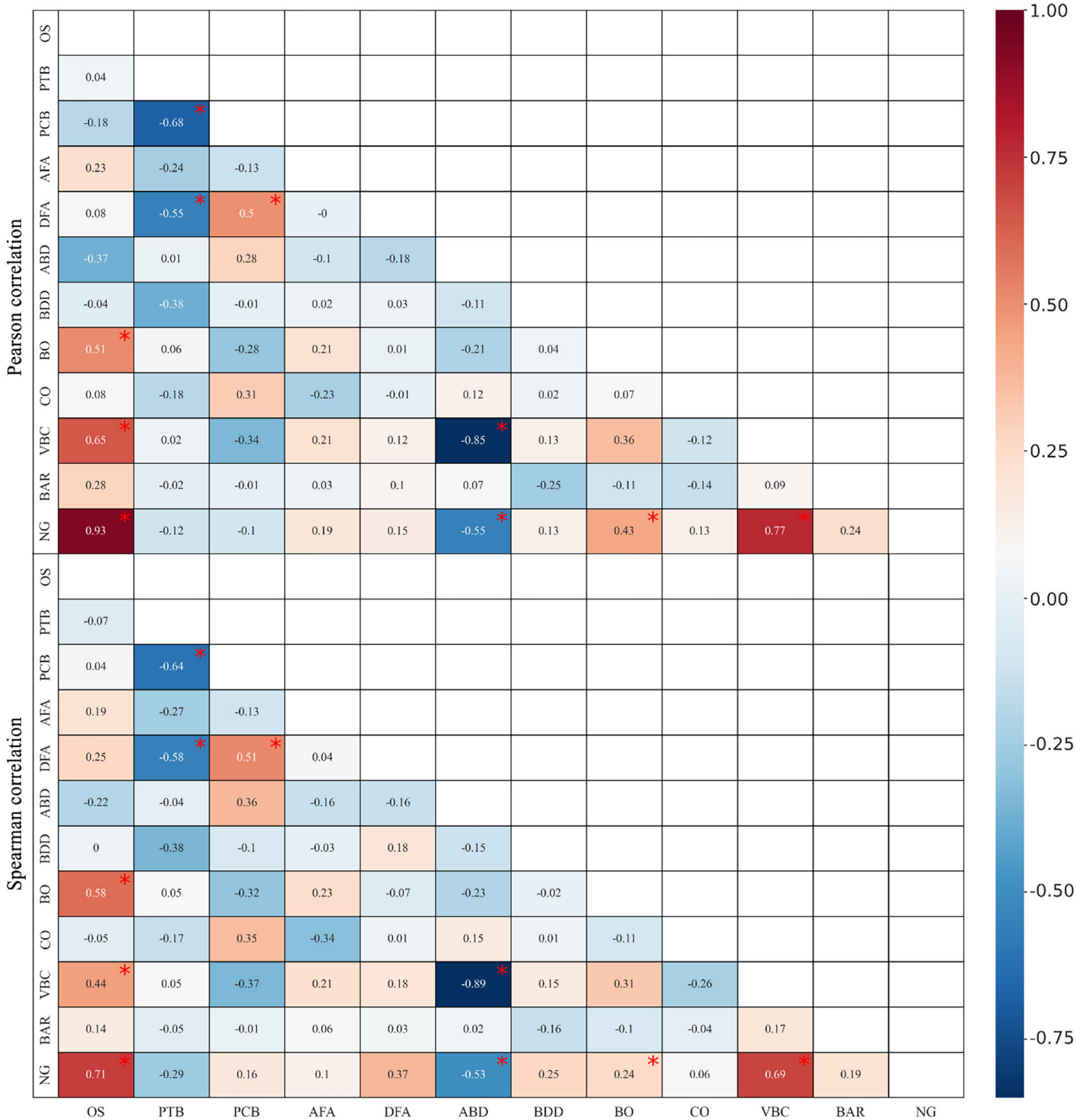

Fig. 9 | Correlation analysis of architectural texture metrics.

as floods and disasters[50]. This contrasts sharply with modern communities and provides a valuable threshold for reference when planning the expansion of villages, supporting the creation of vibrant and adaptable rural spaces.

The building scale dimension reflects the combined influence of regional culture and geography. The uniformity in architectural scale within villages may be linked to traditional construction techniques, norms, and the availability of materials[51], indicating a stable social structure and cultural tradition. However, variations in architectural scale between villages could stem from differing levels of economic development, functional needs, and geographical environments[52], particularly in areas like Miyun, Fangshan, and Mentougou districts. This diversity in architecture and culture reflects the regional reality and offers a foundation for scale control to sustain traditional architectural textures.

The complex boundary patterns result from the interaction between villages and their natural surroundings. This feature reflects the organization of public spaces and facilitates communication between buildings[53]. The boundary elements contribute to landscape formation and spatial definition, and these should be utilized to highlight the region's unique characteristics. The linear constraints emphasize the need to respect the natural conditions of rivers, mountains, ancient pathways, and other resources[54,55] when planning future village development. Maintaining ecological patterns and landscape styles should be prioritized to preserve the village's connection to its environment.

The orientation dimension is deeply influenced by the geographic environment and settlement strategies. Due to the complexity of the mountainous terrain, village buildings do not strictly follow the traditional north-south orientation. Instead, they are flexibly arranged according to topography, sunlight, ventilation, and other natural factors[56]. This diversity not only reflects the residents' wisdom in

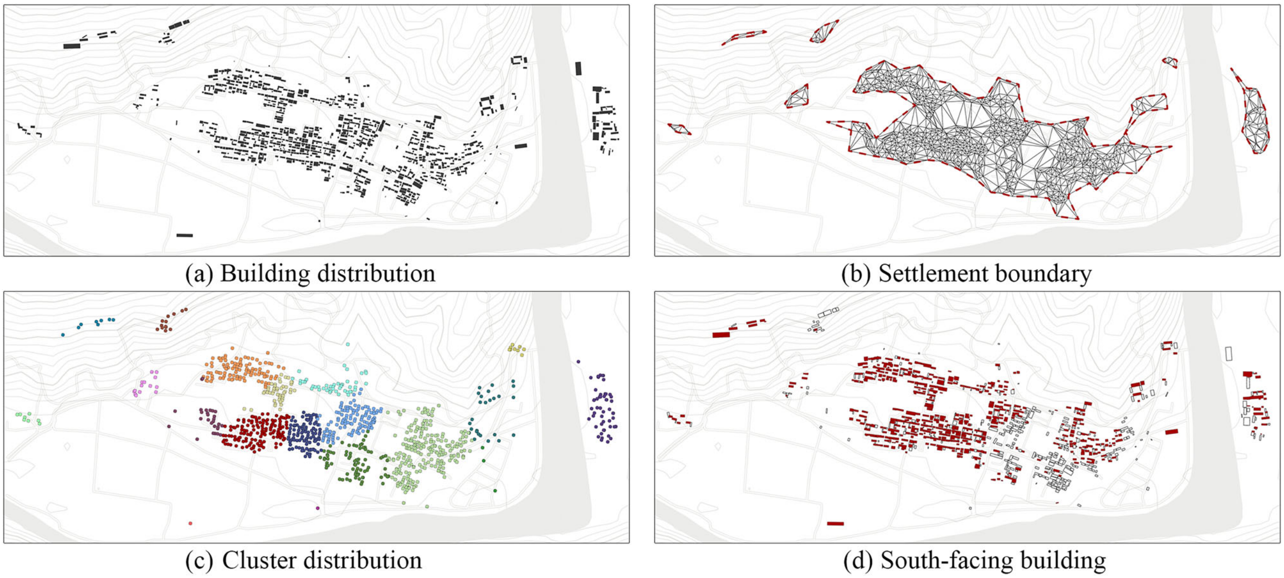

Fig. 10 | Architectural texture of Hexi Village.

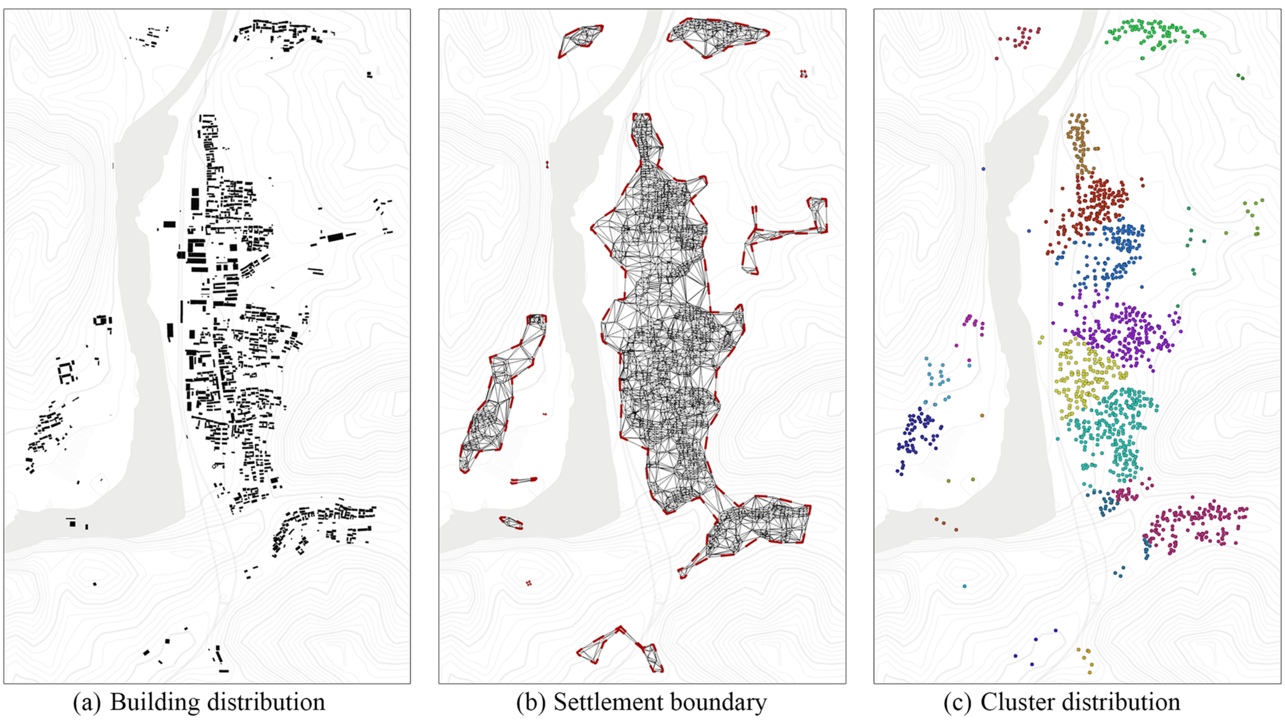

Fig. 11 | Architectural texture of Gubeikou Village.

adapting to their environment but also embodies passive strategies for optimizing lighting, ventilation, and landscape, which are of significant value for modern architectural design.

Third, we further explored the correlation structure of architectural texture through correlation coefficient analysis, which reveals the underlying patterns of village-scale expansion, traditional building distribution, and the development of historical and cultural contexts.

The significant positive correlation between OS and NG, VBC, and BO reveals a series of changing patterns in the process of village-scale expansion. During this expansion, villages such as Hexi Village (Fig. 10), where the surrounding terrain is conducive to construction, have increased public spaces and roads to meet operational needs, thus creating more building clusters. At the same time, they are not significantly constrained by the surrounding mountainous environment, showcasing the advantages of a north-south orientation. Moving forward, small-scale villages should maintain their existing patterns, boundary forms, and building orientations to adapt to terrain-specific construction techniques. Larger settlements, on the other hand, should regulate the expansion direction, boundary forms, and building scales through rational planning to enhance spatial quality and improve the overall landscape.

The correlation between PTB, DFA, and PCB suggests that traditional buildings typically have relatively balanced forms. In contrast, style-coordinated buildings exhibit greater diversity in scale, which leads to an increase in PCB and DFA. On the other hand, a higher proportion of PTB correlates with a decrease in DFA. Villages such as Xihulin Village (Fig. 11) have seen an increase in the number of modern

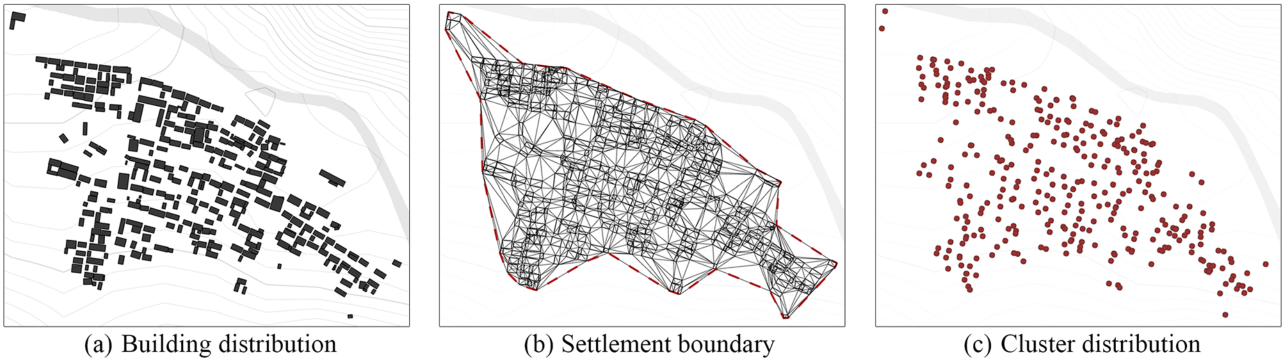

Fig. 12 | Architectural texture of Jijiaying Village.

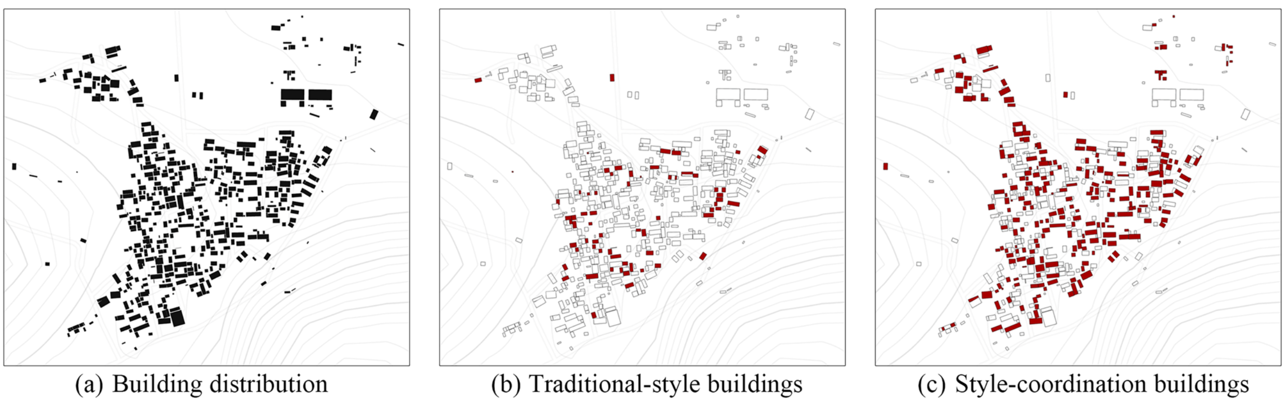

Fig. 13 | Architectural texture of Xihulin Village.

double-slope buildings in recent years due to rapid urbanization, resulting in a more diverse range of building scales and a reduction in the traditional landscape value of the village. In response, future construction standards and scales for style-coordinated buildings should be strictly regulated to prevent the uncontrolled expansion of such buildings from disrupting the village's overall architectural balance. Additionally, targeted restoration and renewal strategies should be developed, such as encouraging residents to adopt traditional building materials and forms for renovations and new construction, in order to minimize the impact of modern building elements on the traditional landscape.

The correlations between ABD, NG, and VBC reflect the unique relationship between history, culture, and village development. Ji Jiaying Village (Fig. 12), for instance, has a relatively high ABD but contains only one cluster, with a VBC of 4.99. In contrast, Gubeikou Village (Fig. 13) has a lower ABD but the highest number of clusters, 24, and a VBC as high as 14.16. While many villages share historical ties to the Great Wall's city ports, Ji Jiaying Village has expanded less beyond the city wall and retains a more military-style settlement layout, with a regular settlement boundary pattern[57]. For villages with a focus on historical and cultural preservation, particularly those that retain military settlement characteristics, it is crucial to maintain the original layout and boundary features. Conversely, villages with more diverse functional needs, such as tourism development or those located in more open geographic environments, may promote boundary space openness. This approach would better accommodate the needs of various user groups and enrich the esthetic experience, based on a moderate increase in the number of clusters and the diversification of boundary forms.

In summary, among all the indicators, NG has the highest number of associated indicators (four), followed by OS with three associated indicators. DFA, VBC, PTB, ABD, PCB, and BO each have two related indicators, while BAR, CO, BDD, and AFA have no associated indicators. Evaluation indicators with a larger number of associations and a higher coefficient of variation tend to have a stronger global influence, and changes in these indicators may drive the evolution of the entire settlement. In the future conservation and development planning of traditional villages, key indicators such as NG, OS, and PTB should be prioritized and managed to ensure the sustainable development of the architectural texture of traditional villages through strategic guidance.

Although this study improves the scientific evaluation of the architectural texture of traditional villages and promotes the application of new technologies in their preservation, there remains room for further improvement in comprehensive assessments of architectural features, initial screening, and dynamic monitoring across a large number of villages. First, since buildings typically consist of three parts: the roof, façade, and foundation, evaluating architectural features solely from the perspective of the roof may lead to one-sided results. Future work should strengthen the extraction of architectural information from multiple perspectives. Secondly, the model's training relies heavily on labeled data, and for some traditional villages with unique architectural styles or specific historical and cultural backgrounds, there may be insufficient data, which could affect the accuracy and generalizability of the model. Additionally, China's assessment model, from local declarations to expert reviews, is susceptible to local biases, national protection policies, and conflicting interests[58]. As a result, some esthetically appealing villages may be overlooked. Therefore, it is worth exploring in depth future training that involves comprehensive architectural labeling, top-down screening, and ongoing monitoring.

Data availability

The datasets used and/or analysed during the current study are available on reasonable request.

Code availability

The code used and/or analysed during the current study is available on reasonable request.

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Author contributions

Yang Shi: Writing–original draft, Methodology, Investigation, Conceptualization. Wenke Wang: Writing–original draft, Software, Methodology, Formal analysis, Investigation, Conceptualization. Jie Zhang: Supervision, Project administration. Dong Li: Software. Fei Liu: Resources. Wensheng Li: Resources.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to Jie Zhang.