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RESEARCH ARTICLE

Traditional village preservation status evaluation and optimization based on YOLOv10 and random forest model—take the Tibetan-Qiang region in northwest Sichuan as an example

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Abstract This study proposes a framework to automate the evaluation of traditional village preservation status and analyze the major influential factors (MIFs) of preservation status and influencing mechanisms through YOLOv10 model and Random Forest model, taking Tibetan-Qiang region of northwest Sichuan as the study area. The framework adopts satellite maps, based on the YOLOv10 model, to comprehensively detect the preservation status of houses in the traditional villages, and calculates the preservation score of the corresponding villages as an evaluation of their preservation status. Further, through the Feature importance of Random Forest model, the MIFs of the village preservation status are filtered from the multiple environmental factors, and the SHAP value resolves the influencing intensity of the MIFs on the preservation status. Finally, for villages with poor preservation status, targeted preservation strategies are proposed. The contribution of this framework is saving the cost of traditional field research and significantly improving the efficiency and scope of the evaluations. Besides, the results also fill the gap in evaluating the preservation status and analyzing their influencing mechanisms of the traditional villages in Tibetan-Qiang region, and support the decision makers to propose more targeted optimization strategies.

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1. Introduction

Tibetan-Qiang region of northwest Sichuan (hereafter Tibetan-Qiang region) is the central area of Qiang and Baima, Khampa, and Jajong Tibetan cultures in China (Wang, 2022). Multi-ethnic cultures and complex geographic and climatic environments have led to the distinctive regional characteristics of the local houses, which have become an essential witness of the local architectural culture and settlement custom (Zu et al., 2024). In 2016, UNESCO designated the Tibetan-Qiang cultural corridor (encompassing Tibetan-Qiang region) in Western Sichuan Plateau as a "Culture Diversity Observatory" (United Nations Educational, Scientific and Cultural Organization, 2016), signifying its recognition as both an international focus area in the built heritage conservation field and a critical preservation area. The traditional villages within this region embody unique Tibetan-Qiang cultural traditions, possessing irreplaceable exceptional historical and aesthetic values. However, these heritage assets face compounded threats from recurrent geological hazards and accelerating modernization pressures, which persistently erode their authentic characteristics and cultural significance. These contexts underscore the urgent need for prioritized conservation interventions toward the traditional villages in the Tibetan-Qiang region.

To filter and preserve traditional villages with substantial historical, cultural and scientific values and their regional characteristics, the "*List of Traditional Villages in China*" and the "*List of Traditional Villages in Sichuan Province*" have been promulgated by the relevant government departments at the national and provincial levels (Ministry of Housing Urban-Rural Development of China, 2016; Liu et al., 2022). Through these lists, researchers can identify the typical study and preservation targets of the local villages and houses (Geng and Zhou, 2015). Relevant government departments can also provide solid political and economic support for the traditional villages to enable their better optimization and promote the preservation of their traditional patterns (Chou, 2015).

However, even with the support of the lists, it is still challenging to evaluate the preservation status and put forward reliable optimizing strategies for the traditional villages in Tibetan-Qiang region: Firstly, the extensive scope of the region, poor transportation conditions, treacherous landforms, and frequent natural hazards (Liu, 2007) render it difficult to conduct region-wide and real-time field surveys due to the enormous time and labor costs. This background has led to a lack of reports and studies on the conservation status of all traditional villages in the whole context of the Tibetan-Qiang region; Secondly, the influence of various factors in the region, including geomorphology, climate, economy, tourism and other factors on the preservation status is complex (Wang et al., 2023), and there is a lack of reliable measure to explain the mechanism of the joint influence of various factors on the preservation status. These contexts have led to difficulties in accurately recognizing the preservation status of the villages and formulating targeted preservation and optimization strategies based on the major influential factors by the relevant personnel (mainly village leaders and villagers).

The development of online open maps has provided the potential for observing and evaluating village preservation status on a wide range scale. Through the APIs provided by open map platforms such as Baidu and Google, researchers can download high-definition satellite maps through the coordinates of traditional villages, to comprehensively observe and evaluate their preservation (Hong et al., 2023). For instance, Zhao et al. (2024) obtained satellite maps of 338 traditional villages in the Miao frontier corridor via the 91-satellite map, concluded the spatial divergence phenomenon of the preservation of traditional villages in this area, and speculated that the natural geomorphic environment, as well as the humanistic and historical backgrounds, are the potential triggers of this phenomenon. Elfadaly et al. (2022) monitored the built heritage in Basilicata Region through high-resolution satellite maps provided by Google Earth Engine (GEE) and summarized the potential risks of geohazards to the heritage characteristics together with geohazard records in the region. In the Tibetan-Qiang region, although the coordinates of traditional villages on open maps are accurate, and the recent high-resolution satellite maps of the region have been updated, there is still a lack of preservation status evaluation indicators for satellite maps of traditional villages. This context has led to the fact that the preservation status of traditional villages, as well as the influencing mechanism of various environmental factors on the preservation status still need to be summarized subjectively by the researchers, which affects the reliability of the conclusions of the existing studies.

Object detection model and Random Forest model have the potential to address the above challenges. Object detection model is a type of image deep learning model. Its training dataset is a series of images labeled with the location and category of the detection targets, and the model is trained to accurately learn the multi-scale image features of detection targets (Alif and Hussain, 2024). The trained model can predict the locations and categories of learned targets in the input images, and count the number of targets of each category (Sapkota et al., 2024). If the preservation status of single houses in some satellite maps are graded and labeled as the training dataset, then the trained model can detect the preservation status of all single houses of the traditional villages in the region, and evaluate the general preservation status of the corresponding villages through the proportion of houses at each preservation level; Random Forest (hereafter RF) is an ensemble learning model (Breiman, 2001) for classification tasks, where the samples at the inputs contain multiple independent variable features and a dependent variable classification (Biau and Scornet, 2016). The model is trained through multiple rounds of machine learning to obtain a mapping rule from the independent variable features to the dependent variable categories, and outputs the contribution of each independent variable to the dependent categories; the higher the contribution, the more the feature tends to be the major influential factor (hereafter MIF) towards the classification results (Archer and Kimes, 2008). If the preservation status of traditional villages in the Tibet-Qiang region are graded and taken as the dependent variable, and the environmental factors that potentially affect the status are taken as the independent variables, the MIFs affecting the preservation status of the villages can be filtered by the output contribution of the model, and then the mechanism of their influence on the status can be analyzed; thus, the targeted preservation and optimization strategies can be proposed.

Based on the above tools, this study proposes a framework that uses satellite maps as a proxy and applies machine learning models for autonomous decision-making, to evaluate and optimize the preservation status of the traditional villages in Tibetan-Qiang region. The contributions of the framework are 1) its operational process is more efficient, quantitative, and can be re-validated compared to the traditional fieldwork methods, and can be applied in studies targeting a broad area and a large number of villages; 2) it fills the gap in evaluating the preservation status of traditional villages and the corresponding influential factors in the entire area of the Tibetan-Qiang region, and facilitates decision-makers in proposing more region-specific preservation strategies.

2. Research data

2.1. Overview of the study area and acquisition of satellite maps of traditional villages

The study area contains Aba Tibetan and Qiang Autonomous Prefecture and Ganzi Tibetan Autonomous Prefecture in Sichuan Province. The region has a typical mountainous highland terrain, with significant variations in precipitation and temperature between sub-regions, and has historically maintained self-governance by ethnic minorities (Preparation team for the Profile of Garze Tibetan Autonomous Prefecture, 1986; Preparation group for the Profile of Aba Tibetan Qiang Autonomous Prefecture & Preparation group for the revised Profile of Aba Tibetan Qiang Autonomous Prefecture, 2009). The above context enables local residents to independently decide on the construction and renovation of their private houses, leading to varying conditions of village preservation status in different sub-regions (Tan et al., 2022).

In this study, the WGS84 coordinates of 466 traditional villages in the study area were determined based on the *"List of Traditional Villages in China"* and the *"List of Traditional Villages in Sichuan Province"*. Google Map has the most accurate recent satellite map of the region (21 zoom levels for the region in 2023), and the URL provided by the website allows unlimited downloading of satellite maps of the target area (Harris and Baumann, 2015). Therefore, we construct a 1 km $\times$ 1 km buffer area around the center of each village based on the coordinates, to obtain high-definition satellite maps of the corresponding village. The area was determined through repetitive experiments to ensure that the satellite maps could present the preservation status of all village central clusters. The traditional village distributions and examples of satellite maps of the villages are shown in Fig. 1. As shown in Fig. 1 (b), in the study area, the roofs of traditional buildings, which are commonly constructed of timber, stone, tiles or rammed earth, are considered to be the priority element for renovation as they are more severely damaged than the walls due to long-term weathering, erosion and exposure to the sunlight and precipitation (Wu, 2012). Besides, during the process of building renovation and reconstruction, the body structure of the house can hardly support the roof, so its original form required to be removed and to be replaced with a more affordable and physically superior roof of modern construction material. Therefore, whether a building has been damaged by abandonment or inappropriately renewed, its preservation status can be greatly reflected by the pattern of the roofs in satellite maps, which thus serve as a reliable proxy for the preservation status of the general village.

Notably, the training complexity of object detection model shows an exponential increase as the pixel size of the images increases (Kim, 2024). Therefore, after repeated experiments, this study sets the zoom level of the satellite map to 19, which ensures its clear display of the village preservation state as well as the training efficiency of the model.

2.2. Environmental factors acquisition

Multiple environmental factors around traditional villages have long affected the routines of residents, and are therefore considered to be the major factors contributing to the variations in the preservation status of the villages (Lawrence and Low, 1990). For instance, traditional villages in northeastern China tend to add thermal insulation in their walls and install thick windows and doors to counteract the extremely cold local climate (Zhang and Jin, 2016); Traditional villages in the Xinjiang have installed solar photovoltaic (PV) panels covering large areas of their roofs to supply electricity and heat, based on the abundant local daylight (Yang and Jiang, 2010). Some traditional villages in the Li County of Sichuan have been abandoned or even naturally damaged due to treacherous terrain and poor transportation (Liu and Wang, 2024). To develop targeted preservation and optimization strategies for traditional villages in the study area, it is essential to analyze the MIFs affecting the preservation state and to summarize the mechanisms of their influence on the state.

In this paper, we refer to relevant field research to select four categories with a total of 12 potential environmental factors, from which we aim to filter the MIFs on the

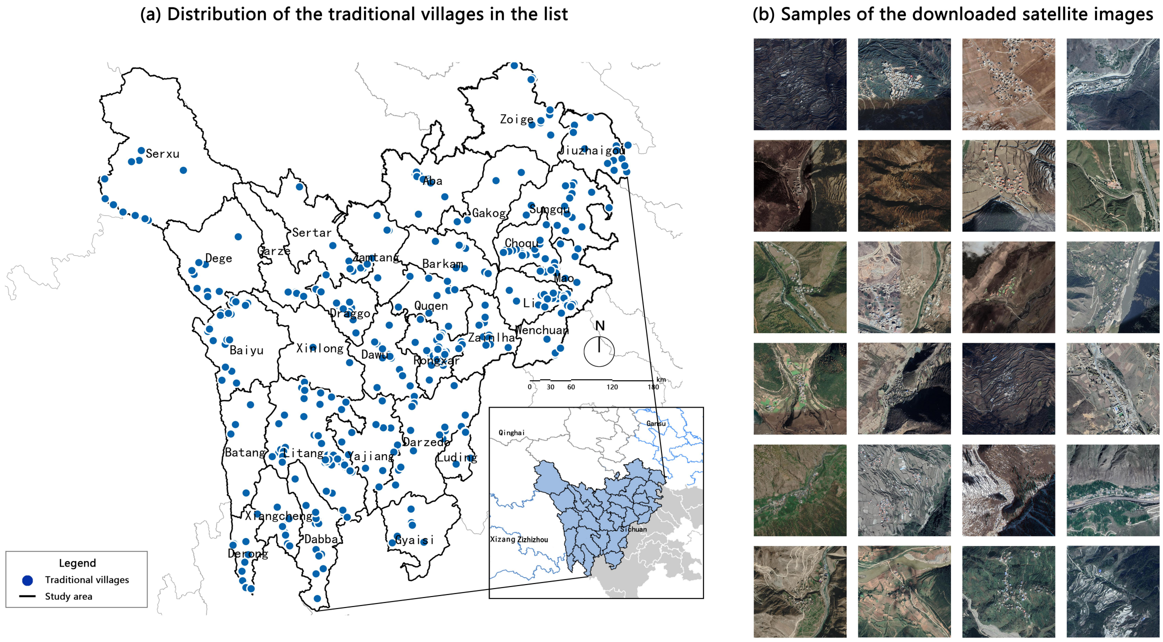

Fig. 1 Distribution and the sample satellite image of the traditional villages.

preservation status of traditional villages. The selection reasons for the factors for each category and their presentations are as follows:

1) Climate factors: Climate can significantly affect the features and preservation status of traditional villages. For instance, excessively high temperatures can cause villages to expand the size of courtyards or reduce the form factor of their buildings; heavy precipitation can force villages to change the building roofs to lightweight, waterproof steel-shingled sloped roofs, or even lead to house collapses and out-migration of inhabitants. Based on the study of the correlation between local climate and village patterns (Shi and Liu, 2022), we chose humidity, temperature, and precipitation as potential impact elements. Their details and the data sources are listed in Table 1(a).
2) Resource factors: The primary occupants and maintainers of villages are the residents, whose willingness to stay receives significant influence from local transportation, agricultural, water, or even other resources. For instance, when villages are located in mountainous areas with poor transportation conditions, water scarcity and lack of food supply, inhabitants will tend to migrate out of the area, and conversely will tend to settle and maintain the village long-term. Based on field surveys and interviews with local traditional villages (Shi et al., 2023), we chose the walking distances from villages to adjacent roads and water systems to measure the access resources and water quality of the villages. In addition, the quality of local cultivated land was measured by NDVI (Normalized Difference Vegetation Index). Their details and the data sources are listed in Table 1(b).
3) Humanity factors: In addition to the traditional agricultural civilization, the humanity elements of the study area, such as the tourism industry, economy, and population, can also significantly influence the inhabitant quality, as well as their tendency to renovate the village. For instance, when villages have a high economic level and a thriving tourism sector, residents tend to settle down permanently and renovate their houses into modern guesthouses to accommodate tourists, while conversely tending to rely on agriculture for their livelihoods or even leaving the village for employment. Based on the research on the local central industries (Tan et al., 2013), we choose three elements as potential impact elements: population, GDP, and tourist check-in records. Their details and the data sources are listed in Table 1(c).
4) Geomorphic factors: In addition to the attributes of the built villages, the surrounding physical landform can also significantly affect their conservation status. For instance, villages located on cliffs are prone to natural disasters, resulting in serious deterioration of buildings, and villages located at elevated altitudes have a strong tendency towards out-migration of inhabitants and loss of village maintenance due to severe living conditions. Based on the typical landscape of the transverse mountains and the western Sichuan plateau in the study area, we chose the three elements of elevation, slope, and breakup phase as the potential impact elements. Their details and the data sources are listed in Table 1(d).

The computed factors were extracted into POIs of all traditional villages by Extraction tool of Arcmap 10.2 (Fig. 2).

Through the inspection of local construction works, the renovation period of the residential buildings is about one year; in other words, the architectural features in the satellite map are mostly affected by environmental factors about one year earlier (Shao and Cui, 2024), so the factors

Table 1 Data sources and descriptions of the environmental factors and geographic contexts.

Name	Data source	Description
Geographic contexts		
Administrative boundaries	National Geomatics Center of China	Shapefile of 2022 administrative boundaries of counties in the study area
Road system	Open Street Map	Shapefile of 2022 township roads and roads of higher level in the study area
Water system	State Key Laboratory of Resources and Environment Information System	Shapefile of 2022 major water systems in the study area
Climate factors (a)		
Humidity (%)	China Meteorological Data Service Centre	Raster of 2022 annual average relative humidity with 500 m $\times$ 500 m resolution
Temperature (°C)	Institute of Tibetan Plateau Research, Chinses Academy of Sciences	Raster of 2022 annual average land surface temperature at 500 m $\times$ 500 m resolution
Precipitation (mm)	China Meteorological Data Service Centre	Raster of annual average precipitation for 2022 at 500 m $\times$ 500 m resolution
Resource factors (b)		
NDVI	Resource and Environment Science Data Platform	Raster of 30 m $\times$ 30 m yearly Normalized difference vegetation index of 2022
Road distance (m)	Baidu Maps API	Distance from each village to neighboring provincial road by route planning function
Water distance (m)	Baidu Maps API	Distance from each village to neighboring water system by route planning function
Humanity factors (c)		
Population	World Pop Hub	Raster of 2022 population distribution of 100 m $\times$ 100 m resolution
GDP (billion CNY)	Resource and Environment Science Data Platform	Raster of 2022 GDP distribution of 100 m $\times$ 100 m resolution
Tourism checkin	Mafengwo	Obtaining the whole checkin records of 2022 in the study area through Python
Geomorphic factors (d)		
Altitude (m)	USGS	Raster of 2022 altitude of 90 m $\times$ 90 m
Aspect (°)	Processing the altitude raster with Aspect tool of the Arcmap10.2	Raster of 2022 aspect of 90 m $\times$ 90 m
Slope (°)	Processing the altitude raster with Slope tool of the Arcmap10.2	Raster of 2022 slope of 90 m $\times$ 90 m

of this study are selected from the data of 2022, to truly reflect their influence on the preservation status.

3. Methodology

3.1. YOLOv10 model

The present range of traditional villages in this study were of 1 km $\times$ 1 km, which required high-resolution satellite images to show the conservation status of buildings in the villages at a fine-grained level. In addition, the number of traditional villages in the study area is only 466, and the size of training dataset is limited. Therefore, the object detection model adopted in this study requires the capability of detecting small objects in high-resolution images through a sample limited dataset.

Presently, the mainstream object detection models are R-CNN (Region-CNN) series, SSD (Single Shot MultiBox Detector) series, DETR (Detection Transformer) series, and YOLO (You Only Look Once) series (Wei et al., 2024). Among them, the R-CNN series have 1) candidate frame generation and 2) classification regression, two detection phases, which enable the models to have high detection accuracy in complex scenarios (Chaves et al., 2018). However, such models have enormous computational complexity in detecting high-resolution images due to generating numerous candidates bounding box (e.g., Faster R-CNN has only 1-2FPS for images with 1500 $\times$ 1500 resolution). The SSD series accomplish target localization by only one single forward propagation (Wang et al., 2023), so the detection efficiency is significantly improved (e.g., SSD512 has 25—35 FPS for images with 1500 $\times$ 1500 resolution). However, the model provides a narrow receptive field for small target features in high-resolution images, which impairs the fine-grained feature extraction capability of the models; The DETR series introduce the Transformer architecture, which specializes in capturing and detecting the composite scale dependence of objects, giving it high detection accuracy for small targets (Muzammul and Li, 2025). However, due to the Self-Attention module in its architecture, the computational complexity of the model increases exponentially with pixel size (e.g., DETR model has 5—10 FPS for images with 1500 $\times$ 1500 resolution) and is prone to GPU memory

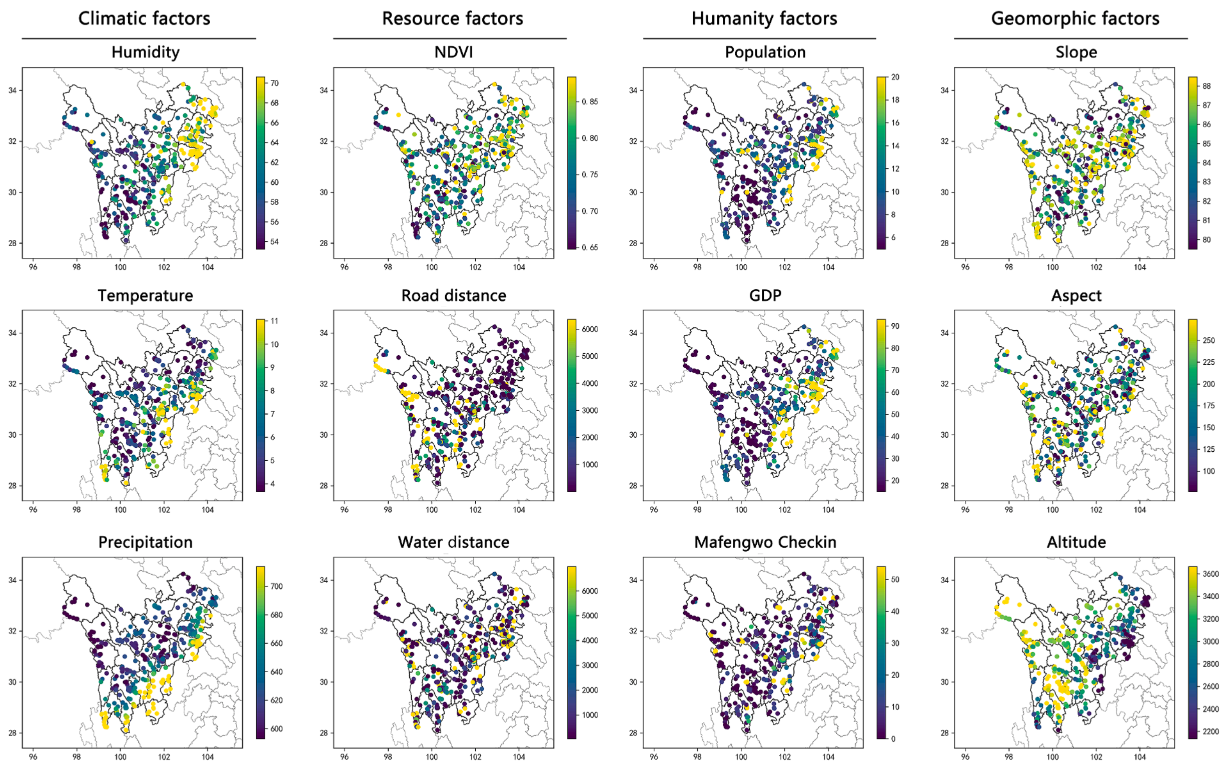

Fig. 2 Distribution of each environmental factor in the traditional villages.

exploding. In addition, it generally requires large-size (normally more than 1000) datasets to achieve precise detection result; The YOLO series is a popular lightweight object detection model, allowing for low computational complexity in high-resolution object detection scenarios (e.g., YOLOv10 has 30—60 FPS for images with 1500 × 1500 resolution). The recently updated YOLOv10 model in this series introduces the dual detection head module (including One-to-one head and One-to-many) (Sapkota et al., 2024). One-to-many head enables the model to assign supervisory information in different scales to the detected objects during training, while one-to-one head enables the model to produce one-to-one detection results, assisting the model to learn the image features of the target at the composite scale and to accurately predict its category (Sundaresan Geetha et al., 2024), increasing its detection sensitivity to small-sized targets (Hussain and Khanam, 2024).

The original satellite maps in this study are of approximately 3400 × 3400 resolution, and after repeated experiments, downsampling it to 1500 × 1500 can guarantee its demonstration of the fine-grained status of the buildings and reduce the computational consumption of the object detection model. After comparing the mainstream models, this study uses the YOLOv10 model from the YOLO series to detect the preservation status of the villages. The application mechanism of the model is shown in Fig. 3.

In this study, the detection performance of YOLOv10 is evaluated by two metrics, mAP50 and mAP50-95, where mAP50 refers to the mean detection accuracy of the predicted bounding box and the real bounding box for all categories of targets at the IoU = 0.5 level, and mAP50-95 refers to the mean detection accuracy of the predicted bounding box and the real bounding box for all categories of targets at the IoU = 0.5, 0.55, … , 0.95 levels of mean detection accuracy for all categories of objects (Liu et al., 2018). Typically, models with a mAP50 reaching at least 0.8 and a mAP50-95 reaching at least 0.5 are considered to be well-performing models (Du, 2018).

3.2. RF model

RF model is a robust machine learning model integrated by multiple decision trees with high prediction accuracy in classification tasks, and can effectively avoid overfitting during training (Rigatti, 2017). The model employs the bootstrap principle to extract multiple sub-sample sets, each with the same sample size as the original dataset, and then assigns a decision tree to each set for independent training, randomly selects partial features as the basis for classification when encountering a split node, and finally determines the classification of the samples by using the category with higher votes from the decision trees. The contribution of each independent variable to the categorization results is measured by the feature importance (hereafter FI) indicator, where the larger the value, the more the corresponding independent variable tends to be the MIF to the categorization results (AlSagri and Ykhlef, 2020). FI can intuitively identify the MIFs affecting classification results from independent variables. However, further interpretation of their influential magnitude and direction (positive/negative influence) requires additional Shapely additive explanation (hereafter SHAP) analysis. SHAP is a metric used to explain the basis of categorization

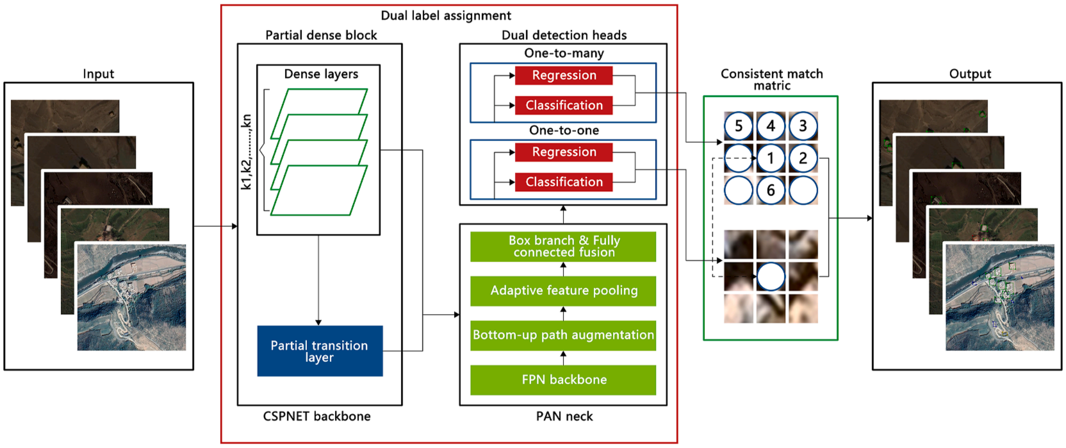

Fig. 3 Application mechanism of YOLOv10 model.

of a random forest model and is calculated by recording the synergistic contribution of all the independent variables while the model outputs the categorization results and calculating the marginal contribution of the respective variables in the process and taking the average value as SHAP value. The larger the indicator, the more significant the effect of the independent variable on the classification results (Nohara et al., 2019). The application principle of the RF model and the calculation process of SHAP value are shown in Fig. 4.

RF model, along with FI and SHAP indicators, has been commonly applied in resolving the causes and impacts of geographic phenomena and has achieved accurate and quantitative results in the traditional village feature evaluation tasks. For instance, Liu et al. (2020) used RF model to calculate FI and SHAP values to derive that spatial distance and climate variation are the main triggers for the distributional differences of village clusters in Paojatun Walled City; Sprague (2013) analyzed the human geographic formation patterns of the differentiated positional connections between traditional villages and dry fields, meadows, and woodlands in the Kanto Plain of Japan through the same model and indicators. Therefore, RF model, and the two indicators, will be adopted to analyze the environmental causes that undermine the conservation status of villages in this study.

3.3. Preservation scores

The study area has inferior transportation facilities and a relatively shallow economy, so the transformation of traditional village preservation status is mainly at the architectural level, and the transportation system and spatial structure around and within them have not changed significantly from the traditional pattern. In addition, even if roads, public squares and other open spaces are inappropriately renewed or impaired, as their maintenance and repair are coordinated by the township governments, and its rehabilitation is not very difficult, the pattern of such open spaces has less impact on the general preservation status of the villages compared to the damages to the original features of the buildings, and it is not the subject of concern in this study. Thus, this study evaluates the preservation status of each house in the satellite map of traditional villages through the YOLOv10 model, and assesses the general conservation status of the entire village

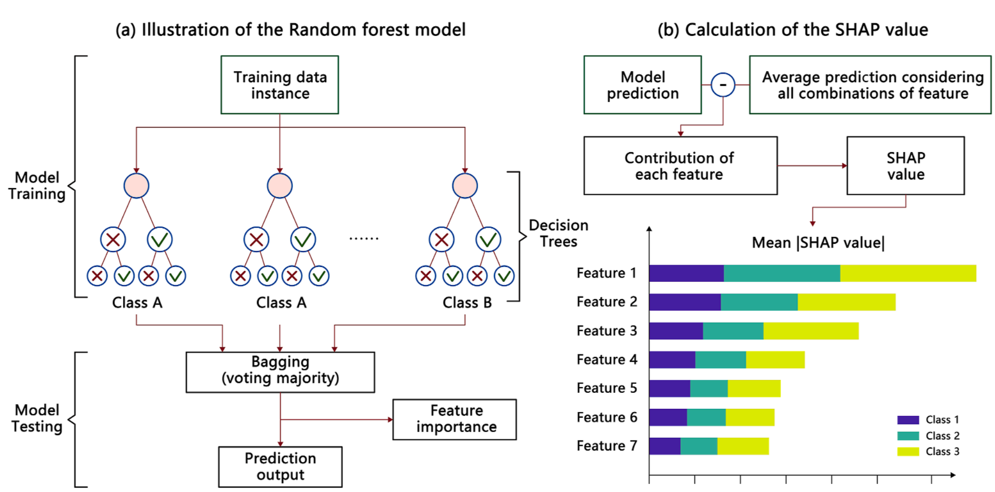

Fig. 4 Mechanism of random forest model and the calculation process of SHAP value.

based on the houses' status. There are two destructive trends in the houses of the region: 1) Improper renew. Due to the relatively inferior structural and physical properties of traditional building materials, residents tend to adopt more affordable, easier-to-install materials with better engineering performance (e.g., concrete, plastic sheds, steel plate roof) for house renovations. However, such modernization practices inevitably compromise the original building features, undermining both the regional aesthetic values and historical significance embedded in the traditional houses (Hu and Feng, 2022); 2) Empty and abandoned. Residents in certain villages have opted to out-migrate due to insufficient living resources, underdeveloped transportation infrastructure, economic disadvantages, and frequent natural disasters. This exodus has resulted in inadequate building maintenance, leaving traditional structures vulnerable to weathering and natural hazards that progressively degrade their original features and patterns. When building deterioration reaches critical levels, the embedded values are consequently diminished or even eradicated, potentially culminating in the complete disappearance of the whole village (Tian et al., 2024). Trend 1 damages the preservation status from the residents' excessive renovation of traditional houses, and Trend 2 damages the preservation status from the residents' insufficient repair and protection of houses, so that the preservation status of the houses can be evaluated by the degree of human intervention.

In this study, the preservation status of houses in the YOLOv10 dataset were labeled according to the human intervention degree using the criteria "destroyed-0, dilapidated-0.5, normal-1, modified-1.5, new-2", and the two categories of other buildings, modern and traditional, were also labeled (as specified in the following section). The labeling of the dataset will be detailed in the subsequent sections. After excluding other buildings, the preservation score (*P*-score) is calculated through Equation (1):

$$P_s = \frac{B_{s1} \times n_1 + B_{s2} \times n_2 + \cdots + B_{s5} \times n_5}{n_1 + n_2 + \cdots + n_5}. \quad (1)$$

In the equation, n_1−n_5 represent the number of houses with five types of preservation status in the village, and B_{s1}−B_{s5} represent the corresponding human intervention degree. P_s is the *P*-score, which evaluates the preservation state of the entire traditional village; the closer to 0, the closer the village is to be destroyed; the closer to 1, the better the preservation of the village; and the closer to 2, the closer the traditional features of the village are to be completely replaced.

3.4. Research framework

The research framework is shown in Fig. 5. Besides the preparation step, three operation steps are included in the research framework as follows:

1) Preservation status evaluation: This step labels the YOLOv10 dataset and trains the model, through the trained model to detect the preservation status of all houses in the satellite map, then calculates the *P*-scores of the corresponding villages, and finally divides the traditional villages into several preservation levels according to the distribution of the scores.
2) Major influential factors identification: This step links the preservation levels of the villages to the corresponding POIs as the dependent classification, and the potential influential environmental factors as the independent variables, to train the RF model and output the FI and SHAP values of each potential influential factor. Then MIFs are filtered by FI and the synergistic effects of the MIFs on the preservation status of the villages of different levels are quantitatively explained by SHAP values.
3) Influencing mechanism interpretation: This step selects sample villages among traditional villages with different preservation levels, uses drone aerial photography to verify the reliability of evaluating preservation status through satellite maps, and takes local resident interviews to understand the influence of the MIFs on their preservation and optimization preferences, so as to verify the reliability of the RF model analysis results. Finally, based on the analysis results of YOLOv10 and RF model, targeted preservation proposals are presented for the villages with different preservation levels.

4. Results

4.1. Results of the preservation status evaluation step

4.1.1. Dataset labeling and YOLOv10 training results

According to the research framework, 456 satellite maps of villages around traditional villages were labeled as the dataset (i.e., the satellite maps of traditional villages were not included in the dataset), which not only ensures that the model can accurately identify various types of detection targets, but also prevents the inflated detection accuracy resulting from identified satellite maps of traditional villages. 356 (about 80% of the total) satellite maps in the dataset were randomly selected as the training dataset, and the remaining maps were the validation dataset. The composition of the dataset and the samples of detection targets are shown in Fig. 6.

In the dataset, the destroyed category is for almost completely destroyed houses, the dilapidated category is for abandoned and partially destroyed houses, the normal category is for well-preserved houses that maintain the traditional architectural features, the modified category is for houses that have been partially reconstructed in the traditional feature with inappropriate building components (e.g., colored steel panels, polyester fiber boards, etc.), the new category is for houses that have been demolished and completely rebuilt in the modern style, the traditional others (others (T)) category is for traditional houses such as temples, pagodas, and livestock sheds, and the modern others (others (M)) category is for modern, non-residential buildings such as office buildings, construction site support buildings, and plastic vegetable sheds. The categories of others were excluded before calculating the *P*-score due to their uneven distribution in different villages and the fact that their renovation and construction originated from the

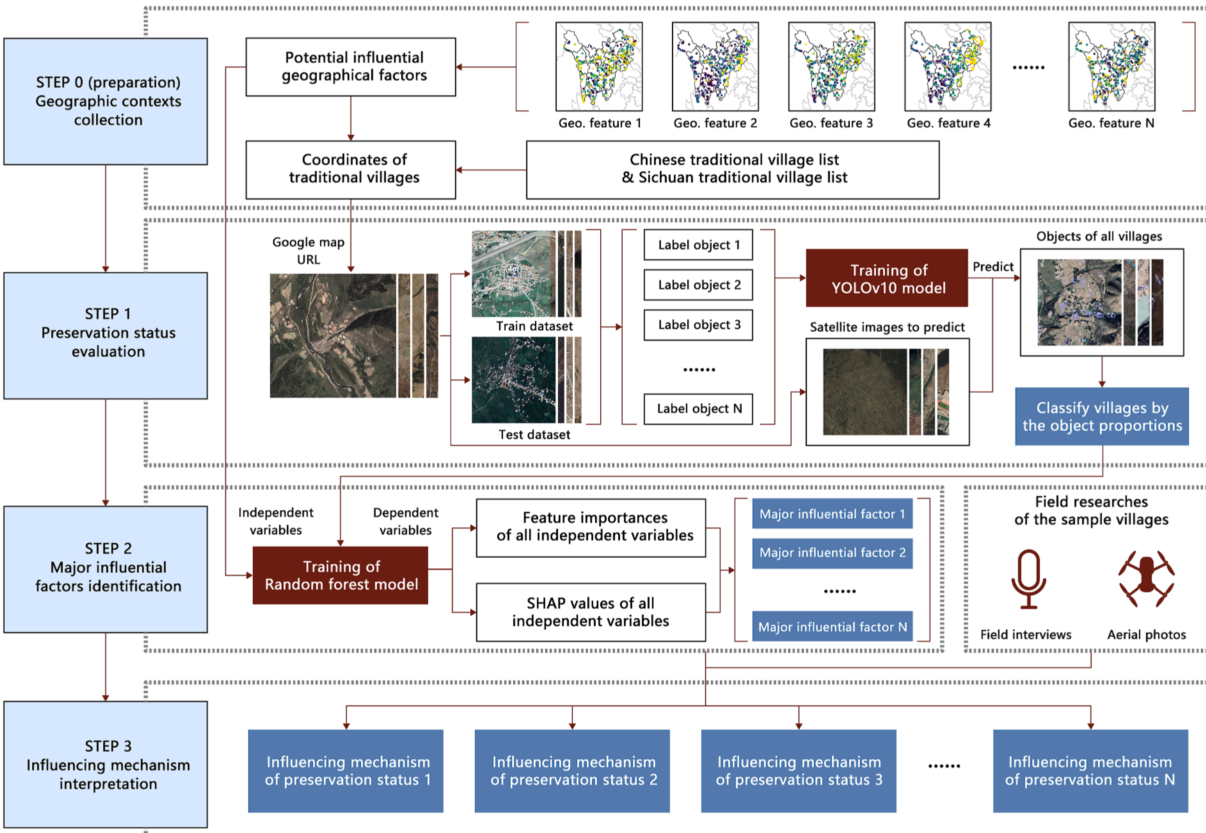

Fig. 5 The research framework.

government and the relevant religious groups, and the residents had no power to direct their preservation.

The dataset was fed into the YOLOv10 model to start training. The model was named the Preservation evaluation model (PEM), and the hyper-parameters and computational equipment utilized in the training are as in Table 2. Quantitatively, the trained model achieved a mAP50 of 0.9329 and an mAP50-95 of 0.7253, while the model rarely suffered from detection misalignment as shown by the confusion matrix (Fig. 7(a)); Qualitatively, the target detection results of the model for the sample villages are basically consistent with the ground truths (Fig. 7(b)). These results indicate that the trained model can accurately evaluate the preservation status of houses in satellite maps.

4.1.2. Classification of preservation levels

Following the research framework, satellite maps of all traditional villages were processed through PEM. After the detection was completed, others objects were excluded, and the *P*-score of each village was calculated. The distribution of *P*-scores of all traditional villages was counted by Histplot tool of Matplotlib module and the results are shown in Fig. 8. In the figure, the preservation of traditional villages in the Tibetan-Qiang region is overall satisfactory (the peak distribution is around 1). In refinement, the mean value of the *P*-scores of all villages is 1.07, indicating that the local traditional villages show a tendency of inappropriate renewal on the foundation of their traditional patterns; meanwhile, the lowest value of the scores is not lower than 0.5, and the highest value is not higher than 1.5, indicating that the traditional villages are still basically capable of embodying their traditional features.

Based on the distribution characteristics of the *P*-scores, villages with scores below 0.8 were classified as Almost destroyed category, villages with scores above 1.2 were classified as Improper renewed category, and the rest of the villages were classified as well preserved category, where the villages in the Almost destroyed and Improper renewed categories were defined as poorly preserved villages (hereafter PPV). The list of villages of each category is shown in Table 3, their location distributions and the satellite maps of sample villages are shown in Fig. 9(a) and (b), and the proportion of the houses in each category of villages is shown in Fig. 9(c).

4.2. Results of the major influential factors identification step

The 16 environmental factors of all villages were normalized as the independent variables, and the preservation levels of all villages were classified as the dependent variable. 70% of the samples were randomly selected as the training dataset, and the rest were the test dataset, which were inputted into the RF model to start training. The accuracy of the trained model was 93.71%, indicating that the environmental factors can well explain the classification results (i.e., the preservation status). Through

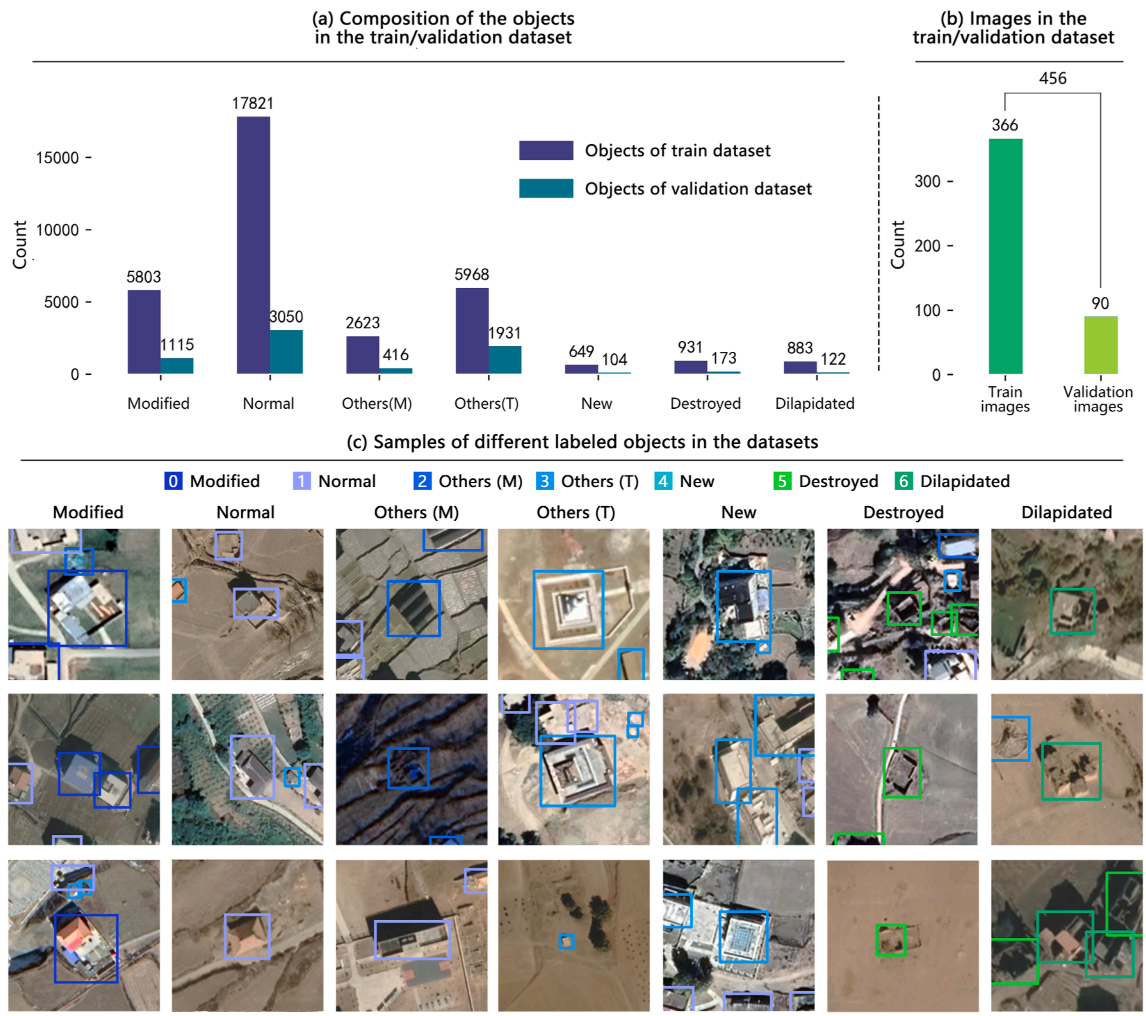

Fig. 6 Composition and object samples of the train and validation datasets.

Table 2 Overview of hyperparameters and computation equipment.

Hyperparameters of YOLOv10						Computation equipment		
Learning rate	Batch size	Epoch	Workers	Maximum detect	Device	Graphic card	RAM	Processor
0.01	16	450	8	300	Cuda	NVIDIA GEFORCE RTX 4070	64.0 GB	Intel Core i7-10870H CPU

the model, FI of each environmental factor and SHAP value of each factor for villages with different preservation levels are output, and the results are shown in Fig. 10 (a). Among the environmental factors, check in, precipitation, slope, and aspect, had significantly higher FI than the others, and were therefore identified as MIFs affecting the preservation status of the villages. In addition, as shown by SHAP values, all MIFs have a significant influence on the preservation status of improper renewed villages; check in the mifs had less influence on the normal village preservation status, and aspect and precipitation had less influence on the almost destroyed village preservation status. In subsequent field interviews, the intervention of MIFs on residents' preservation and optimization preferences will be emphasized.

In addition, the influence of various MIFs on the village preservation status can also be presented by the sample satellite maps (Fig. 10(b)).

4.3. Results of the influencing mechanism interpretation step

Our research group conducted field interviews in 56 case villages based on the geographic distribution of each preservation category of villages, among which normal and improper renewed villages contain 31 and 21 cases respectively, and almost destroyed villages only arrive at four due to their relatively small number and poor traffic roads. The case villages basically cover the entire area of the Tibetan-Qiang region to ensure the reliability and

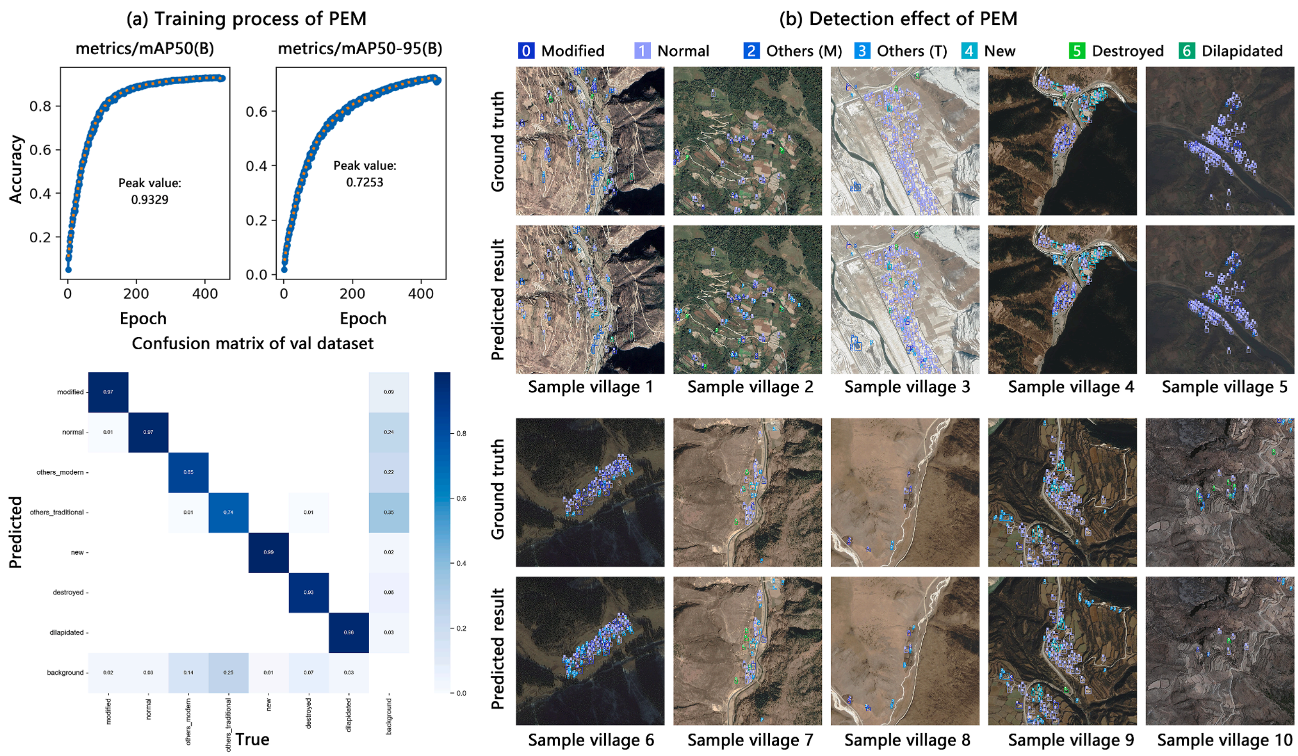

Fig. 7 Illustration of model training process and target detection effect.

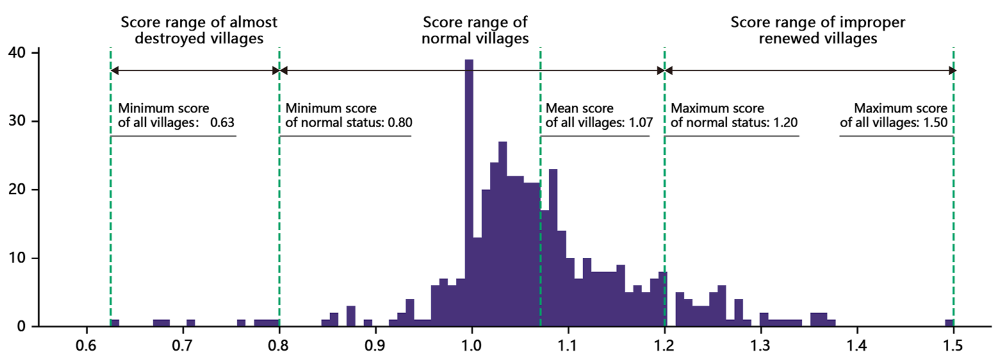

Fig. 8 Histplot of the preservation scores of all target villages.

comprehensiveness of the conclusions. In addition, the mean values of MIFs in all categories of villages were calculated and drawn into a Histplot to visualize the distribution of the factors in each category (Fig. 11(a)). In addition, several interviewed villages have high-definition aerial photographs that can be matched with satellite maps and are distributed throughout the study area, so they are shown in Fig. 11(b) to present the reliability of reflecting the preservation status of the villages through satellite maps.

The interviews centered on the questions around "What is the intention of the residents to renovate their own houses, and what potential factors influence their intention to do so?" The field interviews were conducted from September 13 to 24, 2024, interviewing no less than ten people in each village and lasting no less than 30 min, which led to the following conclusions:

1) Almost destroyed villages: Residents perceived that such villages were seldom visited by tourists due to the lack of attractive tourism resources. Tourism is the main revenue source for traditional villages in the Tibetan-Qiang region (He et al., 2003), so in the absence of income, residents have insufficient economic resources and incentives to preserve and optimize their houses. In addition, the topography of such villages is steep, thus not only incurring greater repair costs, but also facing the constant threat of geologic hazards. As a result, most residents abandoned their houses and moved to places with better living quality and economic security, resulting in the continuous erosion of houses in the original villages by precipitation, falling rocks, mudslides, etc.
2) Improper renewed villages: Residents perceived that these villages have scenic spots or places of interest

Table 3 List of the traditional villages in each preservation status.

Status	Village list
Improper renewed (45)	Qiwan Village, Chuanzigou Village, Exiu Village, Keku Village, Bajiaodiao Village, Hualin Village, Kaxi Village, Jiyi Village, Jiertongshang Village, Gala Village, Aixi Village, Xiade Village, Duotuo Village, Anba Village, Gaxiu Village, Chuanpan Village, Dangba Village, Xinyi Village, Xiner Village, Rijingong Village, Angzhou Village, Changde Village, Cunduo Village, Songgang Village, Genbuxia Village, Taoping Village, Zhengke Village, Shaxue Village, Shabangou Village, Gouerpu Village, Donggou Village, Yake Village, Yuwazhai Village, Jiaerduo Village, Baiyangping Village, Jiaowu Village, Yaogu Village, Canmuzha Village, Xisuo Village, Daqing Village, Yinzhen Village, Cuobu Village, Yaqiao Village, Maidigou Village, Qikaluo Village
Almost destroyed (10)	Baxue Village, Wuyonggong Village, Dingge Village, Dexi Village, Zhage Village, Chaka Village, Kangxia Village, Namo Village, Bazisire Village, Keerjin Village
Normal (411)	All other villages

(e.g., natural landscapes, Tibetan Buddhist temples, and former residences of historical figures) and are located in the rain shadow of mountain ranges, where average precipitation is low and excessive sun exposure is avoided, thus generating sufficient revenue for the villages from the thriving tourism market. Besides, the topography of such villages is gentle and precipitation is low, so the buildings are less exposed to the risk of geologic hazards. These contexts have led to a tendency for the residents to maintain and renovate their houses extensively to the modern style, to improve the living quality and, in due course, to serve as hotels for tourists. The narratives of the residents revealed that the roofs were converted into sloped roofs of colored steel sheets to cope with the occasional and persistent precipitation and to facilitate their rapid replacement, while polyester fiberboards were used to shelter the open areas to ensure lighting and provide shelter for the residents from the wind and the rain.

3) Normal villages: Residents perceived that these villages tend to contain both tourism and agriculture as core industries. Since tourism is less attractive than Improper renewed villages, the residents do not intend to develop village attractions as the focus, but prefer to keep the original style of the houses as a selling point to attract tourists. In addition, due to the demand for agricultural work, the residents tend to plant their crops on gentle south-facing slopes or flats, and live in old houses around the fields for daily plowing, watering, and harvesting. The revenues of the two industries are not high but basically stable, so the residents tend to maintain the original form and basic functions of the houses through less spending, and have no obvious preference for the intervention of modern materials and design patterns; also, due to the concentration of the local precipitation season and the gentle slopes, the frequency and cost of maintenance are not high, which ensures the continuance of the traditional features of such villages.

In general, the factors affecting residents' intention to preserve or optimize are mainly the central industry of the village and the difficulty of repairing their houses. Among them, the development of the tourism industry can be reflected by check in, while precipitation and aspect can affect the agriculture industry. The difficulties in repairing the houses derive from the steep Slope on the one hand, and the threat of Precipitation on the other hand. The interviews qualitatively explain the influencing mechanism of various MIFs on the village preservation status, and the intensity of the influence of these factors is basically in line with the analysis results of the RF model, which confirms the reliability of the research framework. In addition, through the aerial photographs (Fig. 11(b)), the preservation status of the houses in the satellite map are consistent with that of the corresponding locations in the live photo, which also verifies the reliability of evaluating the preservation status of the traditional villages through the satellite map and YOLOv10.

5. Discussion

5.1. Evaluate and preserve traditional villages in Tibetan-Qiang region using satellite maps as a proxy

The proposed research framework offers significant advantages over traditional fieldwork in terms of identification scope and research efficiency, while the process is highly automated and the conclusions are validated by the field interviews. Based on the above findings, the following preservation and optimization suggestions are made for the local PPVs:

1) For Improper renewed villages, the guidelines for the renovation of the building features need to be formulated so that the houses can maintain their original appearance while functionally meeting the development of the tourism industry. For instance, tiles or shingles can be laid on the colored steel roof to meet waterproofing and structural needs while maintaining an appearance that approximates the features of the traditional house. Retractable canopies can be used in outdoor activity spaces, which do not detract from the appearance of the house, but also create shelter in rainy

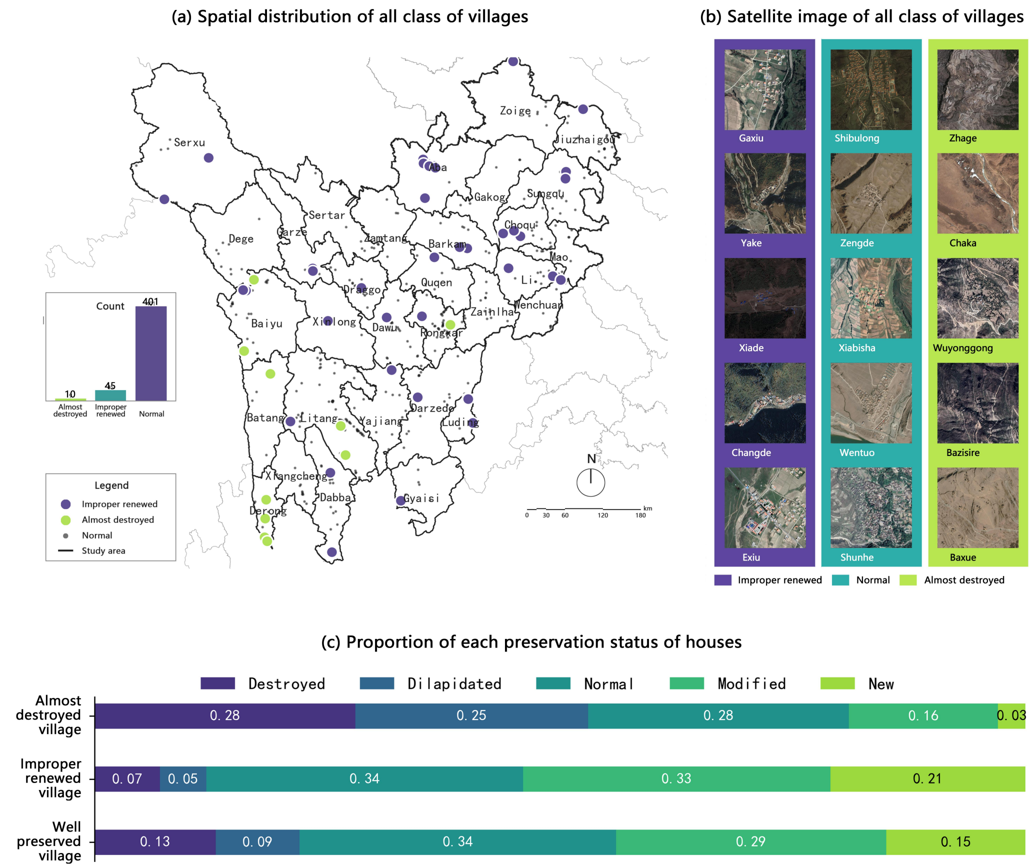

Fig. 9 Distribution of villages in different preservation status and samples of the satellite images.

and snowy weather. Besides, the relevant government departments can select priority villages and monitor village-based traditional feature restoration through tourism check in data on traditional villages and their surroundings. For villages with extremely serious damage to their traditional features, building groups within or around the villages that maintain their original patterns can be adopted for restoration to serve as demonstrations of the traditional features of the corresponding village type.

2) For Almost destroyed villages, industries other than tourism need to be developed to ensure that residents are willing to stay and have the financial capacity to preserve their houses. For instance, with the support of the government and relevant agribusinesses, gently sloping south-facing land in villages can be reclaimed as arable land or pasture, and the purchasing of crops can be organized centrally, so as to provide the residents with a stable income source and a willingness to engage in agriculture. Reinforcing the structure of houses and monitoring the risk of geologic hazards surrounding such villages will, on the one hand, reduce the damage to houses and save repair costs, and, on the other hand, provide a reserve of economic and building materials before and after extreme disasters, and contact villages to formulate tailored plans. Since such villages require extensive repairs, the authorities also need to organize local experienced artisans to undertake the construction work and experts to evaluate their traditional features on a regular basis. For some completely abandoned villages, the government needs to select representative areas of the village for optimization and preservation, as well as increase tourism publicity and incentives for residents to return to the original villages.

In addition, with the support of the research framework, the traditional village list can be updated in real time, and the satellite map of the villages and related environmental factors can be extended. By repeatedly running the framework, we can evaluate the preservation status and the MIFs of the traditional villages, and the government can efficiently formulate preservation strategies, making the satellite map a reliable proxy for evaluating and preserving the traditional villages in the Tibetan-Qiang region.

5.2. Limitations and future work

The major limitation of this study is the source of the satellite map. Google's satellite map has a delay compared to

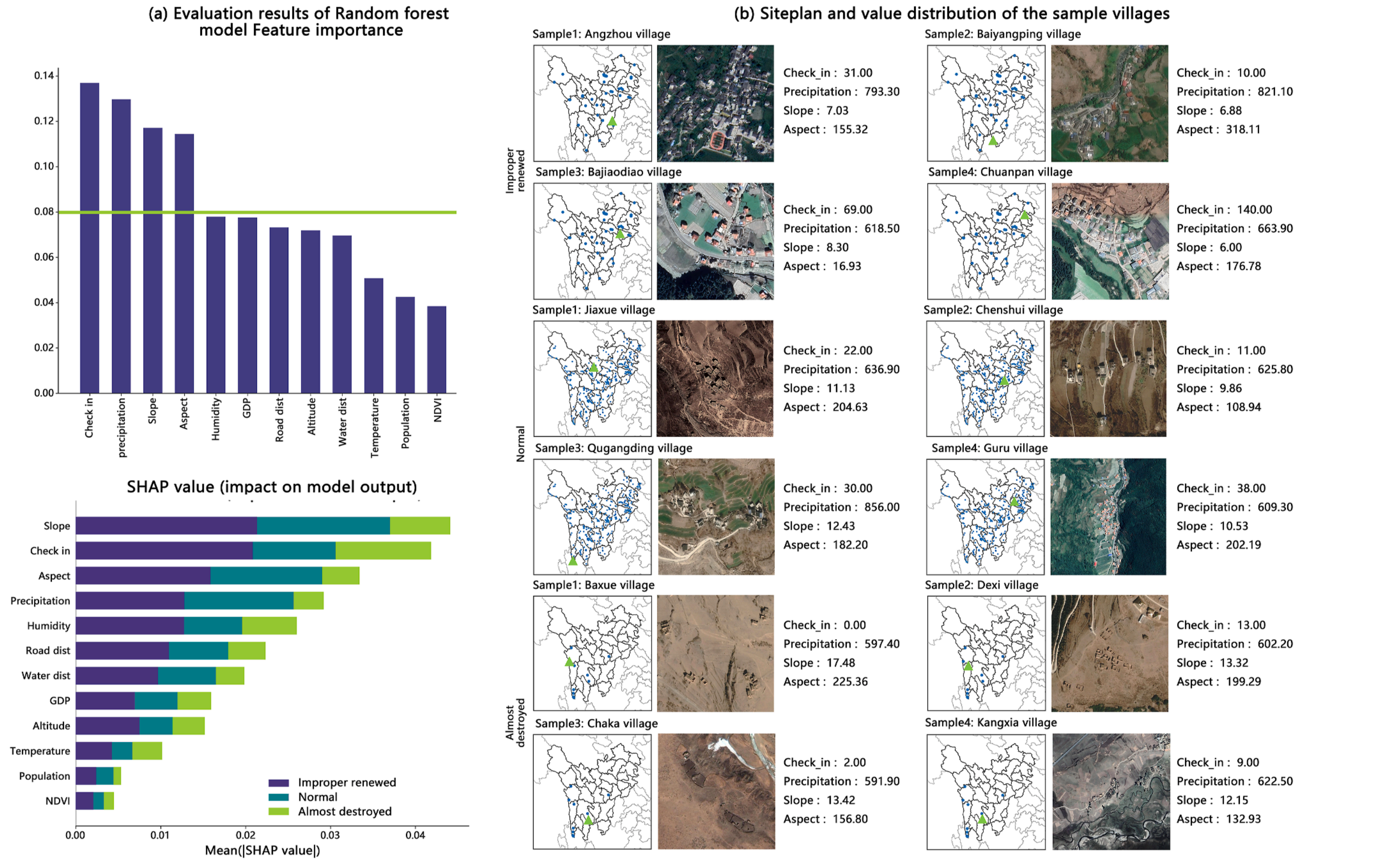

Fig. 10 Evaluation results of random forest model and the illustration of MIFs' influence on the preservation status of traditional villages of different preservation categories.

the real scene (Malarvizhi et al., 2016) and cannot monitor the preservation status of the traditional villages in the Tibetan-Qiang region in real time, so in the future, it is required to broaden the sources of satellite maps so that their presentation of the real-time scene of the villages will be more authentic; In addition, the potential influential factors may still be further expanded so that they can have a more accurate explanatory effect on the preservation status of the villages; Both the model and the dataset for target detection have the potential to be optimized so that the trained model can more accurately distinguish the preservation features of houses in satellite maps and improve the reliability of the conclusions from the framework analysis. Besides, this paper evaluates the preservation status of the traditional villages mainly through the preservation status of the building's original features. Although the evaluation conclusions are secure, the preservation status of elements such as roads and agricultural fields has not been further investigated in this study, and there is still an ongoing requirement to conduct more targeted research on these elements and to explore their restoration strategies in the future. Regarding the preservation status of the buildings, although the top view can basically reflect their preservation status and guarantee the reliability of using the satellite map as a proxy, so that the research framework can be used to evaluate the preservation status of the traditional villages intelligently and quantitatively, it is still necessary to update and record the features of the traditional villages more comprehensively through elevation photography, point cloud collection and other means in the future, so as to make its conclusions more comprehensive and accurate.

The study can be further developed in three orientations in the future: 1) Evaluating the preservation status of the villages around the traditional villages through PEM and comparing them with the corresponding traditional villages. On the one hand, it is expected to reveal the regional impact on village preservation as a result of the inclusion in the list of traditional villages, and on the other hand, to discover villages in the vicinity of the seriously destroyed traditional villages with greater restoration and preservation value; 2) Using satellite maps with higher zoom levels as a proxy, the YOLOv10 model can further evaluate the damage to the building patterns and achieve the monitoring and preservation of individual houses; 3) The research framework can be applied to other study regions to fill the preservation research gaps there, and verify the reliability and transferability of the research framework.

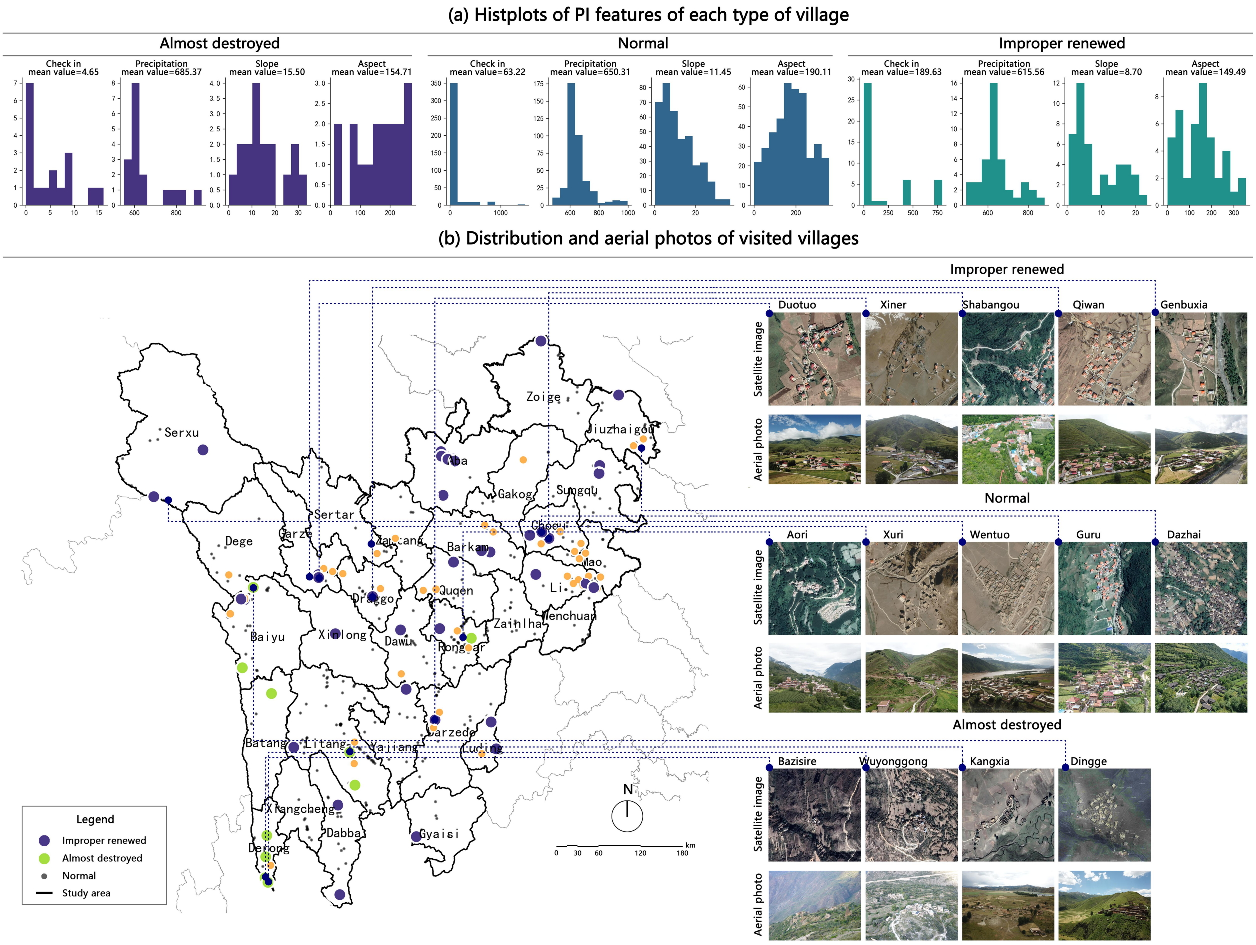

Fig. 11 Histplot of MIFs in different categories of villages and the aerial photos of the visited villages.

6. Conclusion

With the support of YOLOv10 and RF model, this study proposes a framework for evaluating the preservation status of remote villages using satellite maps:

1) Through the detection of the preservation status of houses in the traditional village satellite maps by YOLOv10 and the calculated P-scores, the framework provides a quantitative measure for the preservation evaluation of traditional villages in the Tibetan-Qiang region, and the evaluation process does not require human intervention, which avoids the influence of subjective cognitive bias on the results. Meanwhile, YOLOv10's efficiency in learning and detecting is much higher, which significantly saves the cost of region-wide fieldwork, and its detection effect can be updated in real time with the optimization of the dataset and the model.
2) Through the FI and SHAP value indicators output from the RF model, the influence of various potential environmental factors on the preservation status of traditional villages in the Tibetan-Qiang region is quantified, and based on the analyzed MIFs, targeted preservation and optimization strategies are provided for villages under different preservation conditions.

The framework fills the gap of traditional village preservation evaluation in the whole area of Tibetan-Qiang region. This paper also provides a reference for the application of the framework in other study areas.

In summary, this study has achieved the expected contributions and provided a quantitative, efficient, intelligent, and transferable framework for the preservation and optimization of remote villages through datasets and models of the relevant steps.

Ethical statement

This study does not contain any studies with human or animal subjects performed by any of the authors. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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