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Toward Climate-Adaptive Rural Morphology: A Grid-Based Micro-Mesh Framework for Quantifying Microclimate Drivers

Abstract:

Rapid urbanization in China has transformed traditional village morphologies and weakened outdoor thermal comfort in rural settlements. This study introduces a Rural Micro-Mesh Decomposition (RMMD) framework to quantify village morphology and examine its relationship with thermal comfort. Field measurements were coupled with ENVI-met simulations, and predictive modeling was conducted for three representative villages situated in mountainous, plain, and riverside environments.

The results show that morphology-Universal Thermal Climate Index (UTCI) relationships are nonlinear and geomorphology-dependent. Compact feature sets generally matched or outperformed full feature sets, indicating that a limited number of key indicators can effectively explain village thermal responses. A ventilation-oriented street-and-alley organization improved heat dissipation, while an aspect ratio of 1.1-1.5 and a sky view factor (SVF) of 40%-60% supported a favorable balance between shading and airflow. Green-space ratios of 35%-45% further reduced UTCI-related heat stress.

These findings inform a collaborative “shading-ventilation-humidity control” strategy and provide an interpretable framework to guide climate-responsive rural design.

Keywords: Traditional village, spatial form, microclimate, thermal comfort, street morphology

Nomenclature

Abbreviation	Full Term
ABA	Average Building Area
AH	Average Building Height
ANBS	Average Number of Building Stories
AT	Air Temperature
BDI	Building Depth Irregularity
BHI	Building Height Irregularity
CFD	Computational Fluid Dynamics
FAR	Floor-area Ratio
GBDT	Gradient Boosting Decision Trees
GSR	Green Space Ratio
ISR	Impervious Surface Ratio
LST	Land Surface Temperature

MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MRT	Mean Radiant Temperature
MSE	Mean Squared Error
PET	Physiologically Equivalent Temperature
PMV	Predicted Mean Vote
RF	Random Forest
RMMD	Rural Micro-Mesh Decomposition
RMSE	Root Mean Square Error
RND	Road Network Density
SAO	Street and Alley Organization
SAR	Street Aspect Ratio
SET*	Standard Effective Temperature
SVF	Sky View Factor
S-V-H	Shading-Ventilation-Humidity
UTCI	Universal Thermal Climate Index
WAR	Water Body Area Ratio

1. Introduction

With ongoing urbanization, intensifying extreme heat, and rising living demands, traditional rural environments urgently require renewal to better meet residents' environmental and thermal comfort needs (Fu et al., 2024). Existing rural-renewal strategies primarily focus on preserving cultural value and enhancing visual aesthetics, often neglecting microclimate factors closely linked to residents' well-being. Village microclimates are shaped by the interaction of dwellings, courtyards, streets, vegetation, and water bodies through shading, ventilation, transpiration, and thermal radiation (Azmeer et al., 2024).

Microclimate directly affects outdoor thermal comfort and influences energy use and greenhouse gas emissions. Previous studies have shown that street-space morphology strongly regulates local microclimate conditions. Building form and layout alter shading and airflow (Chatzidimitriou and Yannas, 2017), while vegetation reduces heat stress through canopy shading and evapotranspiration (Yang et al., 2021; Meili et al., 2021). Accordingly, strategies such as optimizing village spatial form, adjusting building configuration, controlling street scale, and increasing greenery and water bodies are important for improving rural outdoor thermal environments and enhancing residents' comfort (Jiang et al., 2021).

This study investigates the influence of rural spatial morphology on outdoor thermal comfort in 32 villages across western Zhejiang, using Lin'an as a representative context. The villages were categorized into three geomorphological settings—mountainous, plain, and riverside. A framework based on 13 key morphology indicators was established, considering

spatial layout, form, and elements.

To achieve this objective, this study proposes the Rural Micro-Mesh Decomposition (RMMD) framework to integrate village morphology quantification, ENVI-met simulation, and grid-based thermal comfort evaluation within a unified analytical workflow. RMMD builds on earlier work in grid-based spatial analysis, morphology measurement, and microclimate simulation (Yang et al., 2025) to examine the fragmented, terrain-sensitive, and blue-green-coupled characteristics of traditional rural settlements. Using standardized 10 m × 10 m micro-mesh units, RMMD captures fine-scale rural spatial heterogeneity and supports morphology–Universal Thermal Climate Index (UTCI) analysis across contrasting geomorphological settings. Village-specific predictive analyses were conducted for representative villages and we employed nested feature scopes (Top 5, Top 8, and All) to derive compact predictor sets for scenario-oriented UTCI prediction and key-driver identification. This approach improves cross-village comparability and supports more context-sensitive scenario-oriented analysis. The results inform a collaborative “shading-ventilation-humidity control” strategy, demonstrating microclimate-friendly design that can measurably enhance outdoor living conditions and support low-carbon, healthy rural development (Yu, 2025).

2. Literature Review

2.1 Current Status of Village Microclimate Research

Microclimate refers to the near-surface boundary-layer climate shaped by surface materials, vegetation, and local terrain conditions (Oke, 1987). Although climatic considerations began to enter architectural research in the 1970s (Rapoport, 1969), early studies often focused on relatively coarse scales and paid limited attention to fine-grained thermal interactions in everyday living spaces, such as the effects of paving materials, courtyard geometry, and shading devices on pedestrian-level heat and airflow. Traditional settlements, however, often embody such micro-scale adaptive wisdom in their spatial forms and construction practices (Oliver, 2006). Subsequent studies further distilled climate-responsive design principles and clarified how vernacular dwellings regulate temperature, ventilation, and solar exposure across different climatic regions (Steemers, 2003; Hyde, 2008).

Over the past two decades, sustainable development and climate change have stimulated village-scale microclimate research (Emmanuel, 2005). Field measurements and modeling studies have revealed local climate-regulation mechanisms (Grimmond and Oke, 1999), while research on traditional settlements has expanded from site selection and construction to broader relationships between settlement form, thermal performance, and sustainability (Ratti et al., 2003; Salat, 2011; Zhai and Previtali, 2010; Wang et al., 2014). At the same time, research

methods have shifted from qualitative description to quantitative analysis. Remote sensing and GIS have been used to link settlement patterns with climate adaptability (Conrad et al., 2015), and computational fluid dynamics (CFD) and ENVI-met simulations have been widely applied to assess the combined effects of spatial form, vegetation, and buildings on ventilation, shading, and thermal comfort (Yang et al., 2013; Blocken, 2014). Meteorological observations and microclimate monitoring have further improved understanding of spatiotemporal variations in temperature, humidity, and wind speed (Liu and Niu, 2017; Middel et al., 2014).

As climate warming and heat-island effects intensify, mitigation strategies have shifted from broad design guidance to mechanism-based approaches. These now integrate blue-green infrastructure, material performance, shading, evapotranspiration, and ventilation enhancement (Ng, 2010; Santamouris, 2014a; Wong and Chen, 2008; Abdulateef et al., 2025; Georgescu et al., 2014; Liu et al., 2014; Gago et al., 2013; Sharmin et al., 2019; Gunawardena et al., 2017). To operationalize the coupling between spatial form, environmental processes, and human thermal comfort, outdoor studies commonly adopt mechanistic thermal-comfort indices based on human heat balance. Among them, physiologically equivalent temperature (PET) and UTCI are the most widely used (Yin et al., 2021). Previous studies show that both indices are highly sensitive to air temperature (AT) and mean radiant temperature (MRT). Wind speed generally mitigates thermal stress, and relative humidity has a comparatively stronger influence on UTCI (Fang et al., 2018). Comparative studies further suggest that predicted mean vote (PMV) is less suitable for outdoor environments, whereas PET, standard effective temperature (SET*), and especially UTCI are more applicable under warm-humid subtropical conditions (Liu et al., 2017; Wang et al., 2020). These findings support the use of UTCI in the present study.

2.2 Current Status of Research on External Village Spaces

Village spatial form refers to the overall manifestation of a village during its growth, with street and alley space being key components. These spaces include tangible elements (e.g., ground surfaces, building facades) and intangible elements (e.g., spatial distribution of social and cultural factors) (Tao et al., 2024). This study primarily focuses on how the tangible components of street and alley spaces influence village microclimates.

While a substantial body of morphology-microclimate research has been developed for urban environments, many underlying physical processes, such as radiative exchange, airflow regulation, shading, surface heat storage, and evapotranspiration, are equally applicable to village external spaces. These shared mechanisms establish a theoretical foundation for selectively applying urban-derived analytical approaches and thermal-comfort indicators to rural contexts. However, rural settlements typically exhibit lower development intensity, stronger topographic dependence, greater integration between built form and blue-green space,

and more irregular and fragmented spatial patterns shaped by vernacular adaptation. These characteristics contribute to greater spatial heterogeneity in rural morphology and constrain the direct applicability of conventional urban analytical units. Consequently, a grid-based micro-mesh framework is proposed for rural studies in this study to capture fine-scale morphological variation, facilitate scale-consistent comparisons across villages, and support the integration of morphology extraction with ENVI-met-based microclimate simulation and morphology-thermal comfort analysis. Therefore, the present study does not directly apply urban design conclusions to rural settlements, but instead adapts relevant process-based knowledge into a rural-oriented analytical framework for morphology-UTCI coupling analysis.

With the development of GIS and computer technology, studies of village spatial forms expanded to the macro scale, using GIS to build databases of morphological attributes and analyze village space evolution (Wu et al., 2023). Climate-related research on street-alley spaces has grown, with studies classifying traditional village forms and proposing optimization strategies based on street-alley features (Nguyen et al., 2019). For mountain settlements, factors like interface types and site elevation have been summarized to provide microclimate design guidance (Clerici, 2025).

Recent studies have analyzed the microclimate-regulating functions of village spaces, using space-syntax theory to explore impacts on user cognition (Gao et al., 2025a). Software simulations have examined how street-alley forms affect wind environments and microclimate regulation (Peng et al., 2025). Field measurements have further explored these connections and ways to improve rural landscapes while maintaining ecological integrity (Gao et al., 2025b).

Over the last decade, research has shifted from morphological descriptions to interdisciplinary, systematic analyses (Guo et al., 2025). Despite acknowledging the benefits of traditional village architecture on microclimate, a quantitative morphological indicator system for assessing the microclimates of village spaces across regions is still lacking. Future research should integrate contemporary technologies and new materials to provide detailed, quantitative data for village space planning and improvement.

2.3 Research gap

Despite growing progress, several key gaps remain in village microclimate research:

(1) Transferable micro-scale morphological quantification remains limited. Existing studies have identified indicators such as canyon geometry, sky view factor (SVF), enclosure, and blue-green configuration, but these are often defined in case-specific ways, applied at inconsistent resolutions, or embedded in village-specific typologies. This weakens standardization, reusability, and cross-study comparison.

(2) Cross-geomorphology comparability and unit-scale alignment remain insufficient.

Thermal comfort is experienced at the pedestrian scale, yet many studies rely on coarse or inconsistent spatial units, making it difficult to compare morphology–comfort relationships across waterfront, mountainous, and plain villages.

(3) Nonlinear effects and threshold behaviors are insufficiently characterized. While morphology, vegetation, and materials are known to influence shading, ventilation, and evapotranspiration, fewer studies explicitly identify nonlinear response patterns, interactions, and practical thresholds (e.g., when floor-area ratio (FAR) or enclosure begins to amplify heat stress), limiting actionable design applications.

(4) Scenario-ready prediction and decision support are underdeveloped. Prior work often looked at correlation or sensitivity interpretation, parsimonious predictor sets and interpretable predictive tools that support scenario testing and generalize across villages are rarely established, constraining practical planning and design implementation.

Collectively, these gaps highlight the need for a framework that standardizes village morphology, captures fine-scale rural heterogeneity, integrates measurement and simulation, and reveals nonlinear, context-dependent morphology–thermal comfort relationships. To address this need, this study proposes the RMMD framework for rural morphology–UTCI coupling analysis. Its main contributions are threefold. First, RMMD uses standardized 10 m × 10 m micro-mesh units, which are better suited to the fragmented and terrain-constrained nature of rural settlements and improve fine-scale quantification and cross-village comparability. Second, it provides an integrated rural-oriented workflow linking morphology extraction, ENVI-met simulation, and village-scale modelling within a unified framework. Third, by combining interpretable machine learning with village-type comparison, RMMD reveals nonlinear and geomorphology-dependent morphology–UTCI relationships across different rural settings.

3. Methodology

This study proposes the Rural Micro-Mesh Decomposition (RMMD) framework to integrate microclimate observation, simulation, morphological quantification, and village-specific prediction within a unified analytical workflow. Fig. 1 illustrates the methodological framework in four steps. In Section 3.1, Step 1 establishes the study’s data foundation, cross-examining geographic information, meteorological conditions, and the preliminary village survey. In Section 3.2, Step 2 measures the microenvironment and integrates ENVI-met simulations to reconstruct near-surface microclimatic conditions. In Section 3.3, Step 3 develops the evaluation metrics, including the definition, calculation, and standardization of RMMD-based indicators for multi-scale spatial morphology and thermal comfort analysis. In Section 3.4, Step 4 integrates spatial analysis, correlation analysis, machine-learning

interpretation, and village-wise predictive modeling to examine nonlinear responses and scenario-oriented relationships between morphology and UTCI. Within this workflow, two complementary modeling tasks are implemented: (1) ensemble-learning models, including XGBoost, random forest (RF), and Gradient Boosting Decision Trees (GBDT), for nonlinear relationship identification and model comparison; (2) an Artificial neural network (ANN)-based village-wise predictive framework under nested feature scopes (Top 5, Top 8, and All) for scenario-oriented prediction.

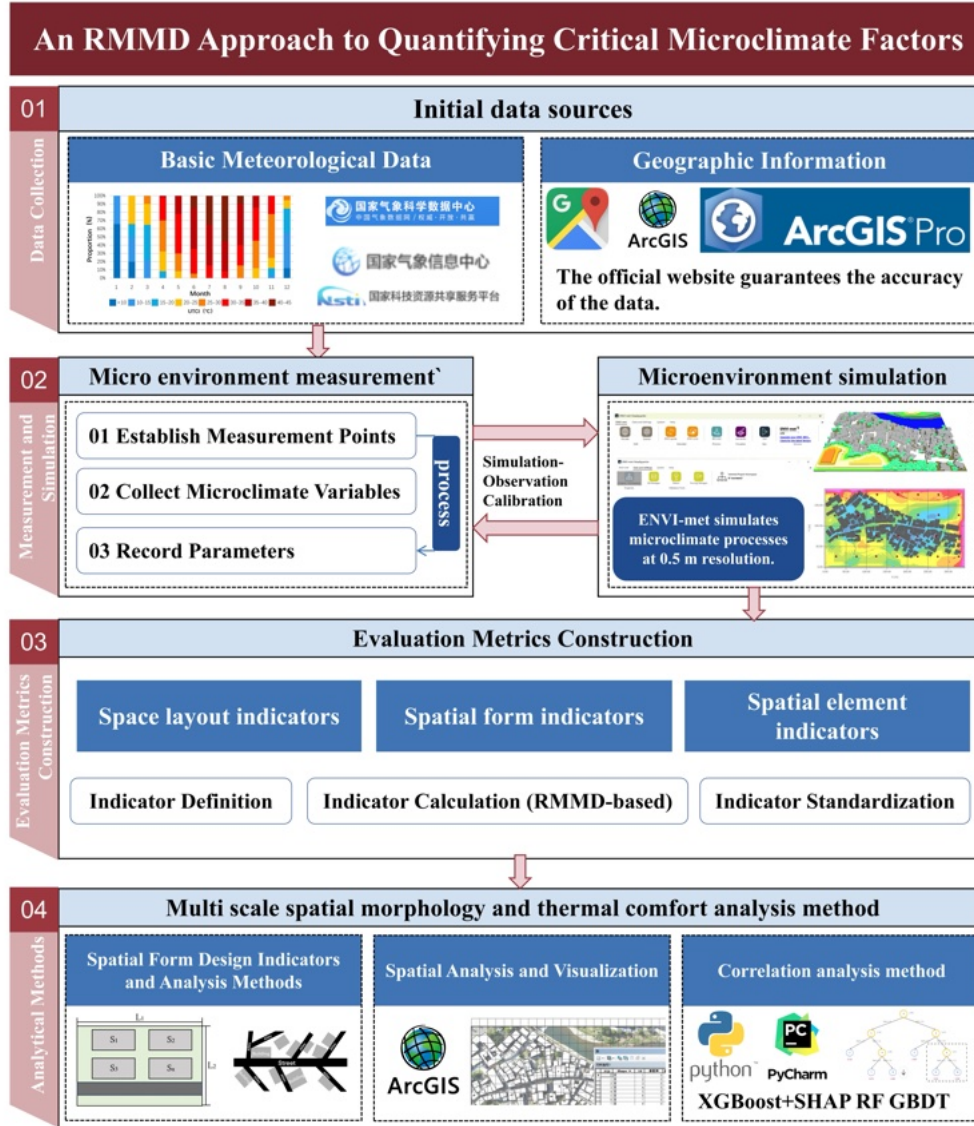


Fig. 1. Overall Research Methodology

3.1 Study Area

3.1.1 Climate Characteristics of Villages in Western Zhejiang

The study area is Lin'an District in Hangzhou, Zhejiang Province, which belongs to the summer-hot and winter-cold climate zone in China and is classified as a humid subtropical

climate (Cfa) according to the Köppen climate classification system (Nan et al., 2022). Meteorological data such as daily AT, relative humidity, wind speed, and solar radiation from the National Meteorological Data Platform were collected for the past decade (2013-2023). Statistical analysis shows that the monthly average temperature in Lin'an ranges from 5°C to 32°C, rising from March to August, decreasing from October to December, and slowly rising again from December to March, as shown in Fig. 2. The hottest months are generally July and August. In addition to temperature, human thermal comfort is also influenced by air humidity and wind speed. This study considers the UTCI to quantify human physiological comfort in outdoor environments. UTCI has been widely used to assess seasonal outdoor thermal comfort in hot-humid regions of China (Li et al., 2018).

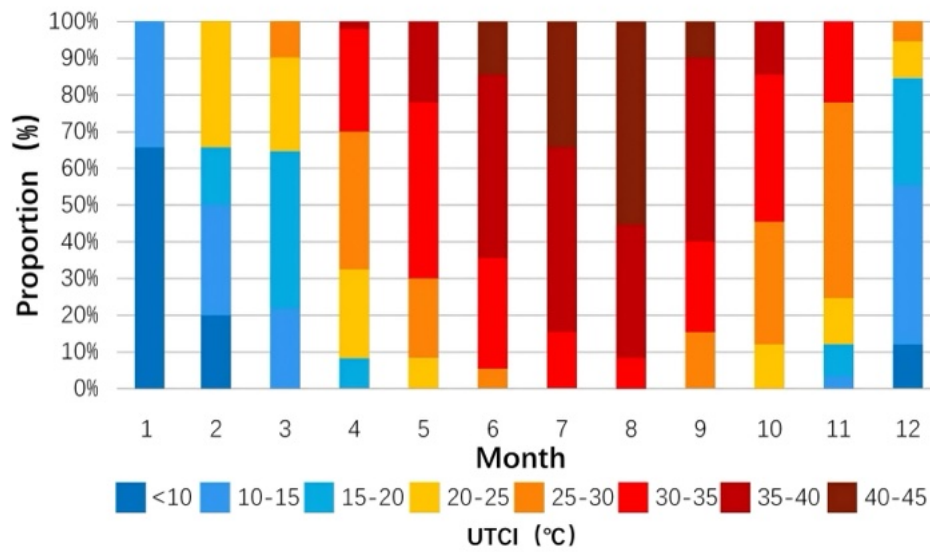


Fig. 2. Distribution of UTCI data in Lin'an over the past decade (2013-2023)

3.1.2 Geographic Location Characteristics

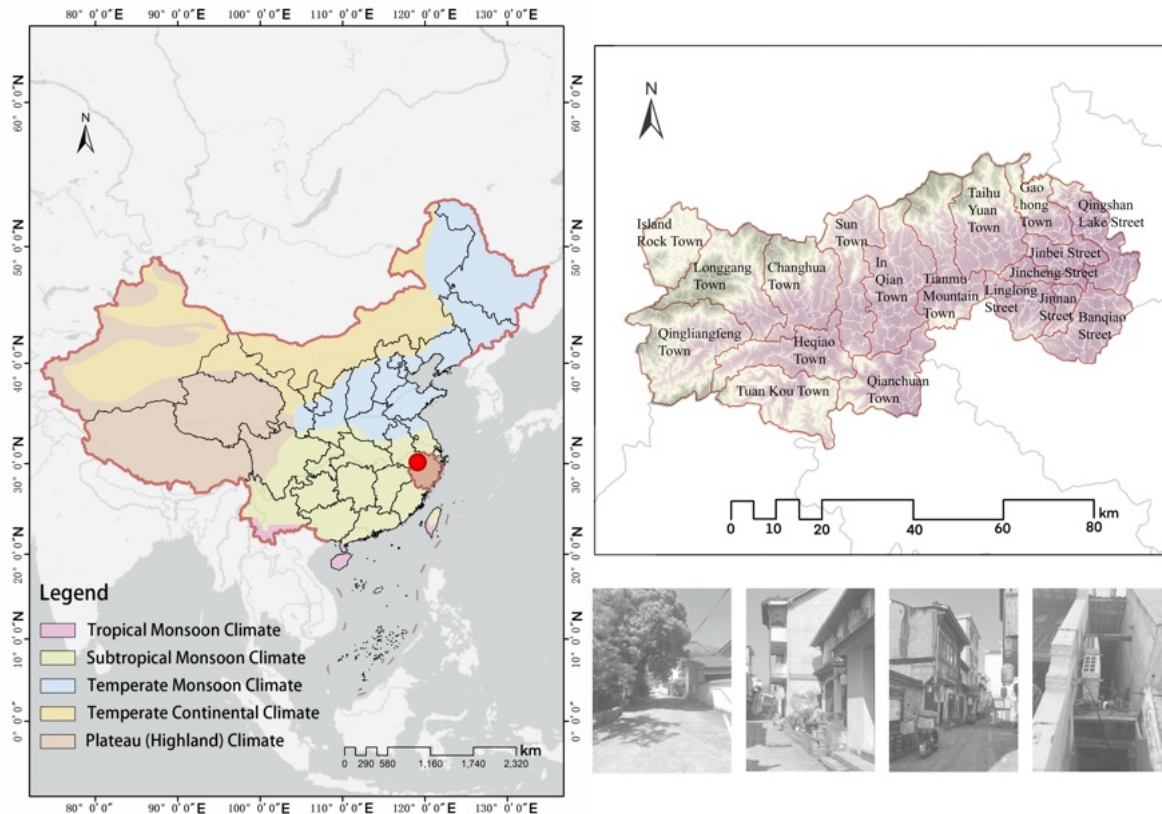


Fig. 3. Location Map of Lin'an

Lin'an District is located in the western part of Hangzhou, in the Tianmu Mountain region of the northwest of Zhejiang Province, approximately 30 km from Hangzhou. It lies within the 4-hour transportation circle of the Yangtze River Delta. The administrative area spans 3,126.8 square kilometers, and it currently administers 5 streets, 13 towns, and 298 administrative villages (Fig. 3). Based on geomorphological features, this study considers villages in the three main types: mountainous, plain, and riverside villages.

In Lin'an, 32 villages were selected for survey, including 11 mountainous, 11 plain, and 10 riverside (Table 1.). Elevation decreases from >1,000 m in the southwest to <100 m on the eastern river-valley plains, producing pronounced east-west relief and topo-climatic heterogeneity. Mountains cover 70-80% of the territory. Mountainous villages (>500 m) are scattered and irregular; plain villages (0-200 m) are centralized and outward-expanding; riverside villages are linear along river courses.

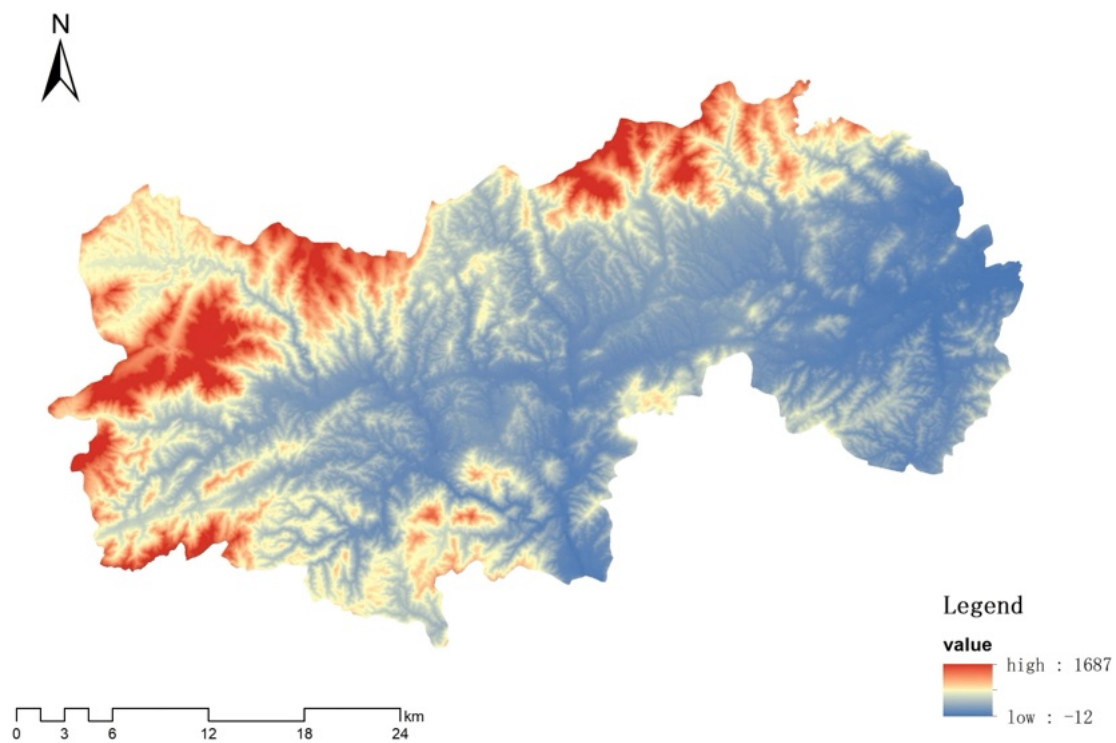
Table 1. Village Investigation Information

Terrain Features	Village Form	Street and Lane Patterns	Village Names	Village Altitude
Riverside villages	Aggregated cluster type	Fish bone	Baixia Village	112m
			Renli Village	525m
		Branches	Shuinan Village	66m
			Panlian Village	66m
		Comb	Yingfeng Village	157m
	Aggregated strip	Fish bone	Heqiao Village	67m
			Tong Shanxia Village	327m
			Zhoujia Village	508m
		Comb	Nanshan Village	92m
			Waitao Village	210m
Mountainous villages	Aggregated cluster type	Fish bone	Island Stone Village	750m
			Jielian Village	520m
		Branches	Fengcha Village	501m
			Guachuan Village	430m
	Aggregated strip	Fish bone	Huangyang Village	723m
		Branches	Huachuan Village	636m
		Comb	Huangchuan Village	506m
	Dispersed type scattered point pattern	Irregular	Sheng Cunwu Village	564m
			Chenghou Village	480m
			Hengling Village	510m
			Lvjia Village	575m
Plain villages	Aggregated cluster type	Fish bone	Hengxu Village	36m
			Jinxiou Village	47m
			Humen Village	102m
		Branches	Qinong Village	44m
			Chishi Village	32m
			Hong Village	43m
			Zhai Village	149m
			Heng Huli	35m
		Comb	Xuechuan Village	305m
	Aggregated strip	Comb	Banqiao Village	21m
			Shangpan Village	66m

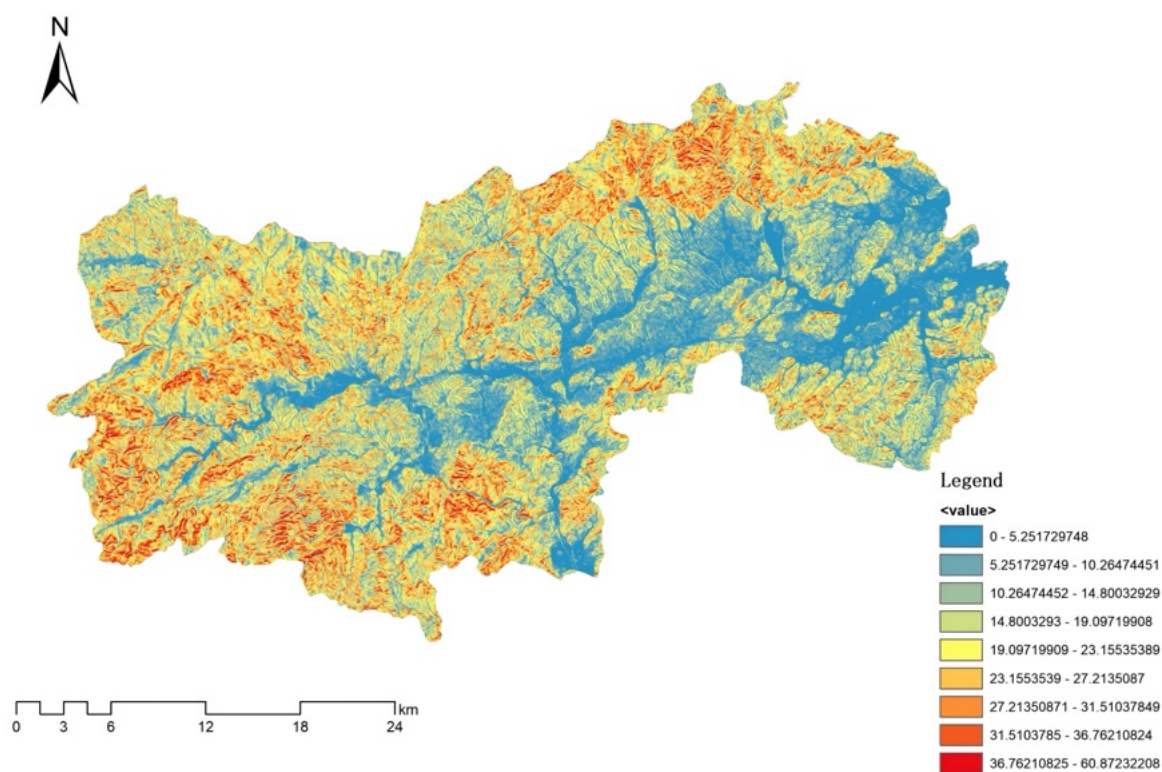
Based on the survey of 32 villages, settlements in Lin'an show a clear elevation pattern associated with the geomorphological setting. Mountainous villages are generally located at higher elevations, often above 500 m, with several exceeding 700 m. Riverside villages are mainly distributed at low to moderate elevations, usually below 200 m, whereas plain villages are concentrated at relatively low elevations, mostly below 150 m. This pattern reflects both

the predominance of mountainous terrain in Lin'an and the humid, rainy climate of western Zhejiang, which makes low-lying valleys more prone to flooding and dampness. In addition, higher-elevation locations often benefit from stronger summer diurnal temperature variation and mountain-valley circulation, which improve natural ventilation and heat dissipation.

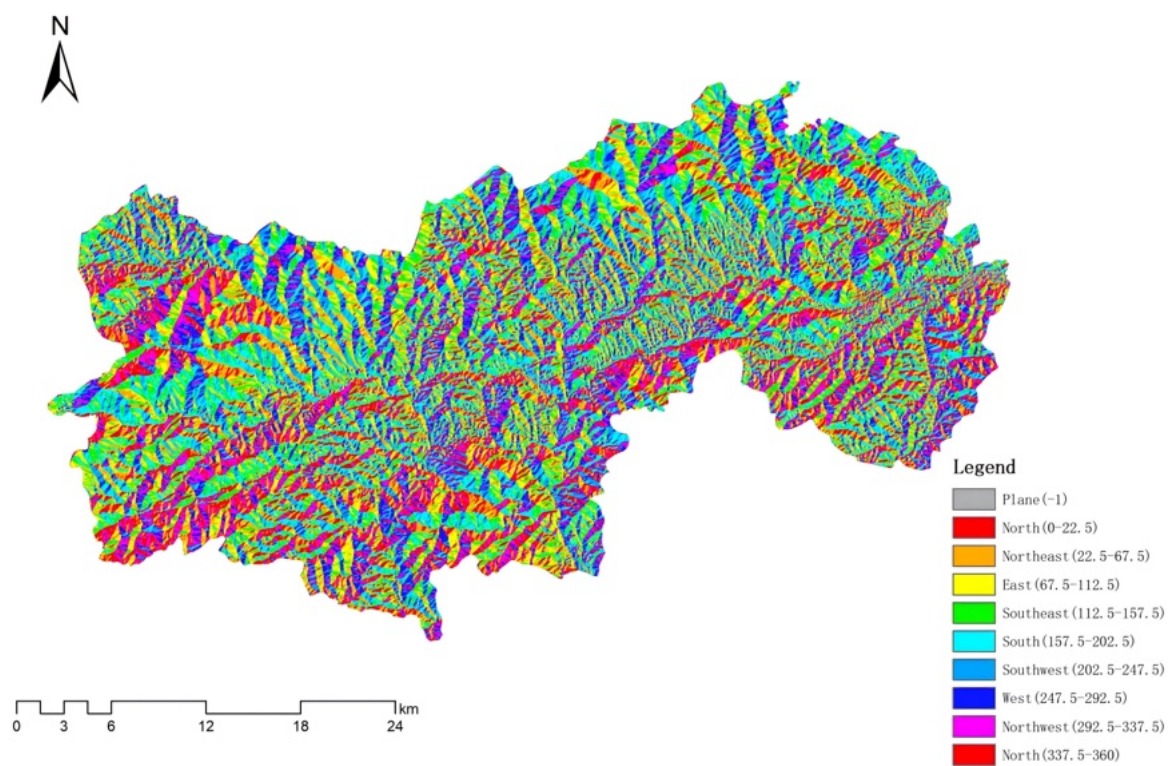
Fig. 4 presents the regional geomorphological and thermal background of Lin'an District, including elevation (Fig. 4a), slope gradient (Fig. 4b), slope aspect (Fig. 4c), and land surface temperature (LST, Fig. 4d). These district-scale layers provide the topographic and thermal context for the sampled villages and support the subsequent village-scale microclimate simulations and RMMD-based morphological analyses.



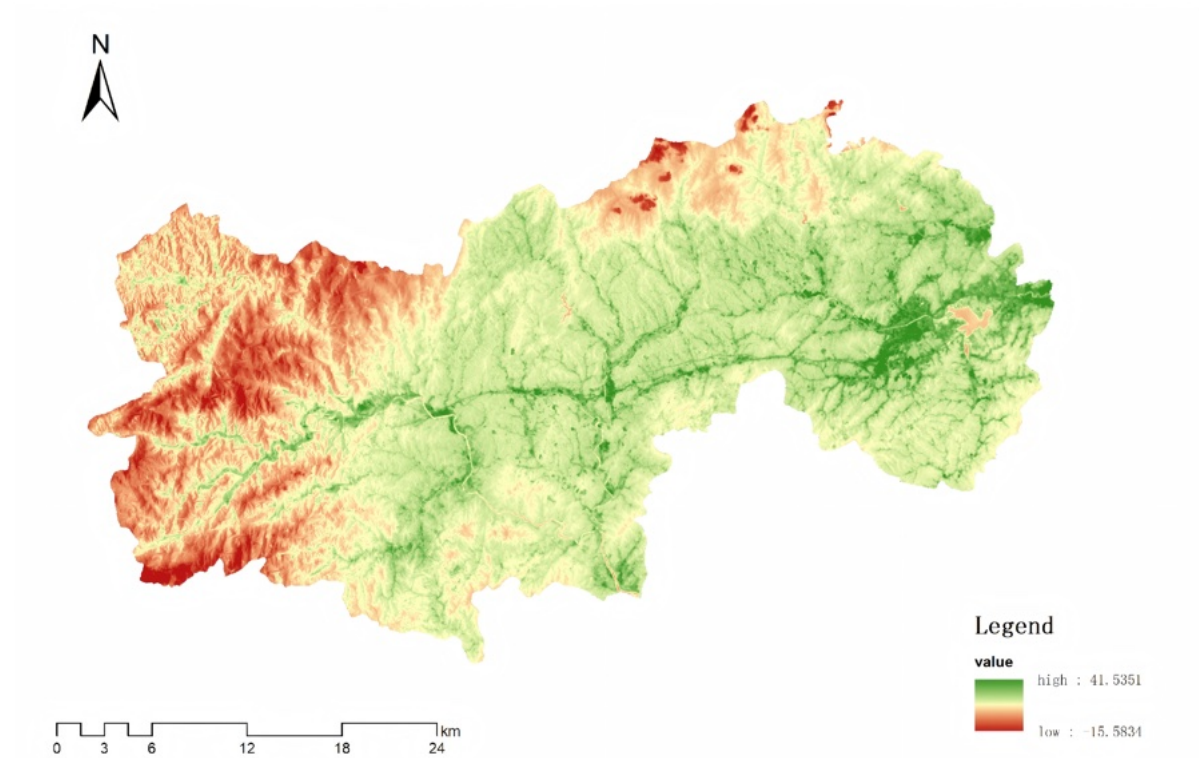
(a) Elevation of Lin'an District



(b) Slope Gradient Map of Lin'an District



(c) Slope Aspect Map of Lin'an District



(d) LST map of Lin'an District

Fig. 4. Lin'an District-scale geomorphological and thermal background

This study selects three representative villages (as shown in Fig. 5) with varying geographical and climate characteristics to examine their outdoor microclimates.

These villages were selected as representative cases of mountainous, plain, and riverside settlements within Lin'an, with the aim of enabling structured comparisons across diverse geomorphological contexts rather than claiming statistical representativeness for all rural settlements.

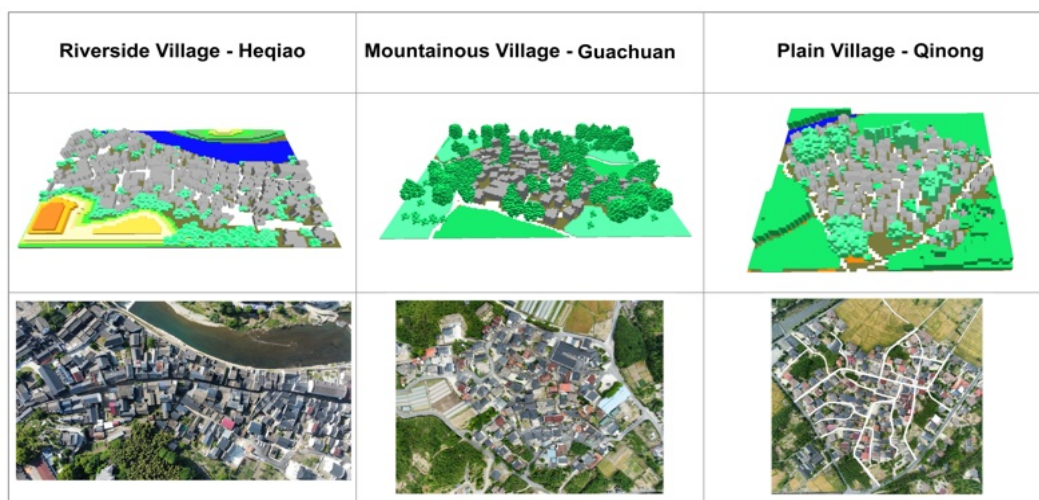


Fig. 5. Representative Villages of Different Types

3.2 Field Measurement of Microenvironment in Western Zhejiang Villages

Field measurements are conducted to characterize local thermal conditions and are employed to calibrate and validate the numerical simulations.

3.2.1 Measurement Plan

This study evaluates outdoor thermal comfort in western Zhejiang villages using the UTCI. Required inputs include AT, black-globe temperature, relative humidity, wind speed, solar radiation, and SVF. AT, relative humidity, wind speed, solar radiation, and black-globe temperature were measured in the field using portable instruments, while SVF was derived from fisheye images following standard procedures.

One representative village was selected from each of the three geomorphological types: plain, riverside, and mountainous. Within each village, 7-10 measurement points were arranged across key outdoor spaces, including main roads, secondary alleys, courtyards, and public squares, with additional points located in areas showing contrasting spatial characteristics such as different street orientations, enclosure levels, building forms, vegetation cover, and proximity to water. Field measurements were conducted on clear, rain-free days from August 7 to August 9 between 09:00 and 18:00. A mobile measurement approach was adopted, in which investigators followed predefined routes and recorded microclimate data at each designated point to ensure spatial coverage and temporal consistency (Fig. 6). All sensors were positioned at 1.5 m above ground level, corresponding to pedestrian height.

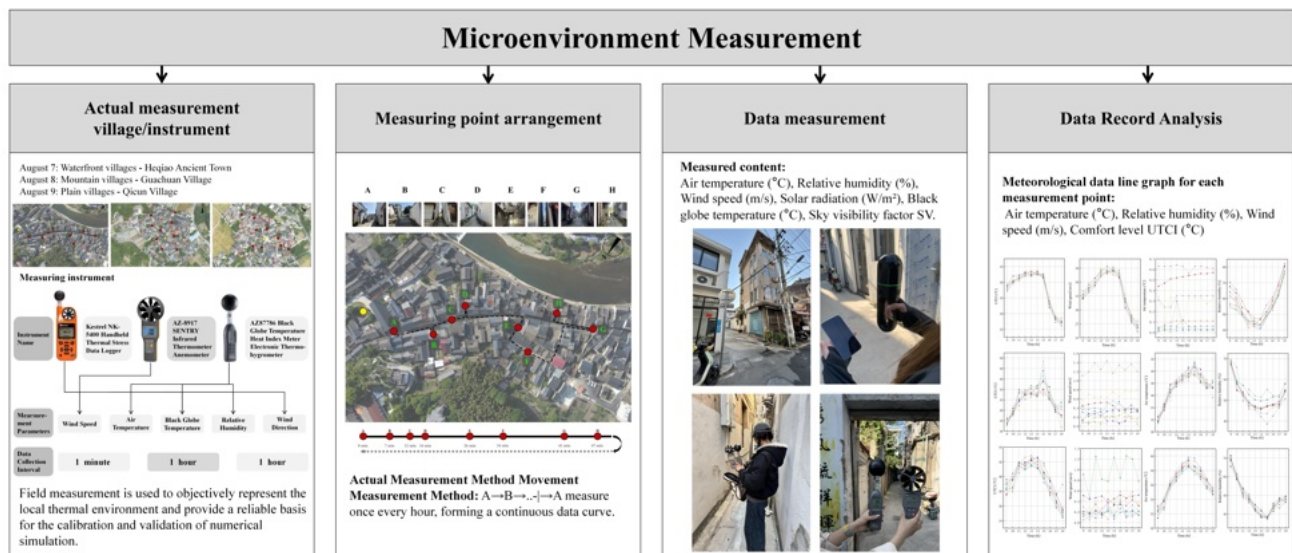


Fig. 6. Microenvironment Measurement Plan and Steps

3.2.2 Measurement Instruments and Equipment

Four measurement instruments were used to investigate the microclimate distribution at pedestrian height. The Kestrel 5500 weather meter was used to collect AT, humidity, wind speed, and wind direction, and it was fixed using a tripod. A handheld black globe thermometer

was used to record black globe temperature, AT, and humidity. A handheld anemometer was used to measure real-time wind speed. A fisheye lens, a camera phone, and a gimbal were used to compute SVF at the main measurement points. The specifications and parameters of the main experimental instruments are shown in Table 2.

Table 2. Technical Specifications of Measurement Instruments

Instrument Name	Instrument Image	Data Collection Interval	Measurement Parameters	Accuracy	Resolution	Measurement Range
Kestrel NK-5400 Handheld Thermal Stress Data Logger		1 minute	Wind Speed	$\pm 0.3\text{m/s}$	0.1m/s	0.4 - 40.0m/s
			AT	$\pm 0.5^{\circ}\text{C}$	0.1 $^{\circ}\text{C}$	-29.0 $^{\circ}\text{C}$ - 70.0 $^{\circ}\text{C}$
			Black Globe Temperature	$\pm 1.4^{\circ}\text{C}$	0.1 $^{\circ}\text{C}$	-29.0 $^{\circ}\text{C}$ - 60.0 $^{\circ}\text{C}$
			Relative Humidity	$\pm 0.2\%\text{Rh}$	0.1%	10% - 90%
			Wind Direction	$\pm 5^{\circ}$	1 $^{\circ}$	0 $^{\circ}$ - 360 $^{\circ}$
AZ87786 Black Globe Temperature Heat Index Meter Electronic Thermo-hygrometer		1 hour	AT	$\pm 0.6^{\circ}\text{C}$	0.1 $^{\circ}\text{C}$	-20 $^{\circ}\text{C}$ -50 $^{\circ}\text{C}$
			Black Globe Temperature	$\pm 0.6^{\circ}\text{C}$		-20 $^{\circ}\text{C}$ -50 $^{\circ}\text{C}$
			Relative Humidity	$\pm 3\%$		0~100%
AZ-8917 SENTRY Infrared Thermometer Anemometer		1 hour	Wind Speed	$\pm 0.3\text{m/s}$	0.1m/s	0 ~ 40m/s

Fig. 7 illustrates measurement points for three selected villages with unobstructed (unshaded) climatic reference points (shaded in yellow) as the baselines. The in-situ measurements for AT ($^{\circ}\text{C}$), relative humidity (%), wind speed (m/s), and solar radiation (W/m^2), were recorded hourly.

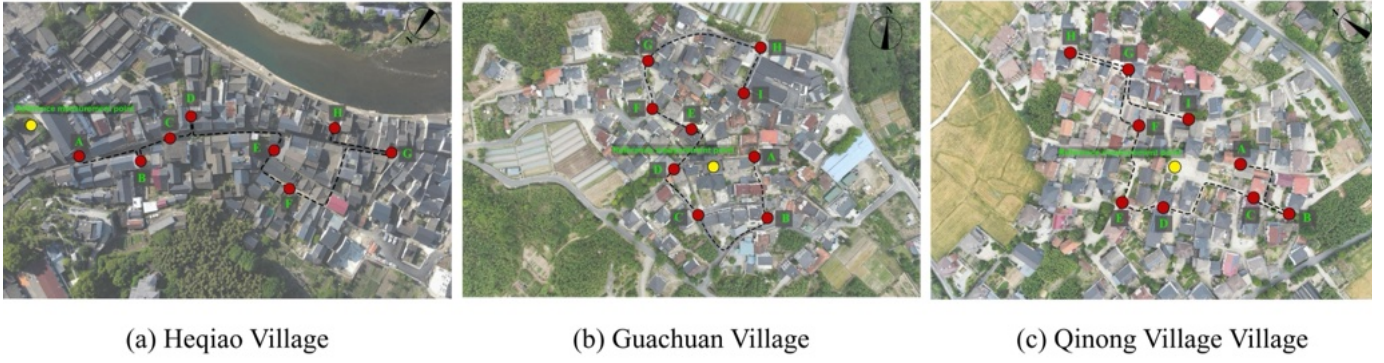


Fig. 7. Measurement Point Distribution and Route

3.3 Microclimate Simulation in Western Zhejiang Villages

3.3.1 Operational Setup for Microclimate Simulations

ENVI-met, based on computational fluid dynamics and thermodynamics, remains a preferred tool for small-to-medium-scale microclimate simulations and has been widely used in environmental research in urban and rural contexts (Bruse and Fler, 1998). ENVI-met couples microclimate processes at grid resolutions down to 0.5 m to model traditional village street-alley spaces. In this study, we developed a GIS-based modeling procedure to import and attribute village layers to construct an INX model. The INX model served as the ENVI-met area-input file that defines the 3D domain, grid, and the spatial layout/material assignments of buildings, surfaces, vegetation, and walls.

For ENVI-met simulations, Nanjing, the nearest city with long-term, quality-controlled meteorological records, was selected to provide atmospheric boundary conditions using the Meteorological Data Set for Building Thermal Environment Analysis developed by the China Meteorological Administration (CMA) and the China Academy of Building Research (CABR) (CMA and CABR, 2018). This dataset has been used in thermal-environment simulations in humid subtropical regions. (Su et al., 2022) Thermal properties of building envelopes were specified following the Chinese National Standard of Building Components and Building Elements-Thermal Resistance and Thermal Transmittance-Calculation Method (GB/T 13475-2008). Specifically, for new buildings with a shape coefficient ≤ 0.4 , the roof heat-transfer coefficient was set to $0.8 \text{ W/m}^2\cdot\text{K}$ and the external wall coefficient to $1.0 \text{ W/m}^2\cdot\text{K}$, representing typical energy-efficient construction. For traditional brick-wood buildings, the external wall heat-transfer coefficient was set to $1.5 \text{ W/m}^2\cdot\text{K}$ (Ding, 2016). The detailed simulation settings for the three representative villages are summarized in Table 3.

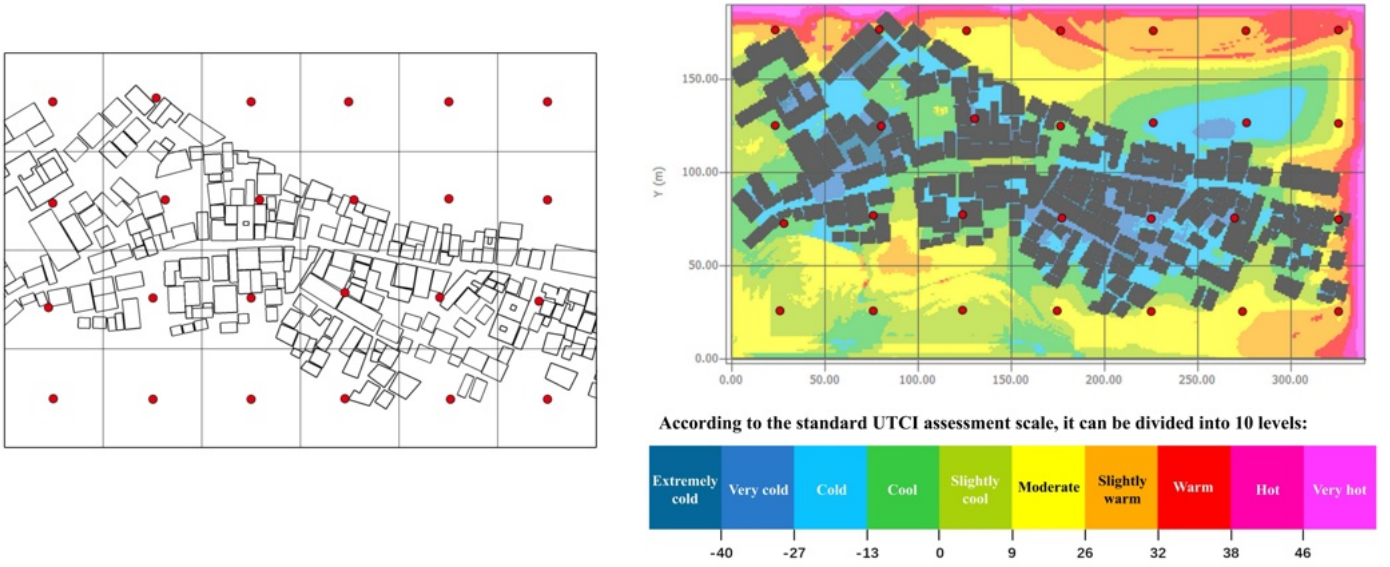
Table 3. ENVI-met simulation parameter settings

Boundary condition	Heqiao Village	Qinong Village	Guachuan Village
Number of grid cells ($x \times y \times z$)	$300 \times 150 \times 30$	$250 \times 200 \times 30$	$200 \times 200 \times 35$
Grid cell size ($x \times y \times z$, m)	$2 \times 2 \times 2$	$2 \times 2 \times 2$	$2 \times 2 \times 2$
Date	2024.08.07	2024.08.08	2024.08.09
Simulation time	5:00 AM-5:00 AM the following day		
AT	25.2°C~39.6°C	24.5°C~39.8°C	26.8°C~40.2°C
Relative Humidity	41%~90%	38%~93%	38%~82%
Wind Speed and Direction (at 10 m height)	3.5 m/s, SE	2.9 m/s, SE	3.1 m/s, SE (terrain-modified)
Wall Heat Transfer Coefficient	Traditional Buildings: 1.5 (W/m ² ·K) New Buildings: 1.0 (W/m ² ·K)		
Roof Heat Transfer Coefficient	Traditional Buildings: 1.28 (W/m ² ·K) New Buildings: 0.8 (W/m ² ·K)		
Ground Reflectivity	Asphalt: 0.2, Cement: 0.4, Stone: 0.3, Water: 0.0, Grassland: 0.2, Cultivated Land: 0.0 (Santamouris, 2014b)		

Note: Cultivated land was treated as a low-albedo, evapotranspiration-dominated surface following common ENVI-met parameterization practices.

Following the meteorological boundary conditions and surface material specifications, ArcGIS's ArcMap module was employed to vectorize raster satellite and aerial image data to create a GIS database of the village. The database contains shapefile layers for the study area, roads, green spaces, streets and alleys, squares, buildings, and trees. With the field survey data, we construct an INX model by combining shapefiles with surface material properties for required model elements in ENVI-met.

Fig. 8 illustrates the grid-based discretization of village space and the extraction of representative sampling points, together with the simulated UTCI distribution obtained from ENVI-met outputs.



(a) Grid discretization and representative sampling points

(b) Spatial distribution of simulated UTCI

Note: The UTCI values shown in panel (b) were derived from ENVI-met simulation outputs based on AT, wind speed, relative humidity/water vapor conditions, and MRT, following the UTCI operational procedure. The legend categories follow the standard UTCI thermal-stress assessment scale. (Bröde et al., 2012)

Fig. 8 Grid discretization and representative sampling-point extraction for ENVI-met simulation

3.3.2 Multi-Scale Spatial Form and Thermal Comfort Analysis Method

This study proposes a RMMD framework with a point-block-settlement analytical hierarchy. Settlement geometry is reprojected into a metric coordinate system and discretized into a regular grid of uniform $10\text{ m} \times 10\text{ m}$ micro-mesh cells covering the built-up area, which serve as standardized, scale-consistent units for multi-scale analysis.

At the point scale, RMMD characterizes street-and-alley organization, street aspect ratio (H/W, SAR), SVF, and surface/material properties to examine their direct effects on UTCI. At the block scale, cross-cell comparison and aggregation quantify neighborhood morphology, including SAR, building depth irregularity (BDI, i.e., the variability of building setback or depth along street edges), building height irregularity (BHI, i.e., the variability of building height along the street interface), mean building footprint area, and green-space ratio. Detailed definitions and calculation methods of BDI and BHI are provided in Section 3.4.2. These indicators are analyzed using nonlinear models (XGBoost with SHAP) to identify dominant drivers and high-leverage factors. At the settlement scale, aggregated cell-level metrics are correlated with overall morphological intensity and structure, such as FAR, mean building height, building density, road-network density, and impervious/water/green ratios, to explain settlement-wide thermal-comfort patterns.

RMMD links local mechanisms with block-level contrasts and settlement-scale outcomes, providing a comparable understanding of morphology-thermal coupling and supporting Shading-Ventilation-Humidity (S–V–H) co-optimization from hotspot identification to design guidance. Table 4. presents all spatial design indicators at various evaluation levels.

Table 4. Spatial Design Indicators at Layout, Form, and Element Levels

Evaluation Category	Design Indicators
Spatial Layout	SAO (Street and Alley Organization)
	FAR (Floor-area Ratio)
	ABA (Average Building Area)
	AH (Average Building Height)
	ANBS (Average Number of Building Stories)
	RND (Road Network Density)
Spatial Form	SAR (Street Aspect Ratio)
	SVF (Sky View Factor)
	BDI (Building Depth Irregularity)
	BHI (Building Height Irregularity)
Spatial Element	ISR (Impervious Surface Ratio)
	WAR (Water Body Area Ratio)
	GSR (Green Space Ratio)

3.4 Morphological Indicators Influencing the Microclimate of Rural External Spaces

This study constructs a preliminary microclimate database for waterfront, plain, and mountainous villages in Lin'an based on field measurements. To analyse rural outdoor microclimate, influencing factors are organized into three levels: spatial layout, spatial form, and spatial elements. Spatial layout describes village-scale geometry and structural patterns, helping reveal how settlement structure and terrain jointly shape wind and thermal conditions. Spatial form refers to the internal configuration of blocks, streets, courtyards, and building groups, providing a basis for optimizing density, orientation, shading, and ventilation. Spatial elements include localized material and ecological components, such as vegetation, water bodies, surface materials, and shading facilities, which regulate microclimate through radiation balance, evapotranspiration, and surface heat exchange. Based on this framework, the study examines the effects of 13 morphological indicators on rural spatial microclimate.

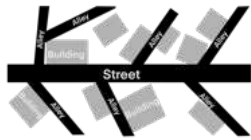
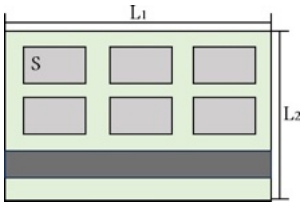
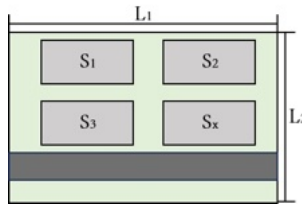
3.4.1 Definition and Scope of Spatial Layout Design Indicators

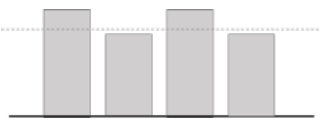
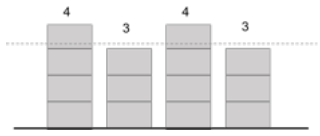
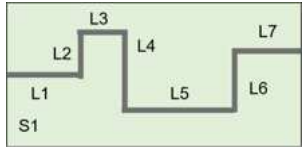
Table 5 summarizes six spatial layout design indicators used to characterize village-scale

spatial organization. These indicators quantify street-and-alley organization, development intensity, building scale, and road-network structure, and serve as baseline spatial metrics for subsequent RMMD-based comparative analyses across villages and settlement types under outdoor thermal comfort considerations.

In this study, street and alley organization (SAO) is a spatial layout indicator describing the overall organizational pattern and directional structure of streets and alleys within a village. It reflects settlement-scale differences in circulation structure and is relevant to solar exposure, airflow paths, and the alignment of circulation space with prevailing winds. FAR, as a key indicator of land development intensity, reveals the relationship between total building area and land area. Average building area (ABA) reflects the average size of individual building volumes and, together with FAR, helps characterize the fragmentation or intensification of the building spatial pattern. Average building height (AH) and average number of building stories (ANBS) represent the overall vertical development level of buildings in the area and are related to both residential density and skyline formation. road network density (RND), as an important indicator of transportation and spatial accessibility, reflects the compactness and connectivity of the regional road layout. Spatial layout analysis therefore helps reveal the underlying land-use pattern, street-and-alley organization, building configuration, and road-network structure.

Table 5. Spatial Layout Design Indicators.

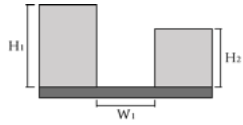
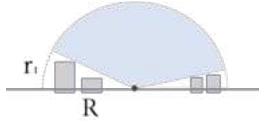
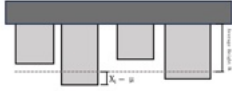
Design Indicators	Fig.	Calculation Formula	Description
SAO (Wu et al., 2024)		N/A	SAO characterizes the overall organizational pattern of village streets and alleys. In this study, it is classified into four typical types-fishbone, comb, branched, and irregular-to reflect differences in directional structure, solar exposure, and ventilation potential.
FAR (Cui et al., 2024)		$FAR = \frac{S_{\text{Overall architecture}}}{L_1 \times L_2}$	The ratio of the total building area to the building land area within the land use scope, which is an important indicator for measuring the intensity of land use.
ABA		$Aba = \frac{S_1 + S_2 + \dots + S_x}{x}$	The average total building area within the land use scope, which measures the average size of a single building.

AH (Cai et al., 2018)		$H_{avg} = \frac{\sum_{i=1}^n H_i}{n}$	The AH refers to the average vertical height of all buildings in the study area, typically measured in meters.
ANBS		$F_{avg} = \frac{\sum_{i=1}^n F_i}{n}$	The ANBS refers to the average number of floors of buildings in the study area.
RND (Forssén et al., 2022)		$RND = \frac{L_1 + L_2 + \dots + L_x}{S_1}$	The ratio of the total length of roads in a specific area to the area of that region.

3.4.2 Definition and Scope of Spatial Form Design Indicators

Table 6 summarizes the spatial form design indicators used to examine street-building configurations at the block scale. SAR, as the ratio of building height to street width on both sides of the street, measures the enclosure and openness of street space. SVF characterizes the visual openness of street space and the degree of solar radiation exposure from the pedestrian perspective, and is therefore an important indicator of sky exposure and spatial comfort. BDI and BHI reflect fluctuations in the street façade along the depth and vertical dimensions, respectively. BDI reveals the spatial layering caused by uneven building setbacks, while BHI reflects changes in the skyline resulting from varying building heights. Together, these indicators describe street-space enclosure, sky exposure, and façade variation at the block scale.

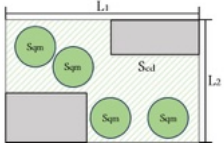
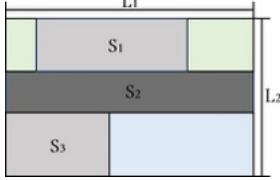
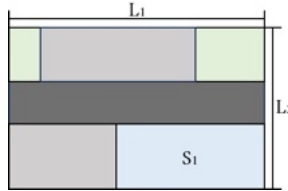
Table 6. Spatial Form Design Indicators.

Design Indicator	Illustration	Calculation Formula	Description
SAR (Cui et al., 2023)		$R = \frac{H_1 + H_2}{2W}$	The ratio of the AH on both sides of the street to the street width.
SVF (Hämmerle et al., 2011)		$SVF = 1 - \frac{\sum_{i=0}^N \sin r_i}{n}$ (n=360)	The ratio of the observable sky range at a height of 1.5 meters within the land use scope, used to measure the degree of solar radiation exposure or the extent of site visual obstruction.
BDI (Hang et al., 2012)		$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^n (X_i - \mu)^2}$	The degree of irregularity in the building depth on both sides of the street.
BHI (Chen et al., 2023)		$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^n (X_i - \mu)^2}$	The degree of irregularity in building height on both sides of the street.

3.4.3 Definition and Scope of Spatial Element Design Indicators

Table 7 summarizes the spatial element design indicators used to quantify land-cover composition and ecological features at the village scale. At the spatial element level, the quality and ecological characteristics of the village environment are often described by the proportions of land cover types. Green space ratio (GSR) reflects the proportion of various green areas, such as grasslands and tree plantations, in the study area. It is an important indicator for measuring the degree of greening coverage and ecological environmental quality. Impervious surface ratio (ISR) reflects the proportion of paved surfaces, such as roads and squares, in the study area. The higher this value, the greater the degree of surface hardening in the region, leading to increased surface runoff and deterioration of the thermal environment. Water body area ratio (WAR) describes the proportion of water areas in the total area. This indicator reflects, to some extent, the region's water landscape resources and ecological regulation functions. Analyzing GSR, ISR, and WAR can uncover ecological coverage, surface hardening, and water resources.

Table 7. Spatial Element Design Indicators.

Design Indicators	Illustration	Calculation Formula	Description
GSR (Fang et al., 2021)		$Gr = \frac{S_G}{L_1 \times L_2}$	The ratio of various types of green spaces to the total area within the land use scope, used to measure the proportion of green space coverage.
ISR (Gao et al., 2022)		$PAR = \frac{S_1 + S_2 + S_3}{L_1 \times L_2}$	The ratio of impervious surface areas to the total area within the land use scope, used to measure the degree of surface hardening.
WAR (Wu et al., 2022)		$Wat = \frac{S_1}{L_1 \times L_2}$	The proportion of water surface area to the total area within the land-use scope; used to characterize blue-space coverage (rivers, ponds, lakes, artificial basins) and its potential cooling/humidity effects.

3.5 Human Comfort Evaluation Index

The international standard ASHRAE 55 defines thermal comfort as "a state of mind that expresses satisfaction with the thermal environment" (ASHRAE, 2020). Specifically, this study considers UTCI to evaluate residents' satisfaction with the thermal environment of outdoor spaces in the village. To calculate UTCI using ENVI-met, required input variables include AT (t), wind speed at 10 meters (V10), water vapour pressure (e), and MRT (T_r). The wind speed at 10 meters (V10) was estimated from the measured wind speed (v) using the empirical relationship (Stull, 2012), $V10 = v/0.667$. Water vapour pressure (e) was derived from relative humidity (f) and AT (t) using the equation (Allen et al., 1998) $e = f \times e_s(t)$, where $e_s(t)$ is the saturation vapour pressure at temperature. The MRT (T_r) was calculated using AT, ground surface temperature, global radiation, and the solar altitude angle (Bröde et al., 2012). The UTCI map shown in above Fig. 8(b) was derived from ENVI-met outputs following the UTCI calculation procedure described in this section.

3.6 Validation of ENVI-met Microclimate Simulations (RMSE and MAPE)

Simulation accuracy is evaluated by comparing measured and simulated temperature and humidity data from Heqiao Village, Guachuan Village, and Qinong Village. Model performance is assessed using two commonly used metrics, root mean square error (RMSE) and mean absolute percentage error (MAPE). RMSE, defined as the square root of the mean

squared error (MSE), quantifies the magnitude of the prediction errors. MAPE represents the mean absolute percentage error, expressing the average absolute deviation relative to the observed values as a percentage. This unit-free metric enables performance comparisons across variables and sites. The calculation formulas are as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - b_i)^2} \quad (1)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|a_i - b_i|}{a_i} \times 100\% \quad (2)$$

In equations (1) and (2), a_i represents the simulated values, b_i represents the measured values, n denotes the number of measurements.

3.7 Village-scale morphology-UTCI predictive modeling

A village-scale morphology-UTCI predictive modeling was developed to quantify how local built form and blue-green infrastructure regulate pedestrian-level heat stress. Each village was discretized into $10 \text{ m} \times 10 \text{ m}$ RMMD grid cells as the base analytical units. For each grid cell, morphology indicators describing spatial layout, building form, and land-use structure were extracted and paired with the corresponding simulated UTCI value, resulting in a continuous village-scale dataset for subsequent nonlinear modeling. In addition to prediction, this framework supports mechanism-oriented analysis by linking village-scale indicator configurations to interpretable nonlinear responses across diverse geomorphological contexts.

To balance model complexity with interpretability, three feature scopes were established for each village. Top 5 scope comprises the five highest-ranked indicators identified through the preceding importance analysis; Top 8 scope extends this set by including additional variables associated with spatial enclosure, ventilation, and morphological heterogeneity. The All scope retains the full set of applicable and informative RMMD-based indicators for each village. For Heqiao Village, the Top 5 set consists of ANBS, WAR, FAR, AH, and ISR, with ABA, BHI, and GSR added in the Top 8 set. For Guachuan Village, the Top 5 set comprises GSR, BHI, FAR, RND, and BDI, with SAR, SVF, and ABA added in the Top 8 set. For Qinong Village, the Top 5 set includes GSR, FAR, ISR, WAR, and ABA, with BDI, RND, and BHI added in the Top 8 set. The Top 5 and Top 8 subsets were determined by descending feature-importance ranking within each village using consistent preprocessing and modelling procedure. This approach ensures that inter-village differences reflect data-driven ranking results. These nested feature scopes are also valuable in rural contexts where comprehensive morphology data are often unavailable, as compact subsets of influential indicators can

approximate the dominant morphology-UTCI relationship. Prior to modelling, abnormal entries were removed, missing values were imputed using within-village means, and all input features were normalized.

For each village dataset, samples were randomly split into training and testing sets at a ratio of 70:30 with a fixed random seed of 42 to ensure reproducible data partitioning and model evaluation, following common practice in machine-learning-based thermal-comfort prediction. (Liu et al., 2024) Based on this dataset, two complementary modeling tasks were conducted. First, XGBoost, RF, and GBDT were used to identify nonlinear morphology-UTCI relationships and compare model performance across villages (Chen and Guestrin, 2016; Breiman, 2001; Friedman, 2001). For the GBDT model, the optimal hyperparameter combination was selected according to 5-fold cross-validation performance, whereas the RF and XGB models were trained with preset hyperparameters. Final model performance was evaluated on the held-out test set using R^2 , MSE, mean absolute error (MAE), and RMSE. Second, fully connected artificial neural networks (ANNs) were trained under the three nested feature scopes to support village-wise predictive analysis. The ANN training procedure followed common machine-learning practice, including Adam optimization, 5-fold cross-validation, and early stopping (Goodfellow et al., 2016; Kingma and Ba, 2014; Kohavi, 1995; Prechelt, 2002). Networks with different depths and widths were implemented with ReLU activation. MSE was used as the primary loss function, while MAE served as an auxiliary performance metric. The optimal feature scope for each village was selected according to out-of-fold and test-set R^2 , RMSE, and MAE. The selected models were then used to support village-wise prediction and scenario-oriented evaluation of morphology-UTCI responses.

In the following sections, Section 4 uses the ensemble-learning and SHAP results to interpret nonlinear morphology-UTCI relationships and their underlying mechanisms, whereas Section 5 compares the predictive performance of the nested feature scopes and identifies the preferred feature set for each village.

4. Results and Discussion

4.1 Discussion of Measured Results

Fig. 9. shows the variations in AT, relative humidity, wind speed, and UTCI from 9:00 AM to 6:00 PM at various measurement points in Heqiao Village, a waterfront village. The temperature in Heqiao Village gradually rises from 9:00 AM to 12:00 PM, peaks at 1:00 PM to 2:00 PM, and then rapidly drops, with a daily temperature difference exceeding 15°C. The humidity fluctuates with a pattern of high in the morning, low at noon, and high in the evening. Wind speed shows significant variation, with point B experiencing the highest wind speed and

point C showing the most noticeable fluctuations. The UTCI rapidly rises from 12:00 PM to 2:00 PM and then quickly decreases thereafter.

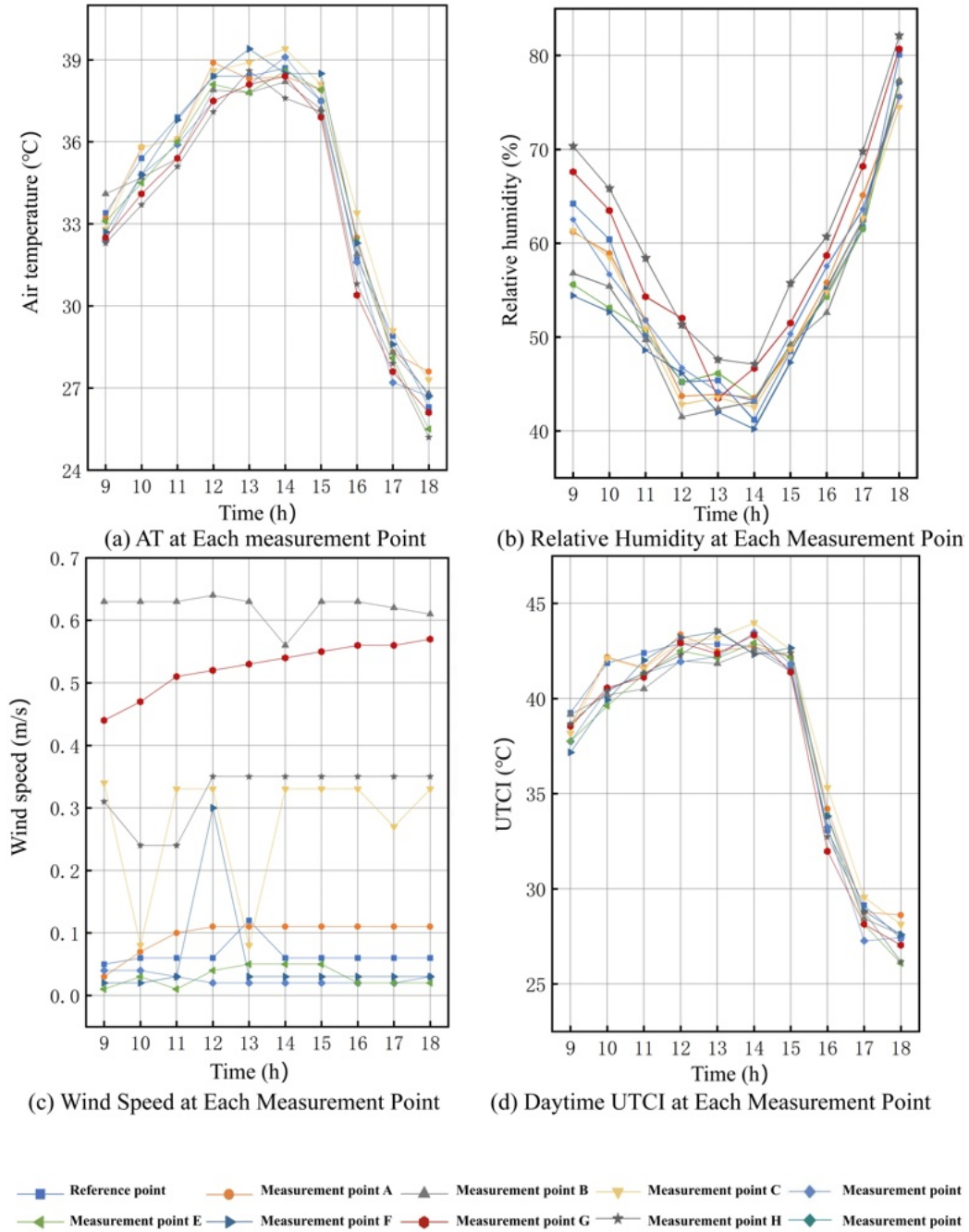


Fig. 9. Daytime Meteorological Data for Each Measurement Point in Heqiao Village

Fig. 10. shows the variations in daytime meteorological data at each measurement point in Guachuan Village, a mountainous village, from 9:00 AM to 6:00 PM. The temperature in Guachuan Village steadily rises from 9:00 AM to 3:00 PM, peaks between 2:00 PM and 3:00 PM, and then drops. The temperature difference ranges from 10°C to 15°C. The humidity gradually decreases, and wind speed remains low, with point H experiencing the highest wind

speed. The UTCI reaches its peak between 1:00 PM and 3:00 PM, before rapidly decreasing thereafter.

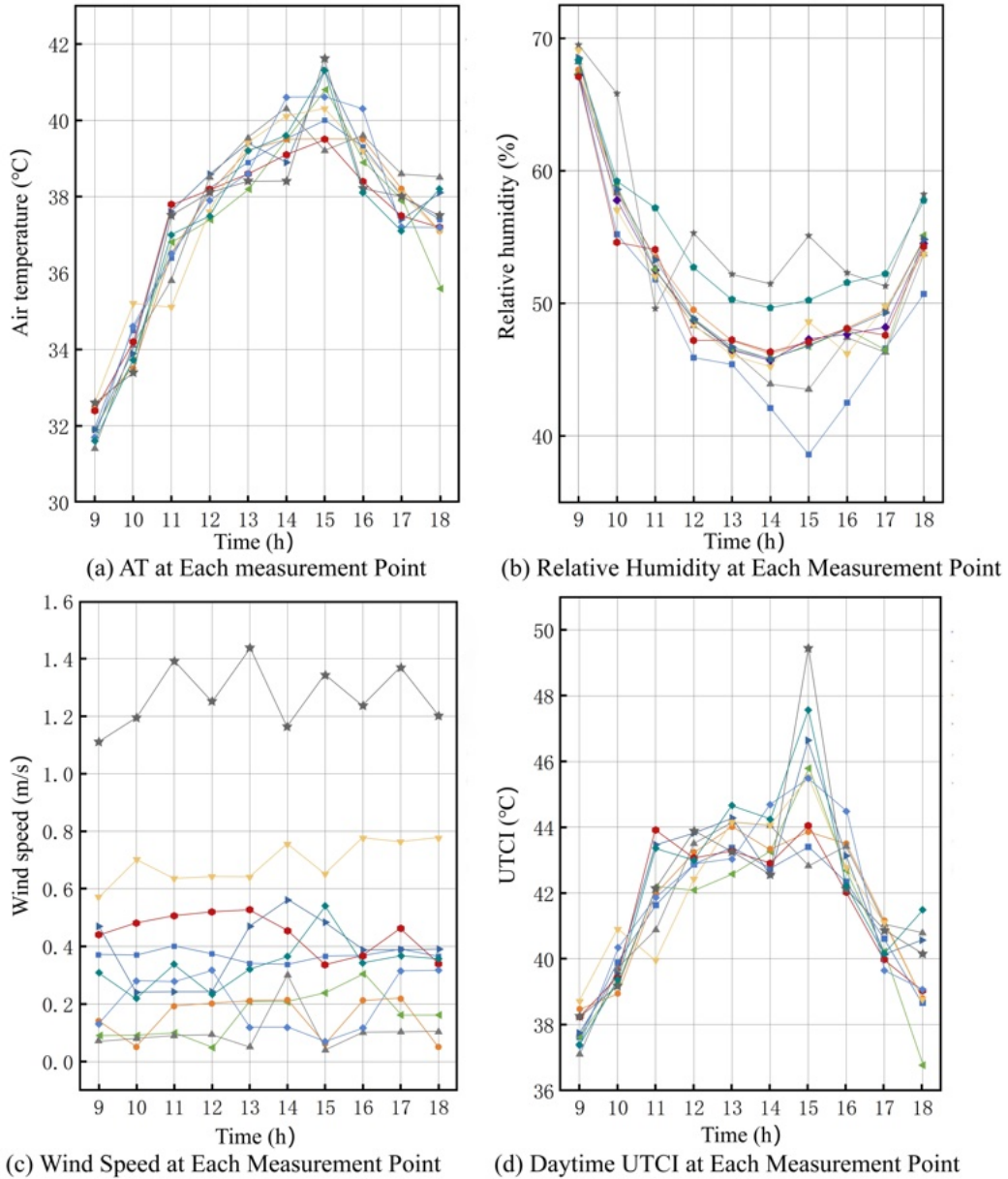


Fig. 10. Daytime Meteorological Data for Each Measurement Point in Guachuan Village

Fig. 11. shows the variations in daytime meteorological data at each measurement point in Qinong Village, a plain village, from 9:00 AM to 6:00 PM. The temperature changes in Qinong Village are similar to those in the mountainous village. The humidity decreases and then increases again, while wind speed remains low. The UTCI reaches its peak between 1:00 PM and 3:00 PM, before rapidly dropping thereafter.

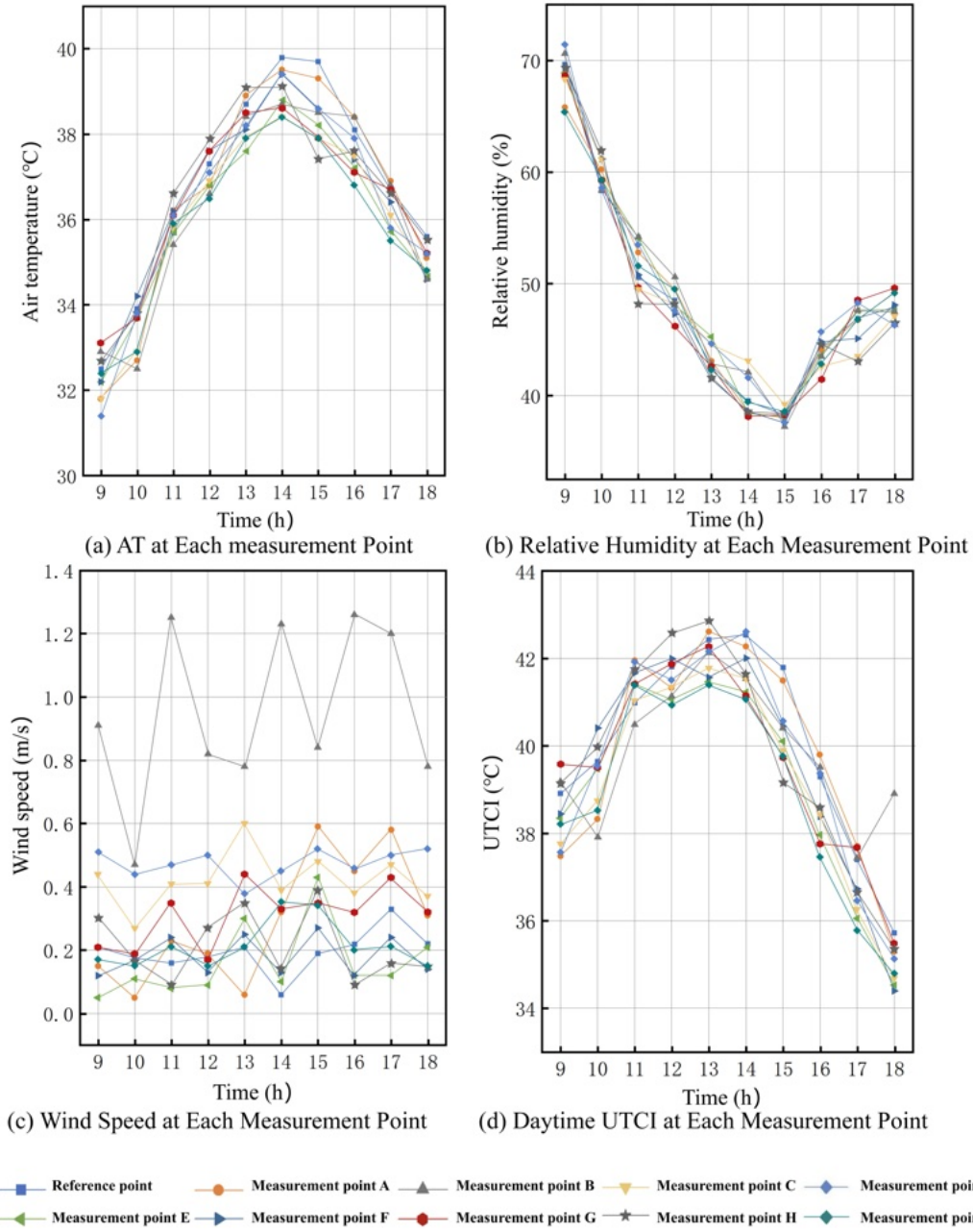


Fig. 11. Daytime Meteorological Data for Each Measurement Point in Qinong Village

Overall, the temperature difference is the greatest in the mountainous villages, while the waterfront villages have the lowest temperatures with smaller fluctuations, indicating a clear cooling effect from the water bodies. In the peripheral areas of the plain villages, temperatures are higher, possibly due to higher building density and reduced green space. Wind speed is generally higher in peripheral areas, and when street and alley spaces are wider, wind speed tends to be greater.

Measured data from six points in each of the three villages were selected for validation against the simulated results, with simulation outputs extracted at a height of 1.4 m above ground. The RMSE and MAPE values for each village are reported in Table 8. The results show

that the RMSE between measured and simulated AT for all three villages is below 1.5 °C, while the RMSE for relative humidity remains below 5%, and the MAPE is below 10%. These error ranges are comparable to those reported in previous ENVI-met validation studies (Crank et al., 2018), indicating the acceptable discrepancies between simulated and measured values. The ENVI-met simulations therefore provide a reliable basis for investigating the microclimatic mechanisms governing outdoor thermal comfort in rural villages.

Table 8. Simulation Accuracy Evaluation Results

village	EvaluationMetric	RMSE	MAPE
Heqiao Village	Temperature	1.22 (°C)	4.40%
	Humidity	1.91 (%)	4.50%
Guachuan Village	Temperature	0.66 (°C)	2.70%
	Humidity	2.23 (%)	5.97%
Qinong Village	Temperature	1.44 (°C)	6.32%
	Humidity	3.77 (%)	6.88%

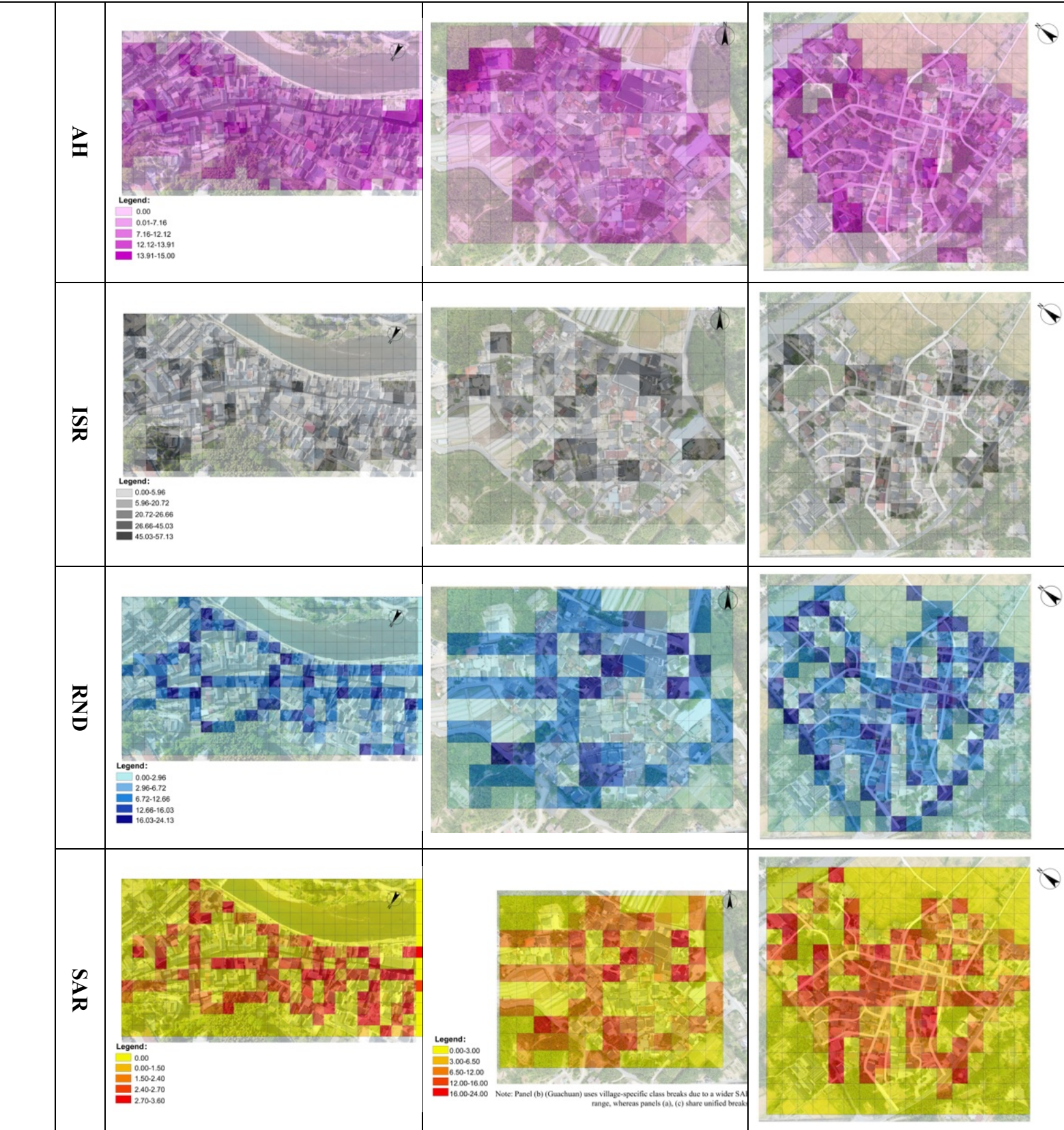
4.2 Discussion of Simulation Results

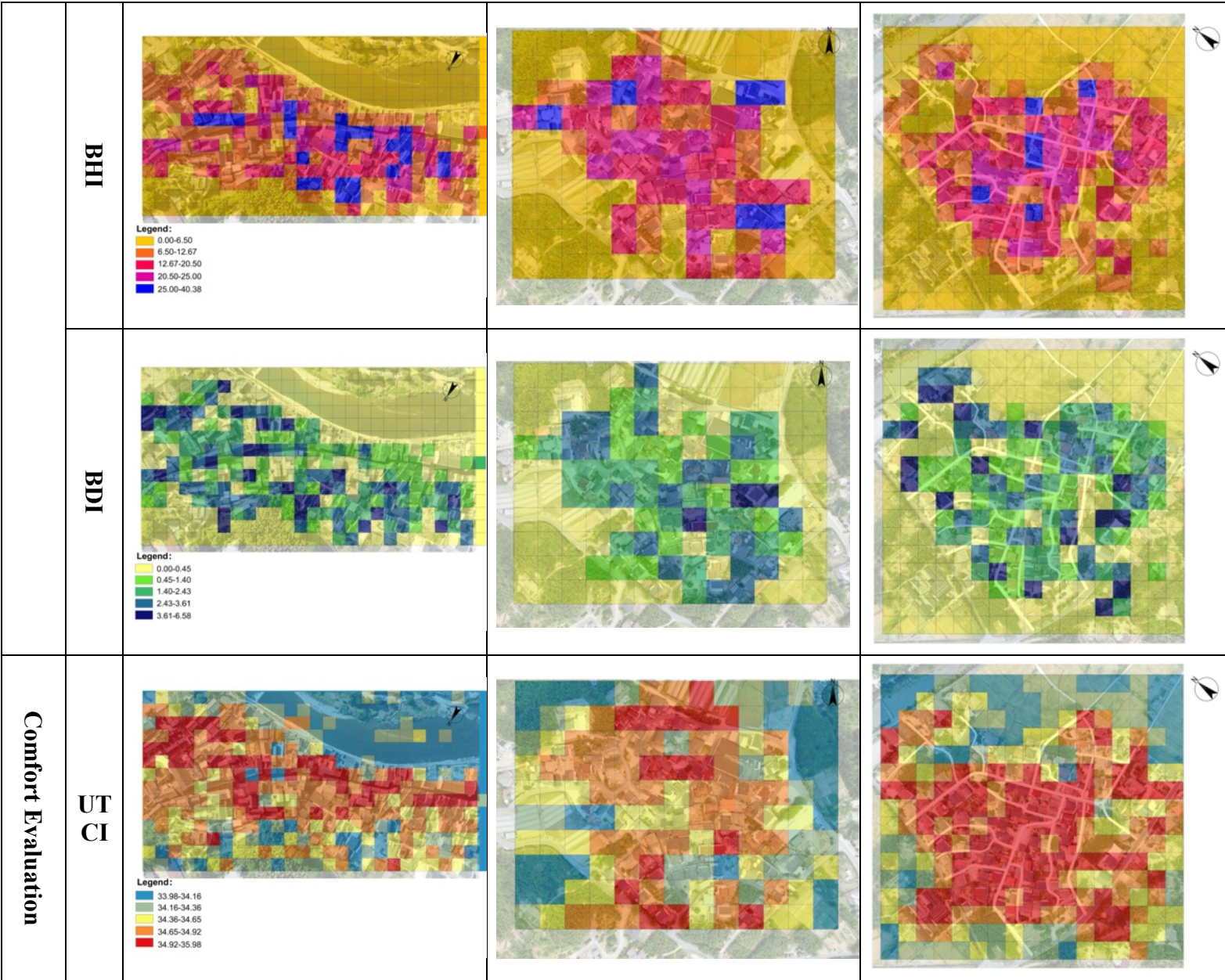
4.2.1 Grid-Based Evaluation

The grid-based evaluation enables quantification of morphological and climatic indicators at a spatiotemporal scale. In this study, a 10 m × 10 m grid is used for grid-based evaluation of 11 indicators: FAR, GSR, SVF, ABA, AH, ISR, RND, SAR, BHI, BDI, and UTCI, with UTCI being derived from the simulation results, as shown in Table 9. In the study, we further examine the coupling mechanisms between external space form and climatic conditions to identify dominant influencing factors on thermal comfort.

Table 9. Grid-Based Evaluation Analysis Diagram.

village		Heqiao Village	Guachuan Village	Qinong Village
Design Indicators Grid Evaluation	FAR	 Legend: 0.00-1.75 1.75-5.32 5.32-8.99 8.99-13.45 13.45-23.68 Note: Panel (a) (Heqiao) uses village-specific class breaks due to a wider FAR range, whereas panels (b) - (c) share unified breaks.	 Legend: 0.00-0.32 0.32-0.91 0.91-1.36 1.36-1.98 1.98-3.51	
	GSR	 Legend: 0.00-10.36 10.36-29.92 29.92-51.37 51.37-79.98 79.98-110.57		
	SVF	 Legend: 0.28-0.35 0.35-0.38 0.38-0.45 0.45-0.55 0.55-1.00		
	ABA	 Legend: 0.00-0.19 0.19-0.53 0.53-0.88 0.88-1.28 1.28-2.23		





Note: Panel (a) (Heqiao) and panel (b) (Guachuan) use village-specific class breaks due to wider FAR and SAR ranges, respectively, whereas the remaining panels share unified class breaks.

4.2.2 Grid-Based Microclimate Comparison

Across the three representative villages, distinct spatial configurations lead to convergent thermal responses, indicating relatively consistent morphology-microclimate relationships under the climatic and geomorphological conditions of the study area.

In Heqiao Village, high FAR and dense buildings in the residential core create UTCI hotspots, while peripheral areas with abundant vegetation and higher SVF serve as cooling zones. Despite shading from narrow streets with high SAR, limited ventilation and high thermal mass exacerbate heat retention.

In Guachuan Village, the “high-density core-low-density periphery” pattern is reinforced

by terrain, with high FAR, low GSR, and low SVF forming thermal hotspots in core streets. Vegetated foothills and peripheral zones act as thermal buffers, emphasizing that in mountainous areas, compact morphology amplifies heat accumulation, especially where green infrastructure is lacking.

In Qinong Village, spatial indicators are more homogeneous, but high FAR, elevated ISR, and limited green space along major roads and built-up axes lead to higher UTCI. Peripheral zones with high GSR and open farmland maintain favorable thermal conditions, highlighting the cooling effect of vegetation even in flat terrain.

The results illustrate a relatively consistent morphology-thermal pattern across the three representative village types. However, these patterns should be interpreted in relation to the climatic, geomorphological, and morphological characteristics of the riverside, mountainous, and plain villages examined in Lin'an. The co-occurrence of high development intensity (high FAR and building volume), insufficient green space (low GSR), limited sky openness (low SVF), and high surface hardening (high ISR) results in persistent thermal hotspots and poor outdoor thermal performance. Conversely, areas with lower density, higher vegetation coverage, and increased spatial openness exhibit significantly improved thermal conditions.

These findings suggest that, within the three representative village types examined here, coordinated density control, green-space provision, and ventilation-oriented spatial design are important for improving outdoor thermal conditions. At the same time, the comparative results indicate different typology-based emphases. In the riverside village, blue-green and water-related factors, together with development intensity, play a more prominent role. In the mountainous village, indicators related to enclosure, canyon geometry, spatial heterogeneity, and road-network structure are comparatively more influential. In the plain village, greenness, imperviousness, development intensity, and basic building-form characteristics are more important under relatively regular terrain conditions.

4.2.3 Nonlinear Correlation Analysis

To examine nonlinear spatial-climate coupling relationships, three ensemble learning methods-XGBoost, RF, and GBDT-were used to construct multivariable regression models for the three representative villages. With detailed modeling settings described in Section 3.7, the comparative results are presented in Table 10.

Table 10. Comparison of the Fitting Ability of Different Models on Training and Testing Data

Heqiao Village	Training Data				Testing Data			
	R ²	MSE	MAE	RMSE	R ²	MSE	MAE	RMSE
XGBoost	0.6065	0.0563	0.1787	0.2373	0.5685	0.0671	0.1869	0.2590
RF	0.7138	0.0437	0.1534	0.2091	0.5005	0.0644	0.1875	0.2538
GBDT	0.6425	0.0546	0.1790	0.2336	0.4982	0.0647	0.1950	0.2544

Guachuan Village	Training Data				Testing Data			
	R ²	MSE	MAE	RMSE	R ²	MSE	MAE	RMSE
XGBoost	0.5366	0.3184	0.4471	0.5643	0.3571	0.5639	0.5603	0.7510
RF	0.7294	0.1653	0.3091	0.4065	0.3129	0.5359	0.5671	0.7321
GBDT	0.5060	0.3016	0.4506	0.5492	0.2648	0.5465	0.5655	0.7393

Qinong Village	Training Data				Testing Data			
	R ²	MSE	MAE	RMSE	R ²	MSE	MAE	RMSE
XGBoost	0.8234	0.1509	0.2897	0.3884	0.6305	0.3688	0.4788	0.6073
RF	0.7925	0.1894	0.3281	0.4351	0.5845	0.3418	0.4342	0.5846
GBDT	0.7274	0.2501	0.3915	0.5001	0.5824	0.3435	0.4465	0.5861

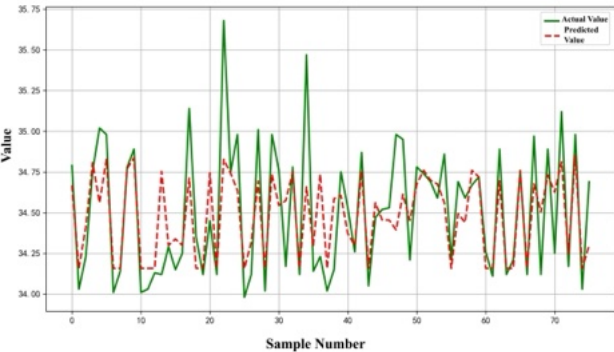
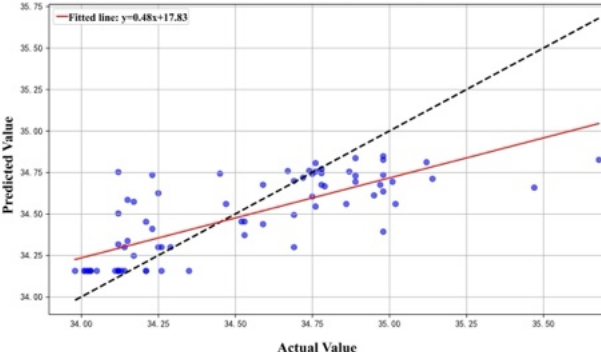
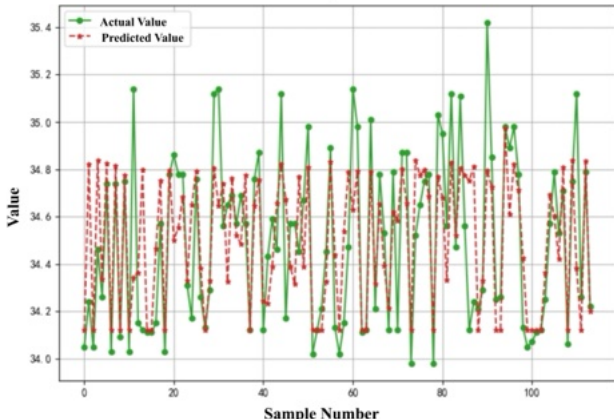
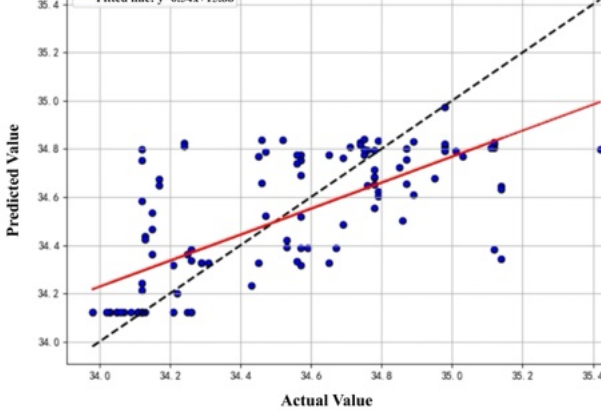
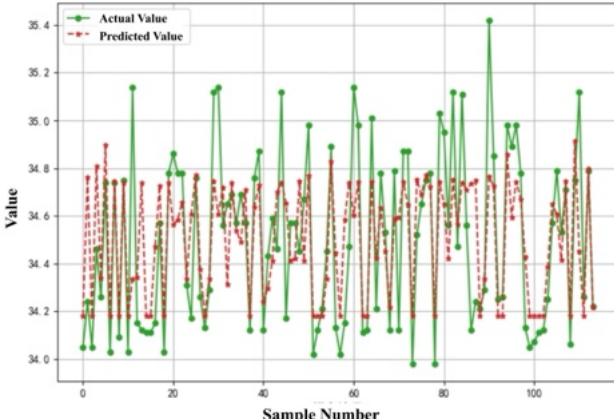
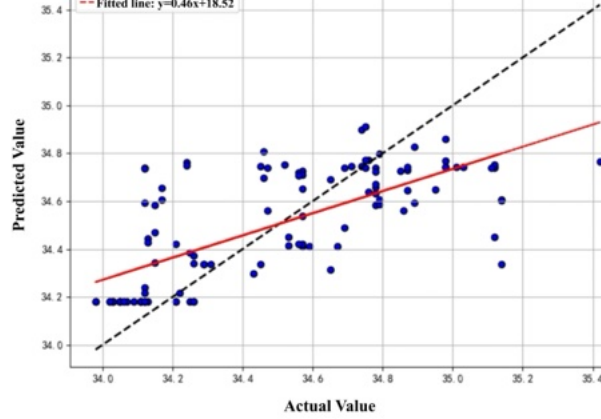
Note: Model performance was evaluated on the held-out test set. For the GBDT model, hyperparameters were optimized on the training set using 5-fold cross-validation, whereas the RF and XGB models were trained using pre-specified hyperparameters. These procedures were adopted to improve the transparency, reliability, and reproducibility of model evaluation.

The modeling results indicate that outdoor thermal comfort is mainly associated with indicators concerning development intensity, greenness, and spatial enclosure, such as FAR, GSR, SVF, SAR, and impervious surface ratio. Feature-importance and SHAP analyses further confirm that these variables influence UTCI through nonlinear responses and interactions rather than simple linear effects. Combinations of high FAR, low green-space ratio, and limited sky openness are consistently associated with thermal hotspots, highlighting the joint role of density, greenness, and ventilation constraints in shaping rural microclimates.

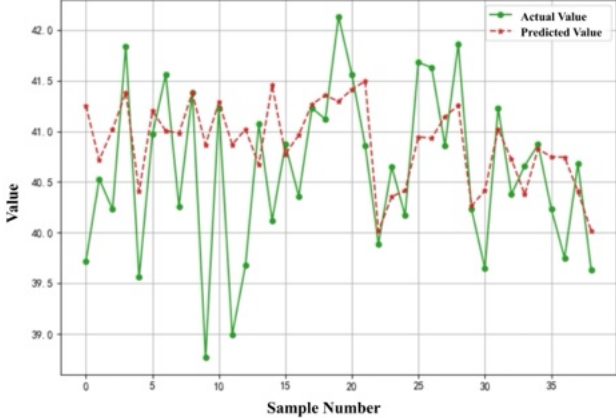
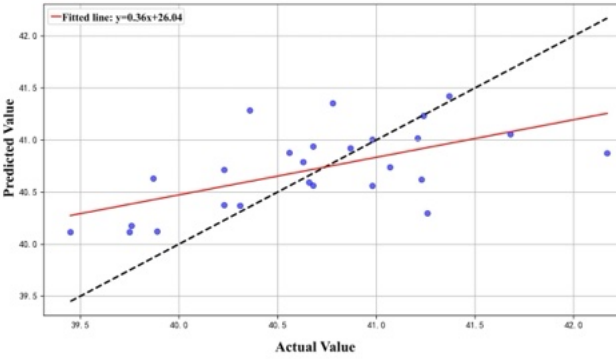
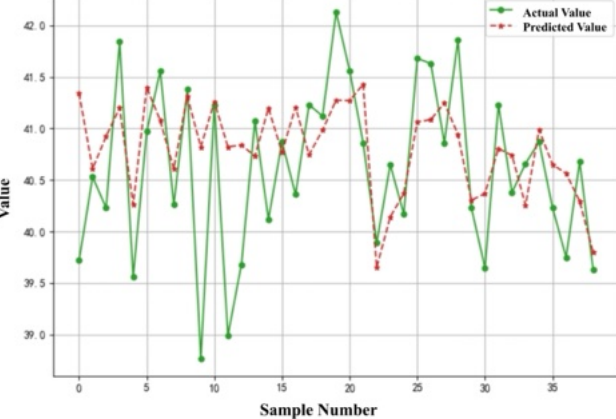
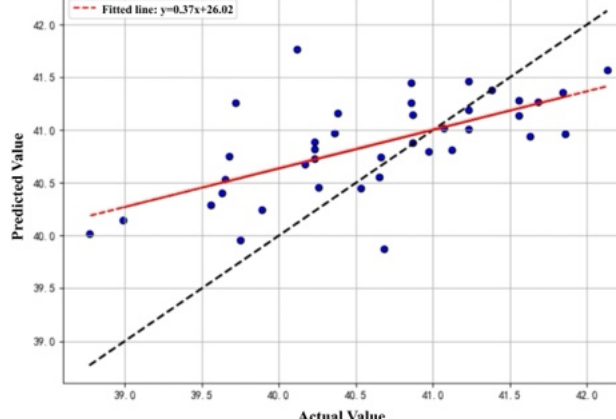
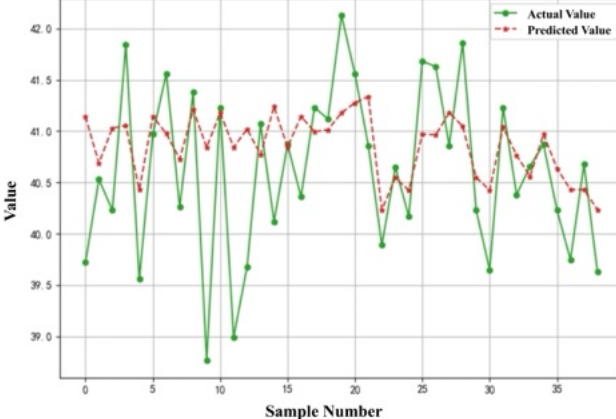
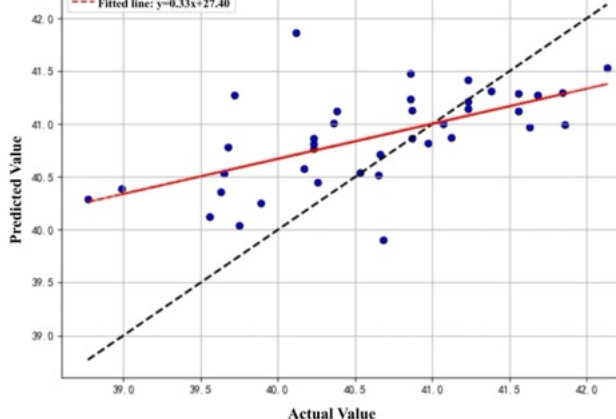
Significant inter-village differences remain evident in the nonlinear morphology-UTCI relationship. Among the three models, XGBoost consistently achieves the highest test-set R² across all villages (Heqiao: 0.5685; Guachuan: 0.3571; Qinong: 0.6305), indicating stronger robustness in capturing context-dependent nonlinear effects than RF and GBDT. In Guachuan, all models perform less accurately, suggesting that mountainous settings involve stronger

spatial heterogeneity and terrain-related microclimatic variability. In Qinong, model performance is generally higher, indicating that the more regular plain-village context is comparatively easier to represent. Heqiao shows intermediate performance, reflecting the combined influence of waterfront conditions and built-form variation.

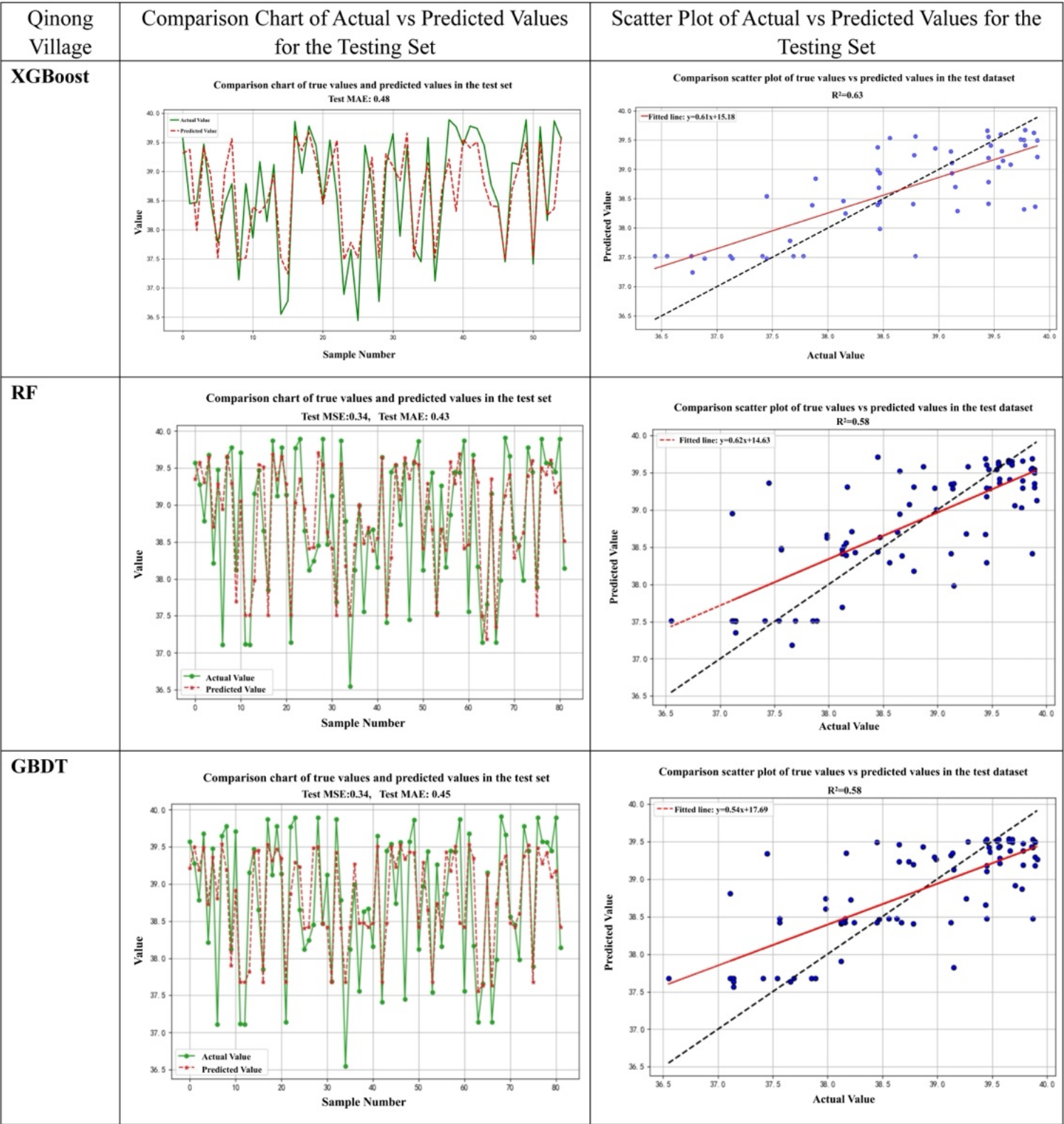
Fig. 12 compares the fitting and generalization performance of the three models on the training and testing sets. Overall, the modeling results confirm that morphology-UTCI relationships differ substantially across village contexts, and that XGBoost offers the most balanced performance for capturing these nonlinear differences. It is subsequently selected as the most suitable model for SHAP-based interpretation and targeted thermal-environment optimization.

Heqiao Village	Comparison Chart of Actual vs Predicted Values for the Testing Set	Scatter Plot of Actual vs Predicted Values for the Testing Set
XGBoost	Comparison chart of true values and predicted values in the test set Test MAE: 0.19 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.57$ Fitted line: $y=0.48x+17.83$ 
RF	Comparison chart of true values and predicted values in the test set Test MSE:0.06, Test MAE: 0.19 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.50$ Fitted line: $y=0.54x+15.88$ 
GBDT	Comparison chart of true values and predicted values in the test set Test MSE:0.06, Test MAE: 0.19 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.50$ Fitted line: $y=0.46x+18.52$ 

(a) Heqiao Village

Guachuan Village	Comparison Chart of Actual vs Predicted Values for the Testing Set	Scatter Plot of Actual vs Predicted Values for the Testing Set
XGBoost	Comparison chart of true values and predicted values in the test set Test MSE:0.56, Test MAE: 0.56 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.36$ 
RF	Comparison chart of true values and predicted values in the test set Test MSE:0.54, Test MAE: 0.57 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.31$ 
GBDT	Comparison chart of true values and predicted values in the test set Test MSE:0.55, Test MAE: 0.57 	Comparison scatter plot of true values vs predicted values in the test dataset $R^2=0.26$ 

(b) Guachuan Village



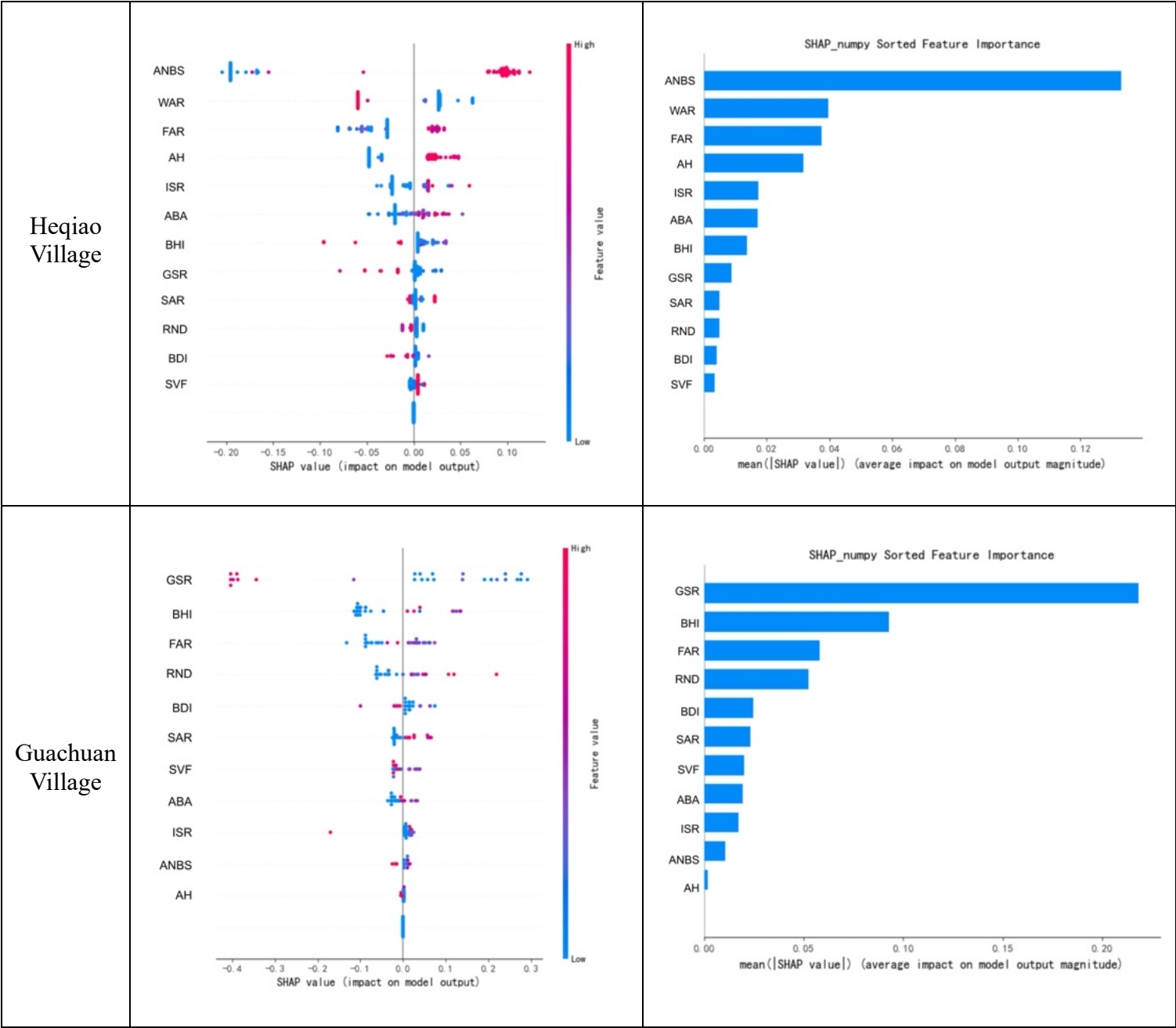
(c) Qinong Village

Fig. 12. Comparison of model fitting and generalization performance on the training and testing sets

As shown in Fig 13, XGBoost combined with SHAP reveals the marginal contributions

and nonlinear effects of multiple spatial form indicators on UTCI across different village contexts. In general, development-intensity indicators such as FAR and ISR exert warming effects, whereas GSR, WAR, and street-space openness tend to show cooling contributions. The asymmetric long-tail distribution of SHAP values further indicates clear threshold and interaction effects among key variables.

Overall, the SHAP results confirm that the morphology-UTCI relationship is strongly context-dependent and governed by nonlinear and interacting effects rather than by simple linear responses.



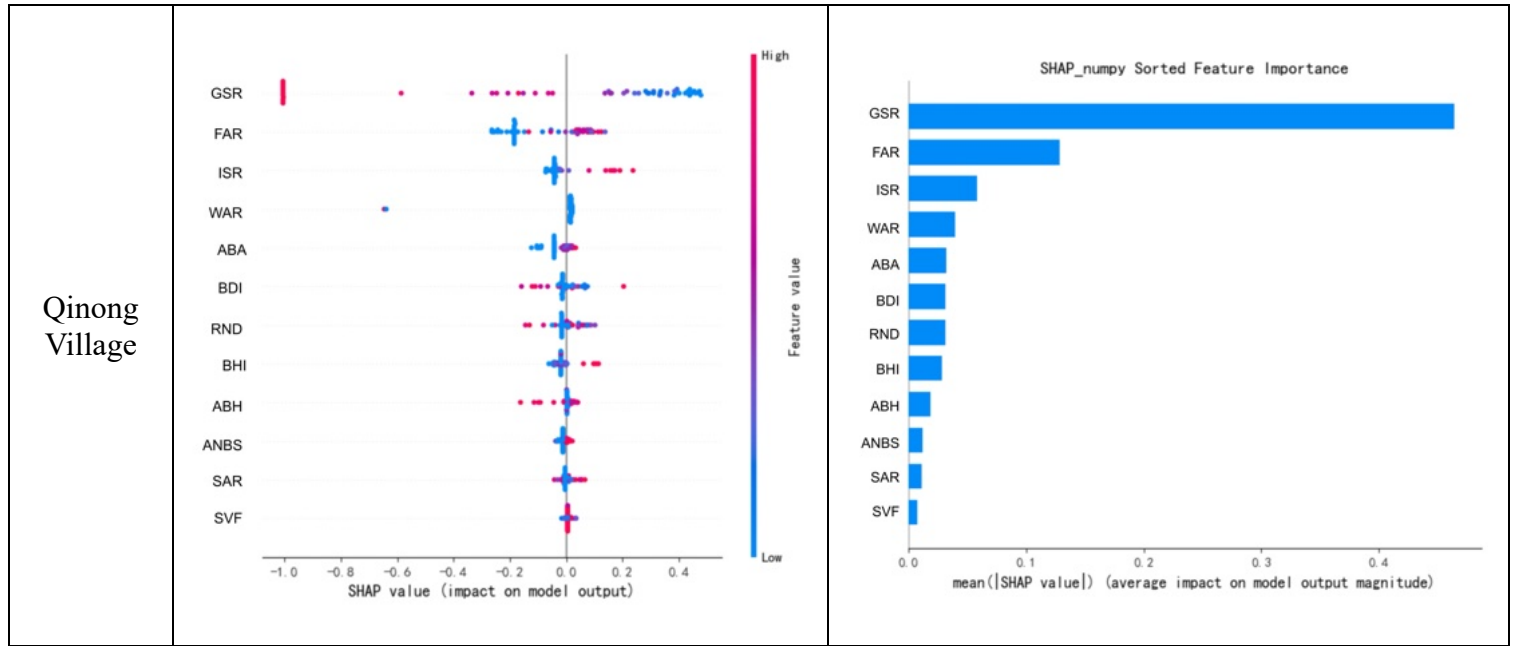


Fig. 13. Visualization of XGBoost+SHAP Analysis for Different Villages

4.3 SHAP-based Effect Interpretation and Core Indicator Consolidation

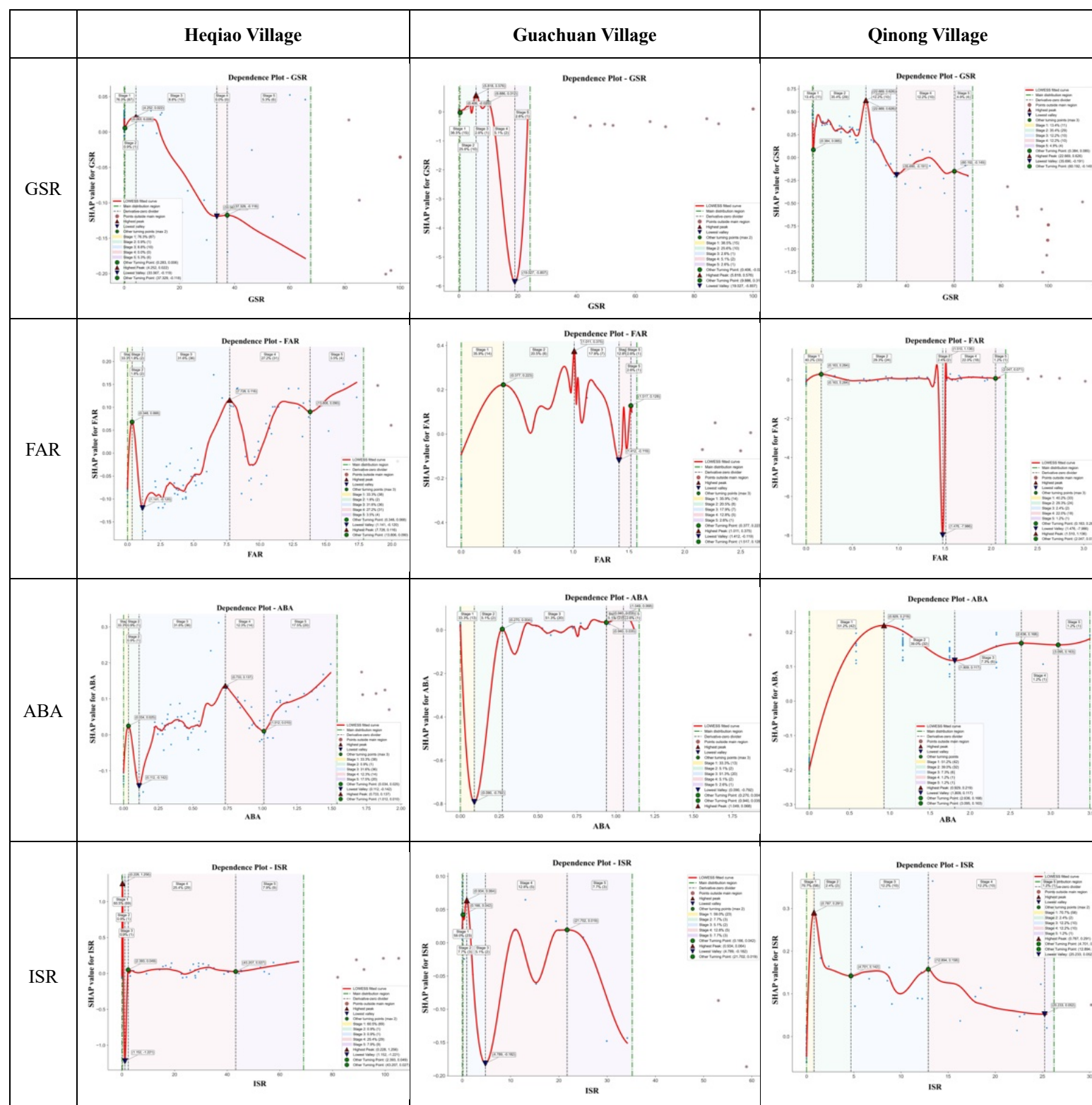
To clarify the coupling mechanisms between spatial morphology and human thermal comfort, SHAP dependence plots were used to examine how individual indicators influence predicted UTCI across their observed value ranges. These relationships are interpreted with reference to microclimate-related changes in local thermal conditions, including shading effects, radiant heat exposure, ventilation conditions, heat accumulation, and moisture-related cooling. The SHAP results illustrate statistical response patterns and also provide process-relevant evidence of how spatial form influences pedestrian-level thermal stress under different village conditions.

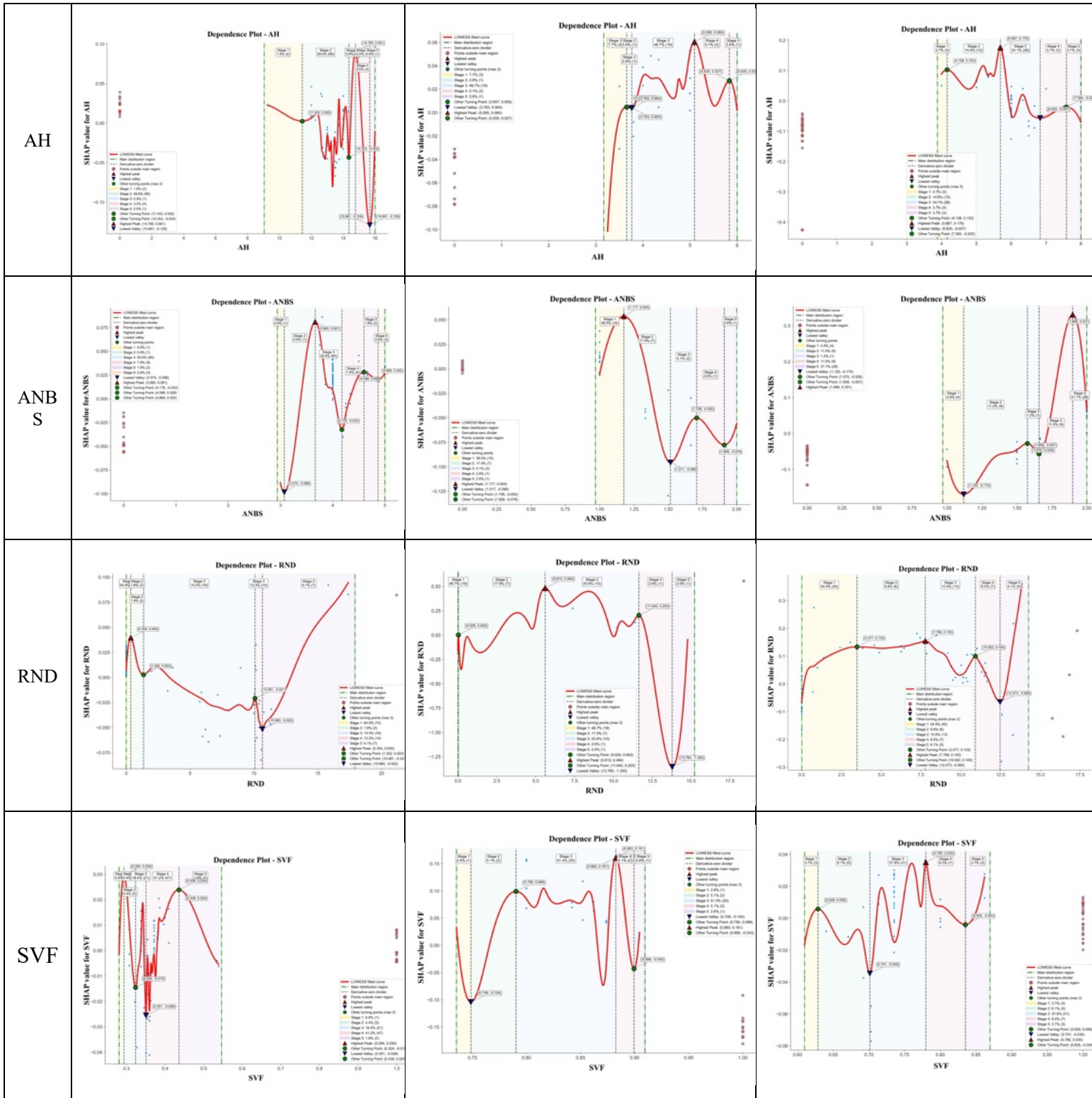
To improve interpretability, LOWESS-smoothed response curves were used to identify the main response trend and key turning regions within the dominant data-distribution range. The SHAP results are interpreted by combining overall response direction with essential quantitative evidence, including the locations of the highest peak and lowest valley, the major turning intervals, and the most important stage-wise distribution characteristics. The threshold-like patterns discussed below quantitatively described local transition structures along the fitted response curves.

To improve cross-village comparability, feature-importance results were further compared across the three representative villages. Indicators showing relatively stable and strong explanatory power under different geomorphological conditions were identified, and nine core indicators—GSR, FAR, ABA, AH, ANBS, ISR, RND, SVF, and BDI—were consolidated as a

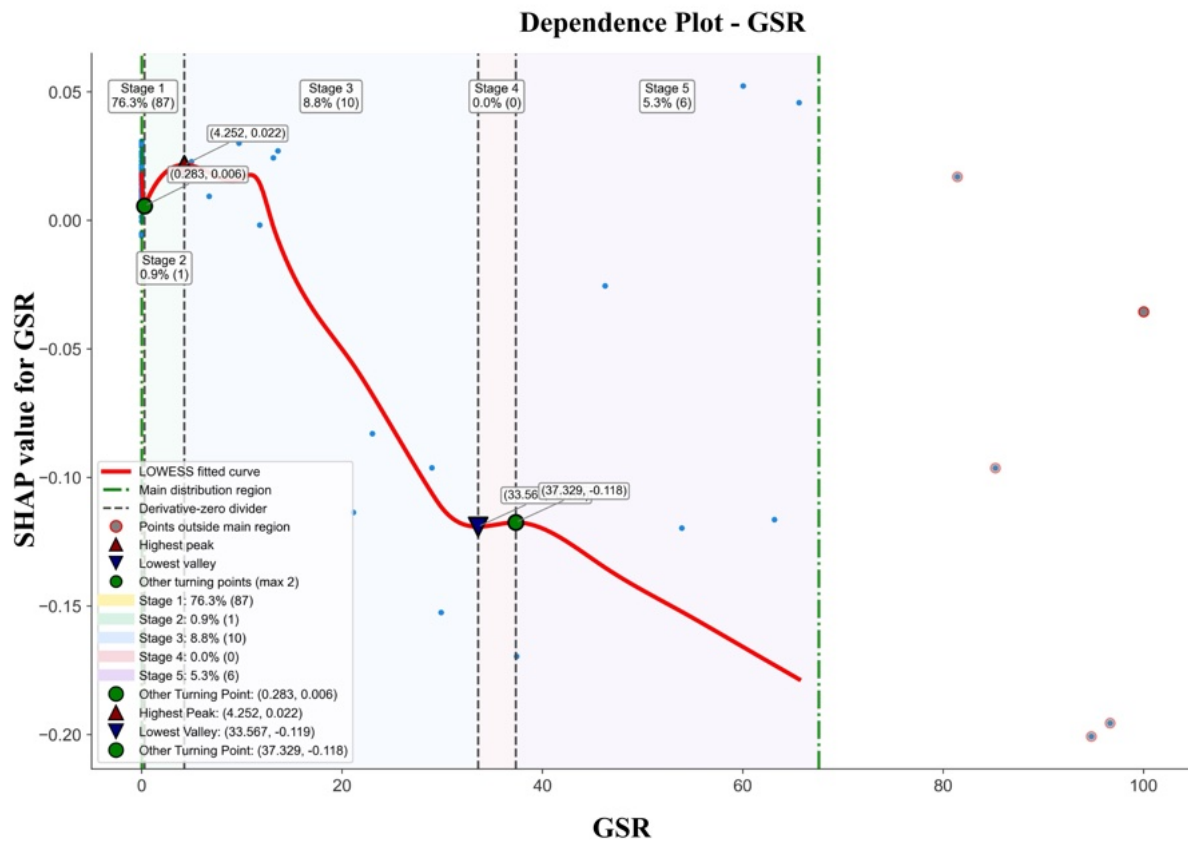
common reference set for comparative interpretation and mechanism summarization (Fig. 14). Based on the SHAP importance rankings and dependence-plot diagnostics, four indicators—GSR, FAR, ABA, and ISR—were selected for focused interpretation because they show relatively strong and recurrent explanatory power across villages and retain clear process interpretability. The following subsections therefore combine village-specific quantitative curve features with process-based interpretation to explain how these key morphology indicators influence UTCI under contrasting geomorphological conditions.

To further support the SHAP-based interpretation with an empirical perspective, village-specific binned mean indicator–UTCI curves for seven representative indicators are presented in Section 4.3.5.



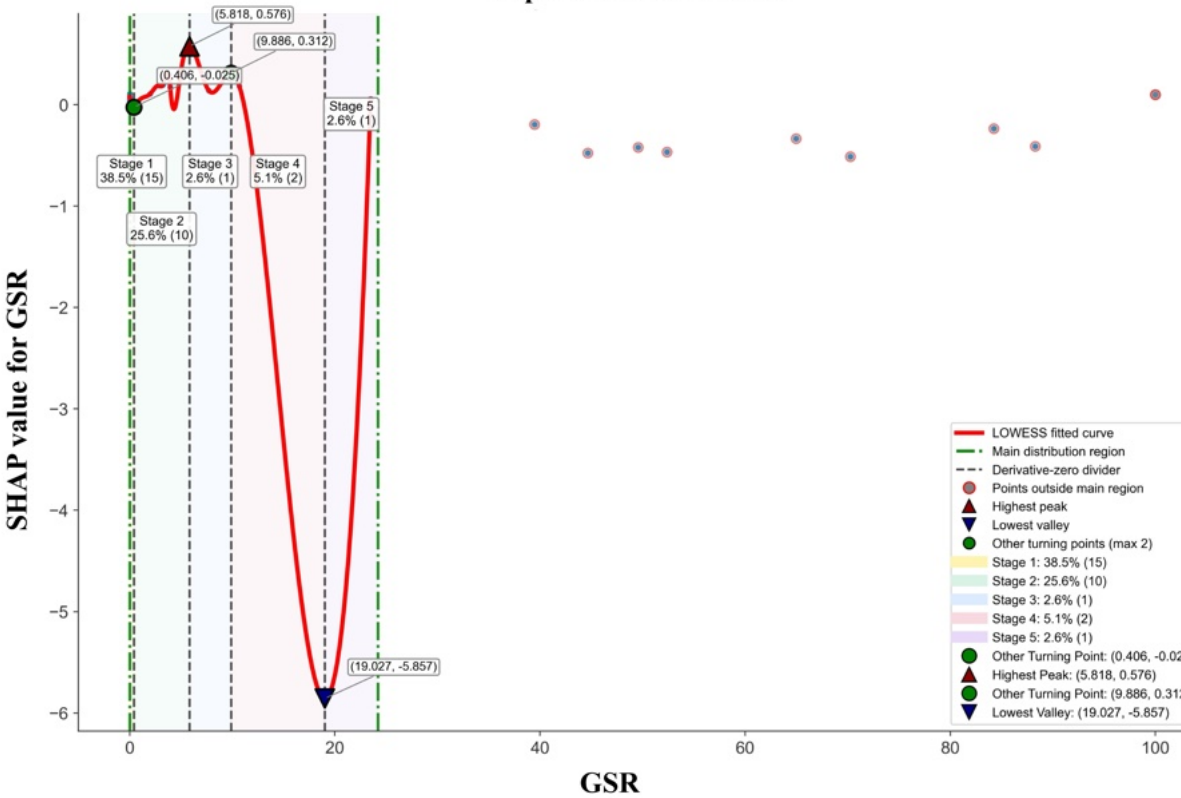


4.3.1 Nonlinear Response and Contribution of GSR

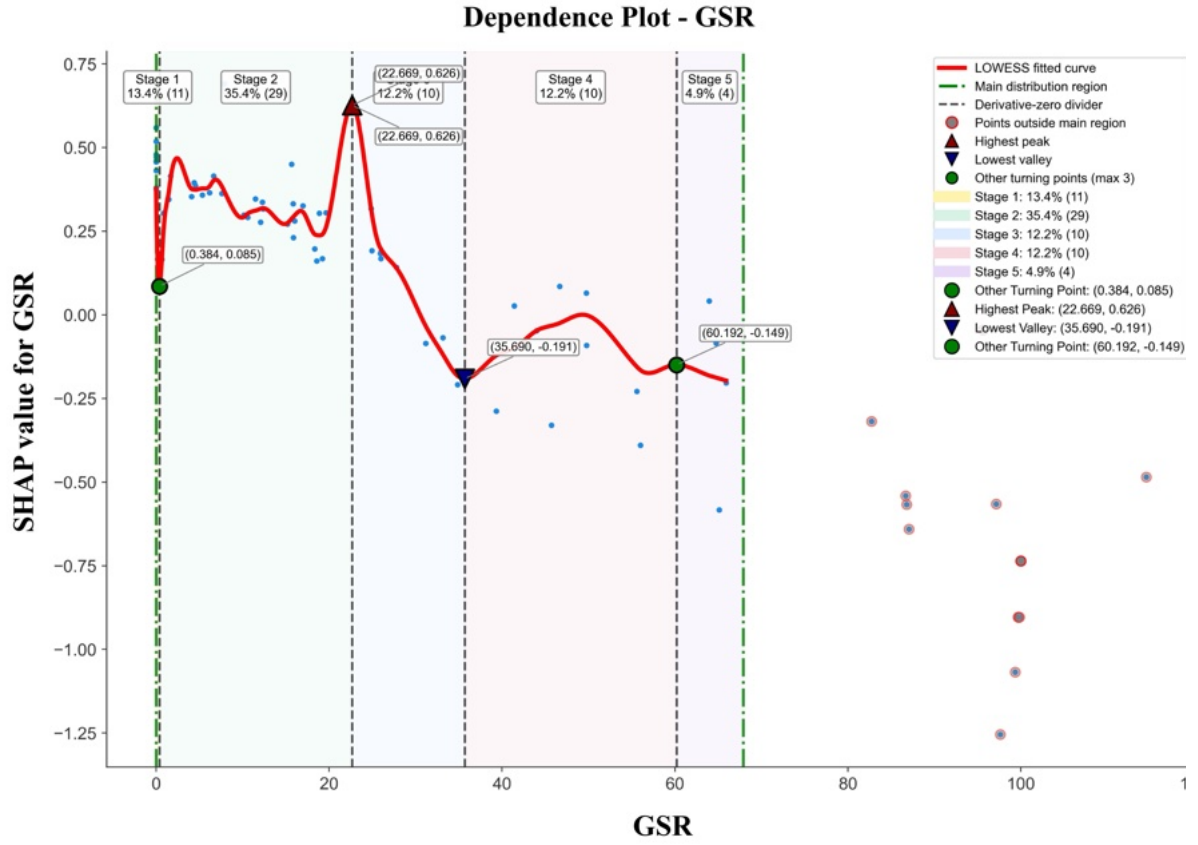


(a)

Dependence Plot - GSR



(b)



(c)

Fig. 15. Local Dependence Plot of GSR. (a) Heqiao Village, (b) Guachuan Village, (c) Qinong Village

Across the three villages, the SHAP dependence plots show that the relationship between GSR and UTCI is nonlinear and strongly village-dependent (Fig. 15). In general, GSR shows a cooling tendency after certain turning ranges, but the response intensity and stage structure differ markedly across geomorphological contexts. In Heqiao (Fig. 15a), the fitted curve shows a relatively weak response concentrated in the low-GSR range. It starts from an early turning point at (0.283, 0.006), rises slightly to the highest peak at (4.252, 0.022), and then declines to the labelled valley at (33.567, -0.119), followed by a later turning point at (37.329, -0.118). The peak-to-valley amplitude based on the labelled points is about 0.141, indicating a moderate cooling shift. In terms of sample distribution, Stage 1 accounts for 76.3% (87) of observations, while Stage 3 and Stage 5 account for 8.8% (10) and 5.3% (6), respectively, suggesting that the Heqiao response is mainly controlled by the low-GSR interval.

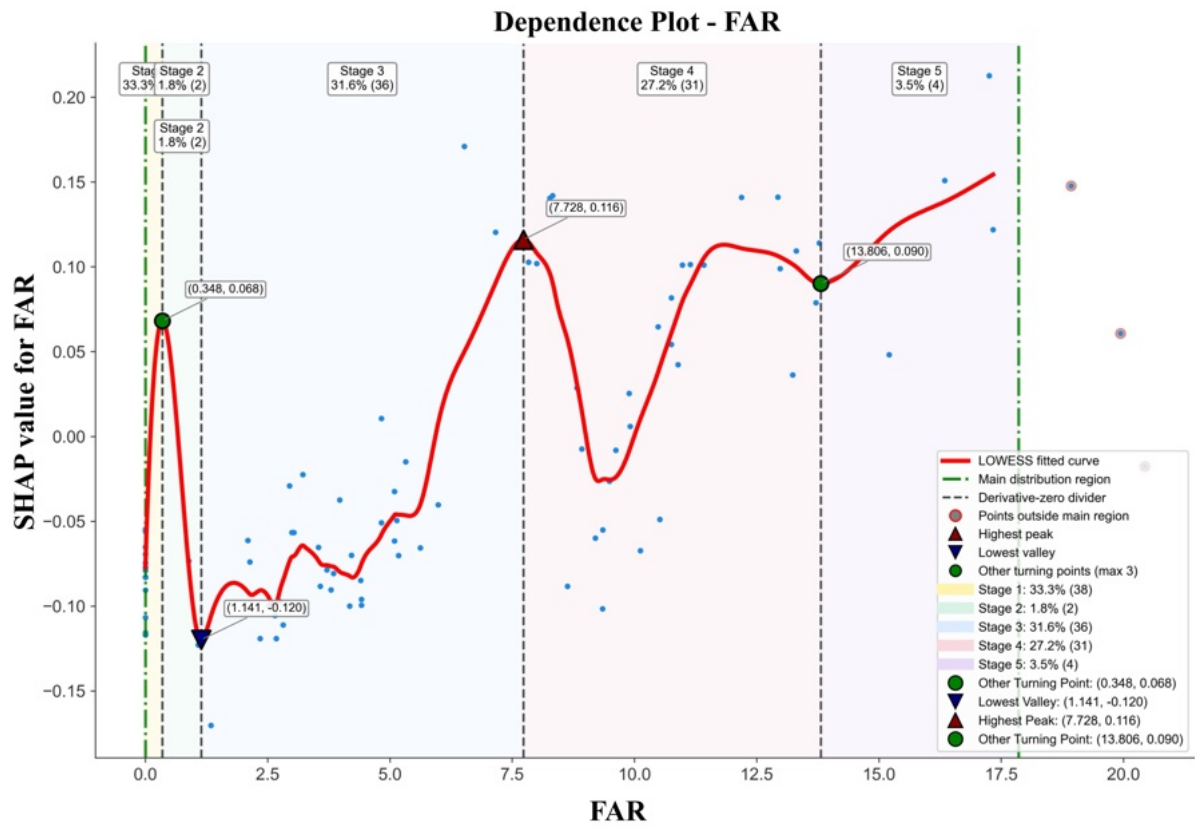
By contrast, Guachuan (Fig. 15b) exhibits the most pronounced threshold-like negative change. Starting from an early turning point at (0.406, -0.025), the curve rises to the highest peak at (5.818, 0.576), then passes through another turning point at (9.886, 0.312) before

dropping sharply to the lowest valley at (19.027, -5.857), producing the largest peak-to-valley amplitude of 6.433 among the three villages. In terms of stage distribution, Stage 1 accounts for 38.5% (15) of observations, followed by Stage 2 at 25.6% (10), while the remaining stages contain only 1–2 samples each, indicating that the GSR effect in Guachuan is highly sensitive and concentrated within the main transition range.

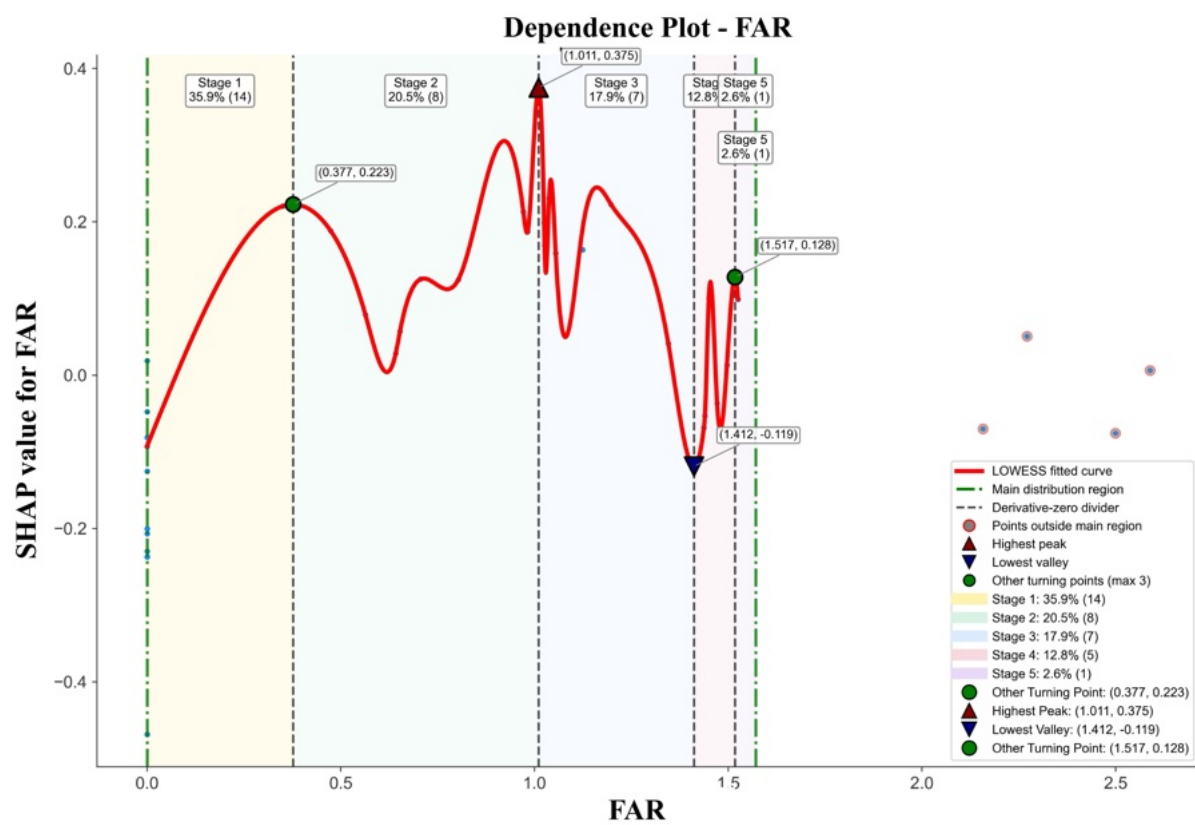
Qinong (Fig. 15c), in contrast, shows a broader and more distributed multi-stage response. The curve begins with an early turning point at (0.384, 0.085), rises to the highest peak at (22.669, 0.626), and then declines to the lowest valley at (35.690, -0.191), followed by a later turning point at (60.192, -0.149). The peak-to-valley amplitude is about 0.817, larger than in Heqiao but much smaller than in Guachuan, indicating a more gradual rather than abrupt negative shift in the response. The stage distribution is also more dispersed, with Stage 2 accounting for 35.4% (29), followed by Stage 1 at 13.4% (11) and Stages 3 and 4 at 12.2% (10) each, confirming that the GSR effect in Qinong operates across a wider value range.

These differences are consistent with the coupled effects of shading, evapotranspiration, and local surface cooling. In practical terms, greening intervention is beneficial across the three village types, but its response pattern is more low-range concentrated in Heqiao, more threshold-sensitive in Guachuan, and more broadly distributed in Qinong.

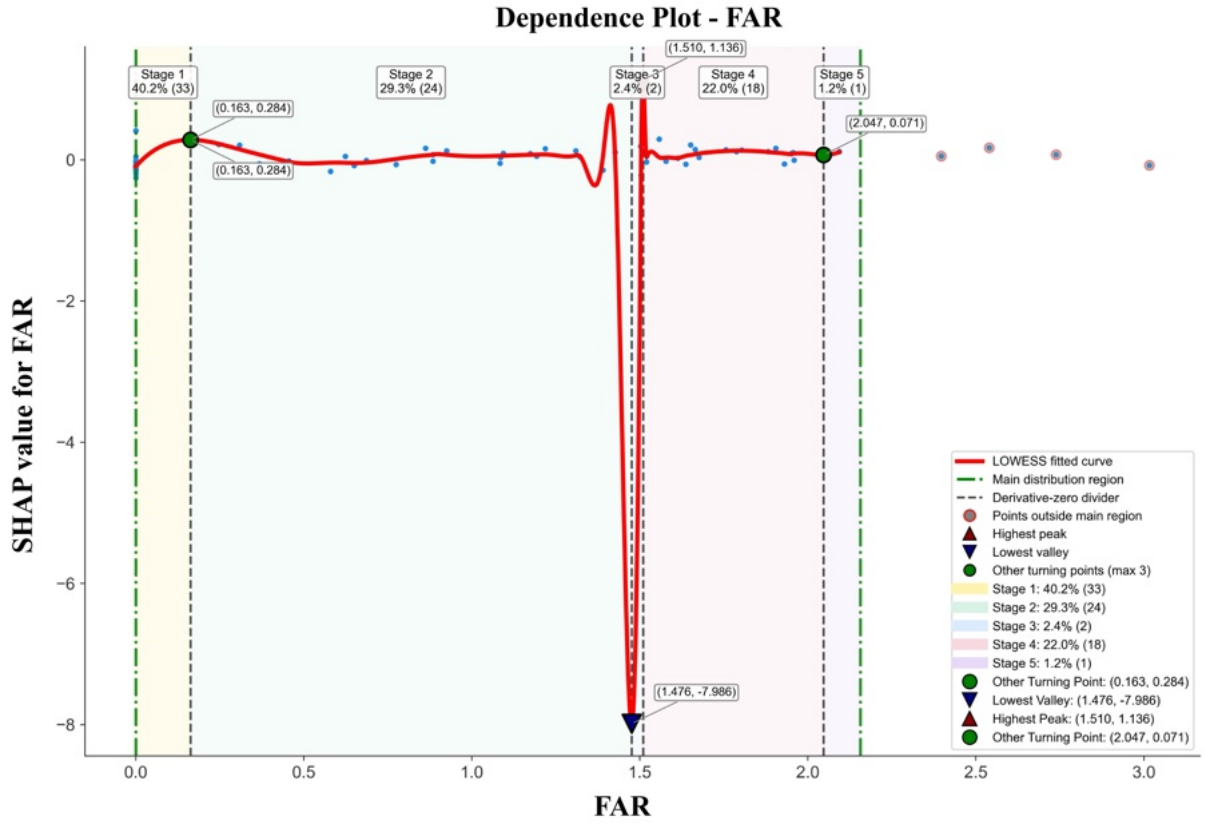
4.3.2 Nonlinear Response and Contribution of FAR



(a)



(b)



(c)

Fig. 16. Local Dependence Plot of FAR. (a) Heqiao Village, (b) Guachuan Village, (c) Qinqong Village

The SHAP dependence plots indicate that FAR influences UTCI in a nonlinear and strongly context-dependent manner across the three villages (Fig. 16). In Heqiao (Fig. 16a), the fitted curve shows a clear multi-stage structure. It begins with a small early positive contribution at (0.348, 0.068), then drops to the lowest valley at (1.141, -0.120), indicating a local cooling-like phase at very low FAR values. After this early minimum, the curve gradually recovers and reaches the annotated peak at (7.728, 0.116) in the middle range, before passing through another turning point at (13.806, 0.090) and continuing toward a positive response in the later range. The peak-to-valley amplitude based on the annotated peak and valley is approximately 0.236. This response is mainly supported by Stage 1 [33.3% (38)], Stage 3 [31.6% (36)], and Stage 4 [27.2% (31)], indicating that the FAR effect in Heqiao is distributed across low, middle, and later value ranges.

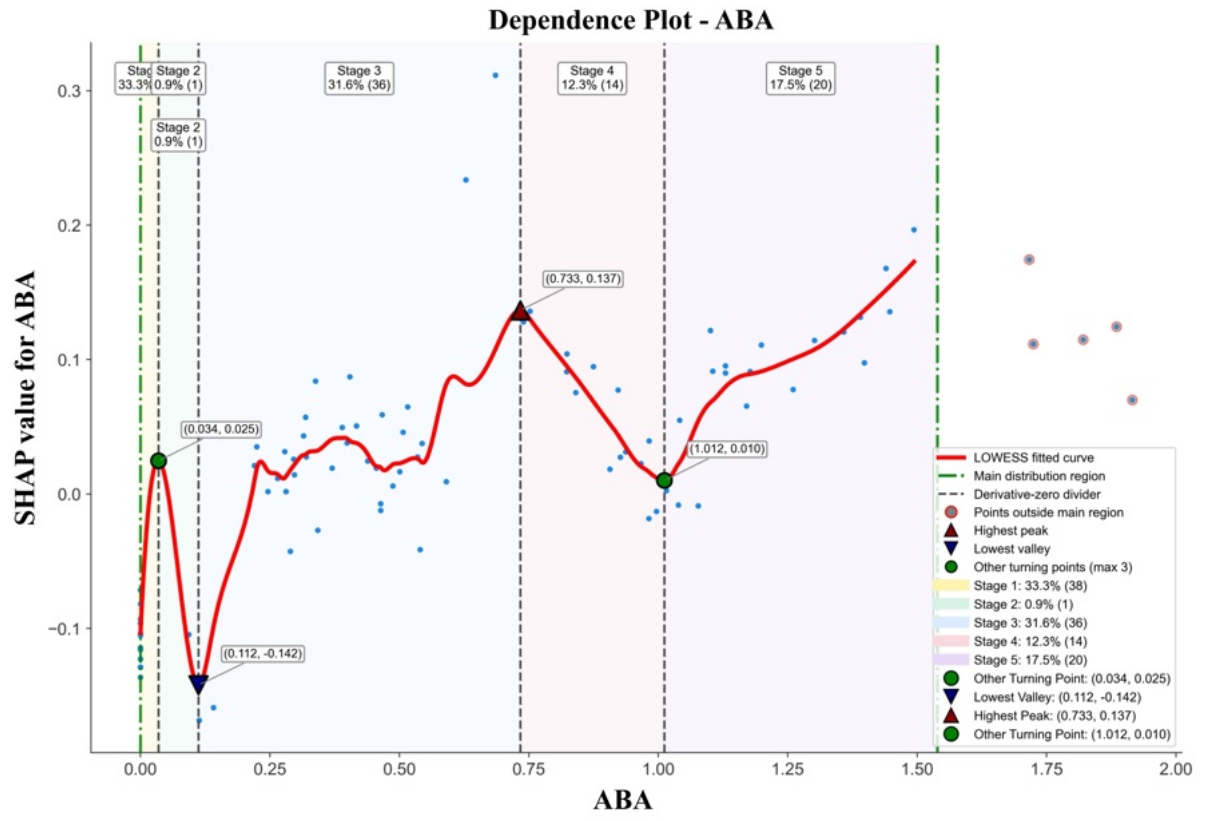
By contrast, Guachuan (Fig. 16b) shows sharper small-range fluctuations and stronger sensitivity to FAR changes. The curve first rises to a turning point at (0.377, 0.223), continues to the highest peak at (1.011, 0.375), and then falls abruptly to the lowest valley at (1.412, -0.119). It subsequently rebounds to another turning point at (1.517, 0.128) near the upper

boundary of the main distribution region. The peak-to-valley amplitude reaches 0.494, indicating a more unstable and segmented FAR response than in Heqiao. The stage distribution is concentrated within a narrow FAR range, with Stage 1 [35.9% (14)], Stage 2 [20.5% (8)], and Stage 3 [17.9% (7)] providing the main empirical support, while later stages contain fewer samples.

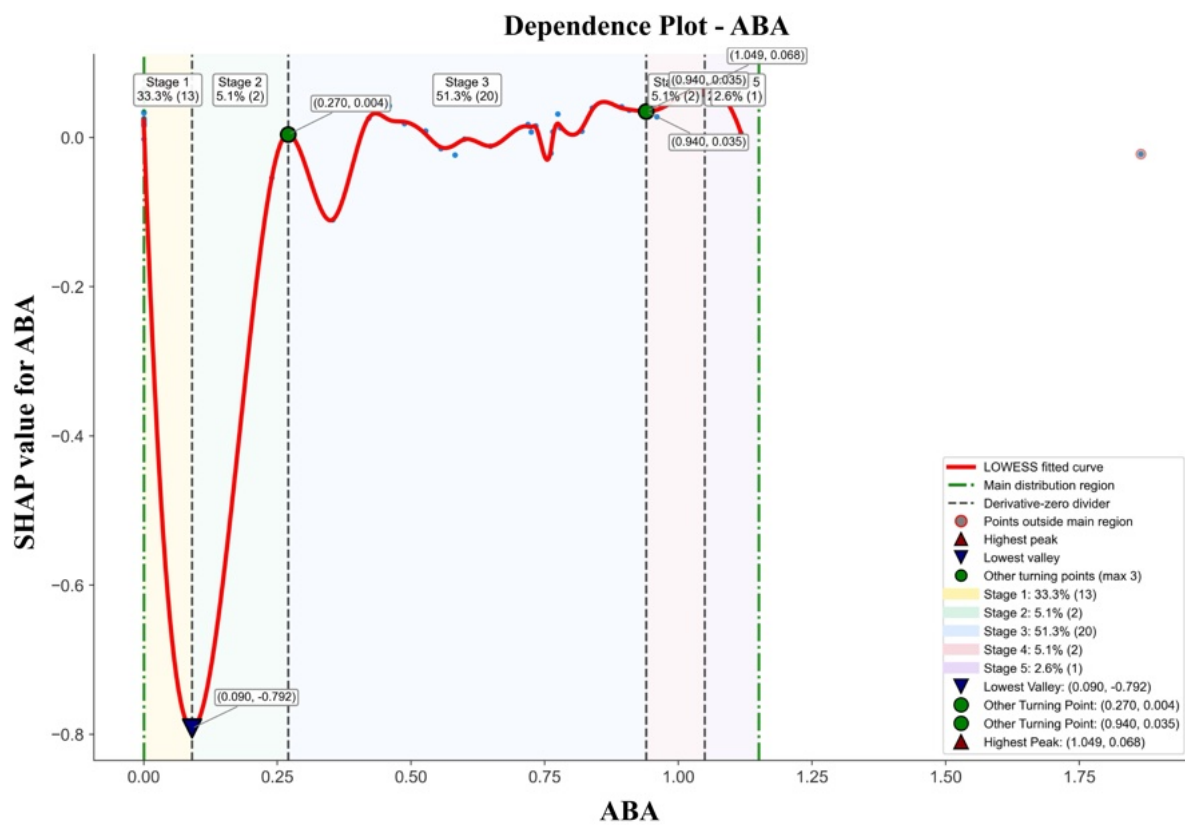
Qinong (Fig. 16c), in contrast, exhibits the strongest local fluctuation around the middle FAR interval. The curve starts with a low-FAR turning point at (0.163, 0.284) and remains relatively weak over much of the early-to-middle range. It then drops sharply to the lowest valley at (1.476, -7.986) and rapidly rises to the highest peak at (1.510, 1.136), producing the largest peak-to-valley amplitude of approximately 9.122 among the three villages. A later turning point occurs at (2.047, 0.071), after which the response returns to a weakly positive level. The stage structure is dominated by Stage 1 [40.2% (33)], Stage 2 [29.3% (24)], and Stage 4 [22.0% (18)], suggesting that most observations are distributed before and after this sharp middle-range fluctuation.

Mechanistically, these patterns reflect the combined effects of radiative trapping, heat storage, and ventilation restriction as built intensity increases. However, the FAR–UTCI relationship does not follow a single universal threshold across the three villages. Heqiao shows a moderate multi-stage response, Guachuan presents narrow-range oscillatory sensitivity, and Qinong exhibits the strongest local valley–peak fluctuation around the middle FAR interval. This indicates that the thermal role of development intensity depends strongly on enclosure, openness, and surrounding spatial configuration in each geomorphological context.

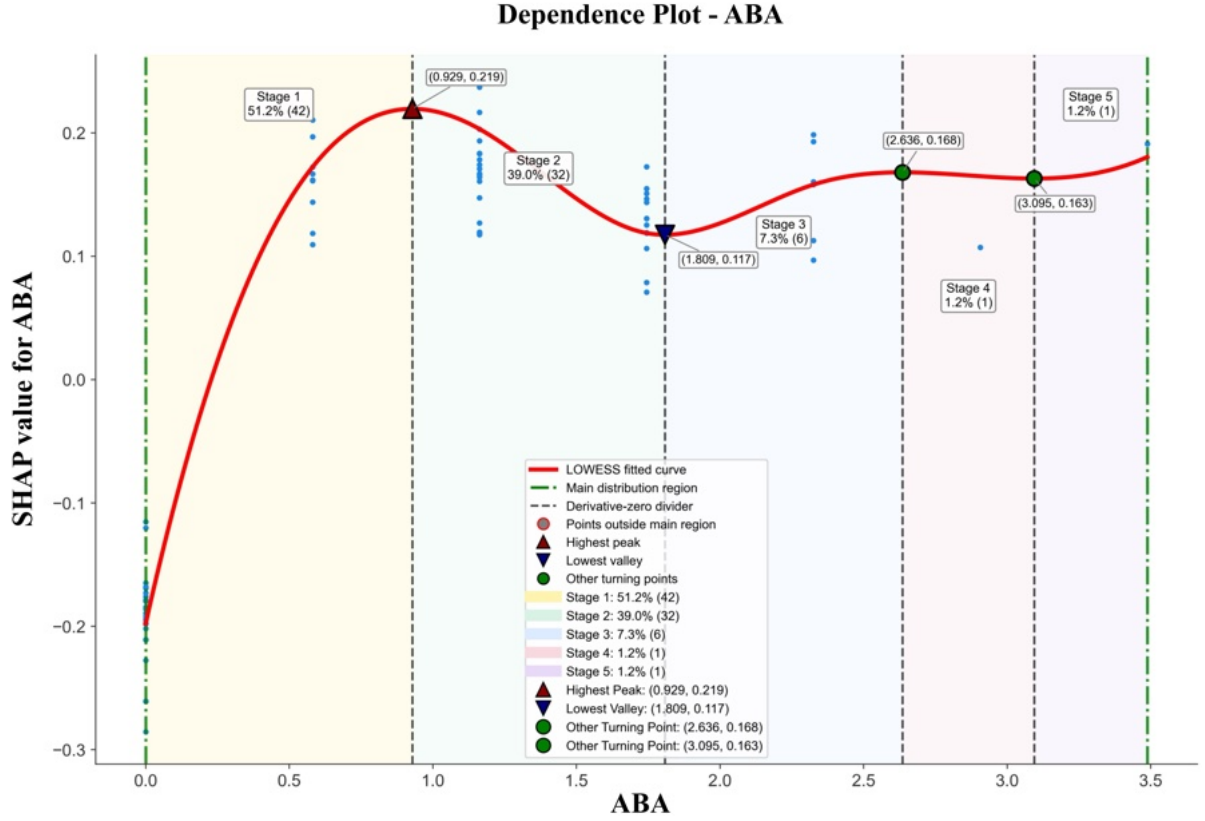
4.3.3 Nonlinear Response and Contribution of ABA



(a)



(b)



(c)

Fig. 17. Local Dependence Plot of ABA. (a) Heqiao Village, (b) Guachuan Village, (c) Qinqong Village

The relationship between ABA and UTCI is also nonlinear and differs substantially across the three villages (Fig. 17). In Heqiao (Fig. 17a), the fitted curve shows a mixed and multi-step response. It begins with a small early positive contribution at (0.034, 0.025), then drops sharply to the lowest valley at (0.112, -0.142), indicating a local cooling-like phase in the very low-ABA range. After this early minimum, the curve rebounds and rises to the highest peak at (0.733, 0.137), before declining toward a near-neutral turning point at (1.012, 0.010) and then increasing again in the later ABA range. The peak-to-valley amplitude is approximately 0.279, suggesting a moderate ABA-related fluctuation. This structure is mainly supported by Stage 1 [33.3% (38)], Stage 3 [31.6% (36)], and Stage 5 [17.5% (20)], indicating that the Heqiao response is distributed across low, middle, and later ABA ranges rather than being controlled only by the earliest segment.

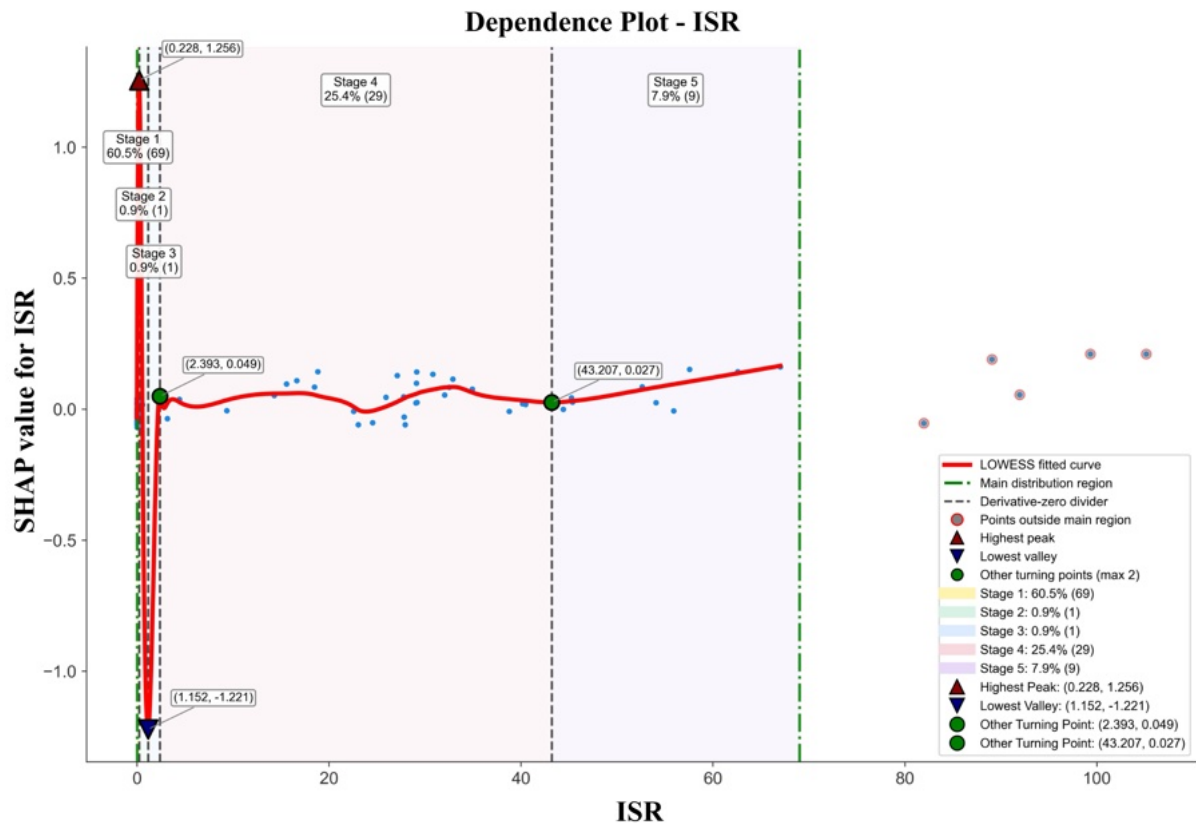
Guachuan (Fig. 17b) shows the strongest early negative response and a weak oscillatory structure around zero after the initial drop. The curve plunges almost immediately to the lowest valley at (0.090, -0.792), which is much deeper than that observed in the other two villages,

and then rebounds toward near-neutral values, passing through turning points at (0.270, 0.004) and (0.940, 0.035) before reaching the highest peak at (1.049, 0.068). The peak-to-valley amplitude is approximately 0.860, indicating a pronounced early negative shift followed by weak positive adjustment. The stage structure is dominated by Stage 1 [33.3% (13)] and Stage 3 [51.3% (20)], while the other stages contain only one or two observations. This suggests that Guachuan is characterized by one strong early cooling-like phase followed by a longer interval of weak near-zero adjustment.

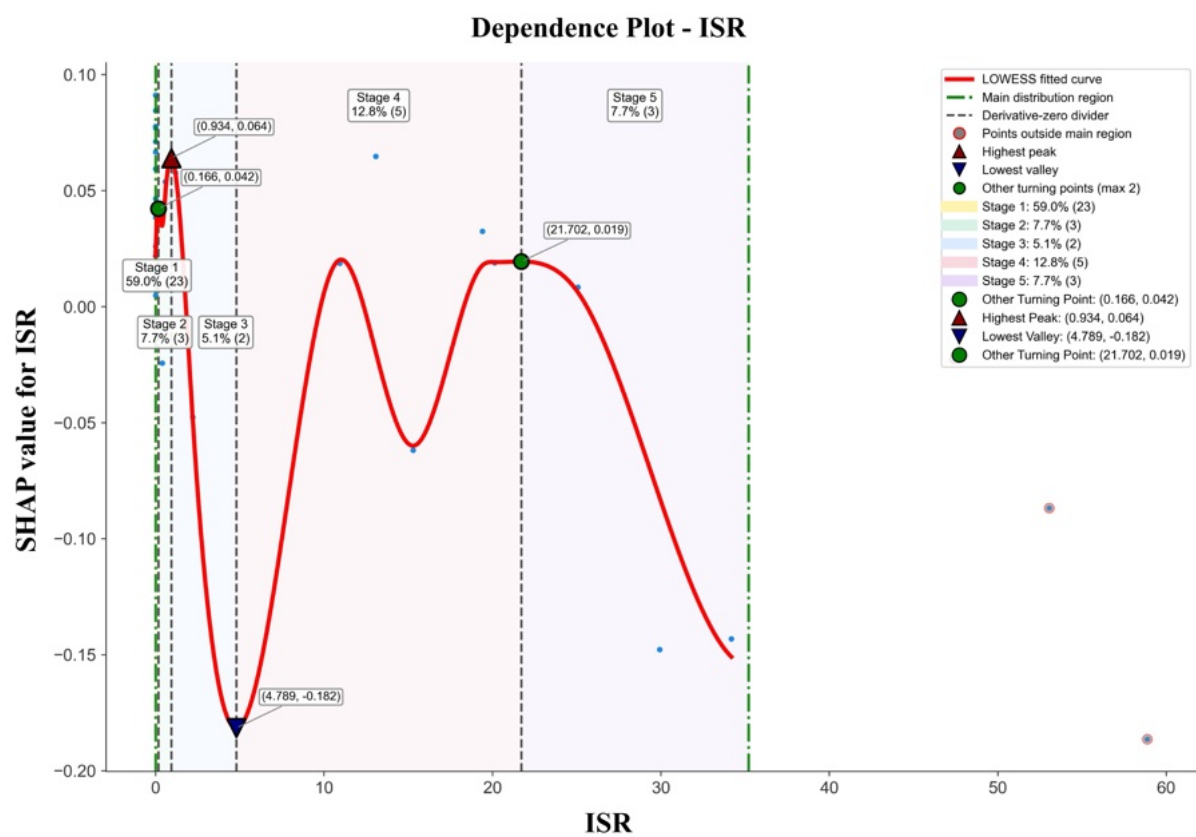
Qinong (Fig. 17c), by contrast, shows the most consistently positive ABA response. The curve rises from the initial low-ABA range and reaches the highest peak at (0.929, 0.219), then declines to the lowest valley at (1.809, 0.117). Importantly, this valley remains positive, indicating that ABA weakens its warming-like contribution but does not reverse into a cooling-like phase. After this local minimum, the curve rebounds through later turning points at (2.636, 0.168) and (3.095, 0.163), suggesting a gentle recovery and stabilization in the higher ABA range. The peak-to-valley amplitude is relatively small, about 0.102. The response is strongly supported by Stage 1 [51.2% (42)] and Stage 2 [39.0% (32)], which together account for 90.2% of observations, while later stages contain few samples.

These differences suggest that the thermal role of building area is shaped not only by its magnitude, but also by how building massing interacts with enclosure, local radiant exchange, and surrounding spatial structure. In Heqiao and Guachuan, ABA shows clearer local reversals and stronger low-range instability, whereas in Qinong, its effect is smoother and more persistently positive across the main distribution region.

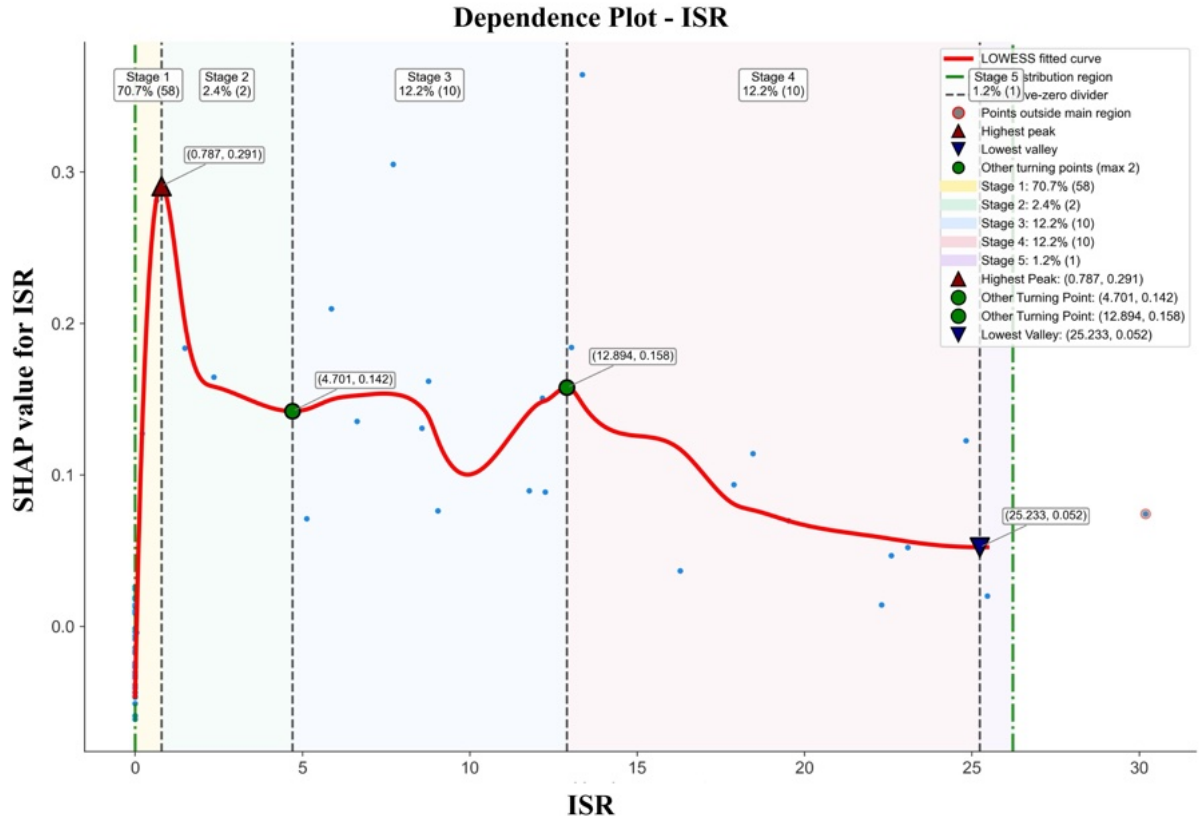
4.3.4 Nonlinear Response and Contribution of ISR



(a)



(b)



(c)

Fig. 18. Local Dependence Plot of ISR. (a) Heqiao Village, (b) Guachuan Village, (c) Qinong Village

Across the three villages, ISR shows a nonlinear and highly uneven relationship with UTCI (Fig. 18). In Heqiao (Fig. 18a), the fitted curve exhibits an extremely sharp early peak-to-valley transition. The curve rises rapidly to the highest peak at (0.228, 1.256) and then descends to the lowest valley at (1.152, -1.221) within a very short ISR interval, producing a peak-to-valley amplitude of approximately 2.477. After this abrupt transition, the curve rebounds to weakly positive values around (2.393, 0.049) and then remains close to zero through the later turning point at (43.207, 0.027). This structure is primarily influenced by the earliest low-ISR interval, where Stage 1 accounts for 60.5% (69) of the observations, while Stage 4 [25.4% (29)] and Stage 5 [7.9% (9)] provide support for the later weakly positive branch.

Guachuan (Fig. 18b) shows a more moderate but still clearly nonlinear ISR response. The curve begins with a weakly positive turning point at (0.166, 0.042), reaches the highest peak at (0.934, 0.064), and then declines toward the lowest valley at (4.789, -0.182), marking the strongest cooling-like phase in the Guachuan curve. The peak-to-valley amplitude is approximately 0.246, much smaller than that in Heqiao. After this valley, the response recovers

to a weak positive turning point at (21.702, 0.019) and then declines again in the higher-ISR range. The stage structure is dominated by Stage 1 [59.0% (23)], while Stage 4 [12.8% (5)] and Stage 5 [7.7% (3)] contain fewer samples, indicating that the ISR effect is mainly concentrated in the low-ISR range with limited later-stage support.

In contrast, Qinong (Fig. 18c) exhibits a broader and mostly positive ISR response. The curve rises rapidly to the highest peak at (0.787, 0.291), then declines to a lower but still positive turning point at (4.701, 0.142). It subsequently rebounds slightly at (12.894, 0.158) and then gradually declines to the lowest labelled valley at (25.233, 0.052). The peak-to-valley amplitude is approximately 0.239, indicating a moderate weakening of the ISR effect rather than a strong reversal. Since the lowest valley remains positive, ISR in Qinong maintains a warming-like contribution throughout the labelled response structure. The stage distribution is highly concentrated in Stage 1 [70.7% (58)], while Stage 3 [12.2% (10)] and Stage 4 [12.2% (10)] provide support for the middle and later ranges. This suggests that the ISR effect in Qinong is mainly driven by the low-ISR range but remains weakly positive across the broader value range.

These differences align with the mechanisms of sensible heat accumulation, reduced moisture availability, and weakened evaporative moderation over hardened surfaces. However, the ISR–UTCI relationship does not follow a single universal threshold across village types. Heqiao shows the sharpest early reversal, Guachuan presents a weaker but still nonlinear response with an early cooling-like valley, while Qinong maintains a broader and mostly positive response pattern. This suggests that the thermal effect of impervious surfaces depends on local surface conditions, ventilation, and surrounding spatial structure within different geomorphological contexts.

4.3.5 Cross-village empirical support for morphology–UTCI mechanisms

To further support the SHAP-based interpretation with an intuitive empirical view, village-specific binned mean indicator–UTCI curves were constructed for seven representative indicators (Fig. 19), namely ANBS, FAR, AH, GSR, BHI, RND, and ISR. These indicators were selected from the union of the top-ranked SHAP indicators across the three representative villages based on recurrence and process interpretability. These curves are not intended to replace the SHAP-based dependence analysis, but to provide an empirical complement for examining whether the major process-oriented patterns identified in Sections 4.3.1–4.3.4 are also reflected in the observed village-level distributions. Because the observed value ranges of several indicators differ across villages, the following comparisons are interpreted within each village’s actual range rather than as strict one-to-one comparisons at identical indicator values.

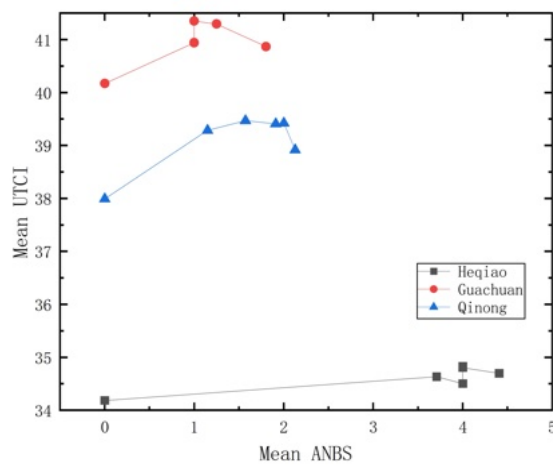
Overall, the empirical curves show clear inter-village differences in both absolute thermal

level and response trend. Specifically, across most indicator gradients, Guachuan remains the warmest village, Qinong occupies an intermediate position, and Heqiao remains the coolest and least variable. For warming-related indicators, such as ANBS, FAR, AH, and BHI, Guachuan and Qinong generally show an increase in mean UTCI from the lower observed bins toward the middle bins, followed by stabilization or only slight decline toward the terminal bins. In contrast, Heqiao remains comparatively flat from the initial to the terminal part of the curves. To illustrate, for ANBS, mean UTCI increases from about 40.2°C in the lowest observed bins to a local high of about 41.3°C in Guachuan, and from about 38.0°C to about 39.5°C in Qinong, before remaining high or easing slightly toward the end of the curve. By contrast, Heqiao stays within a narrow range of about 34.2–34.8°C throughout. A similar end-to-end tendency is observed for FAR. When FAR is close to 0, mean UTCI is about 40.2°C in Guachuan, 38.0°C in Qinong, and 34.2°C in Heqiao; as FAR increases to roughly 1–2, mean UTCI rises to about 41.4–41.5°C in Guachuan and 39.4–39.5°C in Qinong, and then remains relatively high or declines only slightly toward the terminal bins, whereas Heqiao shows only a weak increase and still remains below about 34.8°C across its broader FAR range. Similarly, AH follows the same broad pattern: the lowest observed bins correspond to mean UTCI values of roughly 40.2°C in Guachuan, 38.0°C in Qinong, and 34.2°C in Heqiao, while the middle AH bins correspond to higher values of about 41.4°C in Guachuan and 39.5°C in Qinong, after which both curves remain high or change only modestly toward the end. Heqiao again remains comparatively flat. When considering BHI, the lower observed bins correspond to about 40.4°C in Guachuan, 38.3°C in Qinong, and 34.3°C in Heqiao, whereas the middle-to-higher bins correspond to higher UTCI values of about 41.5°C in Guachuan and 39.6°C in Qinong, with only limited change toward the terminal bins; Heqiao still varies only slightly and remains below about 34.8°C.

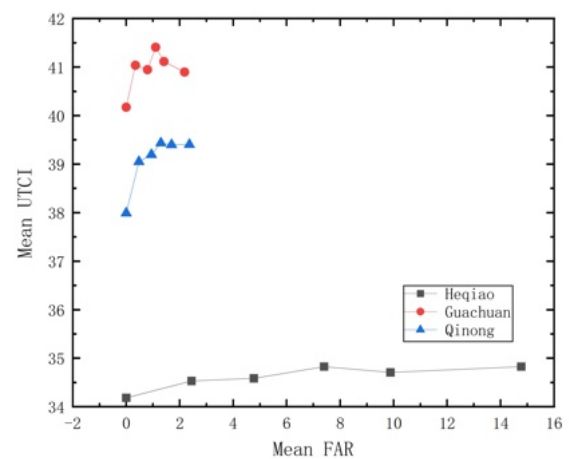
By contrast, GSR shows the clearest end-to-end cooling pattern. When GSR is in the lowest observed bins, mean UTCI is about 41.3°C in Guachuan and 39.5°C in Qinong. As GSR increases toward the higher and terminal bins, mean UTCI declines to about 40.2°C in Guachuan and 37.6°C in Qinong. This indicates that the cooling effect associated with greening is evident in both villages and is stronger in Qinong than in Guachuan. In comparison, Heqiao again shows only weak variation, remaining around 34.4–34.8°C from the initial to the terminal bins. RND and ISR show weaker monotonicity but still reveal clear village-level contrasts from one end of the curves to the other. For RND, Heqiao remains within about 34.4–34.8°C across the low-to-high observed bins, Qinong mostly ranges from about 38.4°C to 39.4°C, and Guachuan fluctuates between about 40.6°C and 41.3°C. This indicates that similar road-network-density gradients correspond to different thermal backgrounds across village contexts.

For ISR, Heqiao stays relatively low and flat at about 34.4–34.7°C across a broad observed range, whereas Guachuan remains persistently high, from roughly 40.7°C in the lower bins to about 41.1°C in the higher bins, and Qinong fluctuates within a warmer band of about 38.6–39.6°C as ISR increases across its observed range.

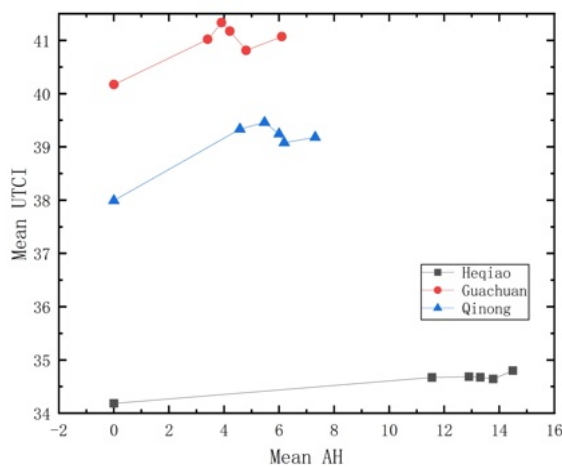
Taken together, these empirical curves reinforce the view that the morphology–UTCI relationship is strongly context-dependent. Within the observed village-specific ranges, development-intensity, building-scale, and vertical-irregularity indicators generally correspond to stronger warming responses in Guachuan and Qinong, whereas higher greening corresponds to clearer cooling, especially in Qinong. By contrast, Heqiao shows flatter end-to-end UTCI responses across several indicator gradients, suggesting a weaker or more constrained thermal response under its observed morphology distribution. Overall, Fig. 19 provides additional empirical support for linking village morphology to different microclimate change tendencies under contrasting geomorphological conditions.



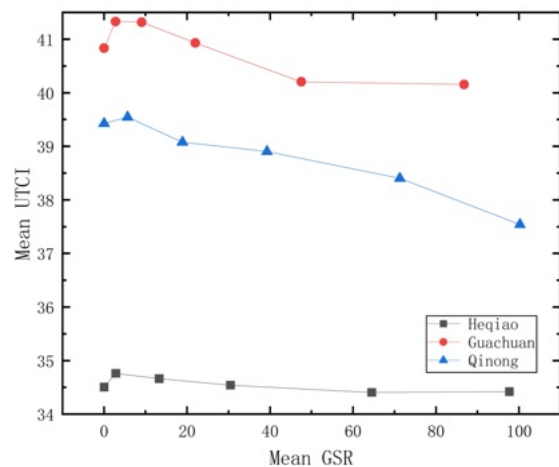
(a) Relationship between ANBS and UTCI



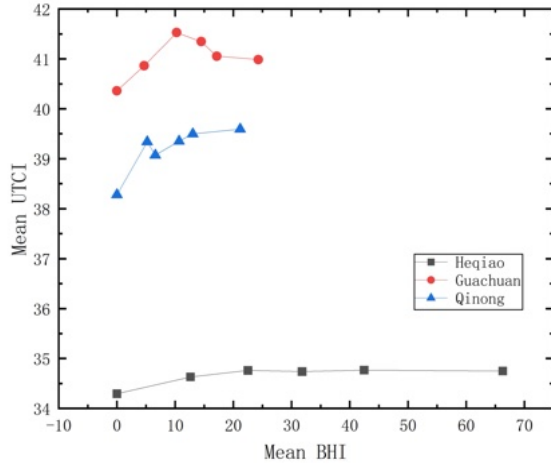
(b) Relationship between FAR and UTCI



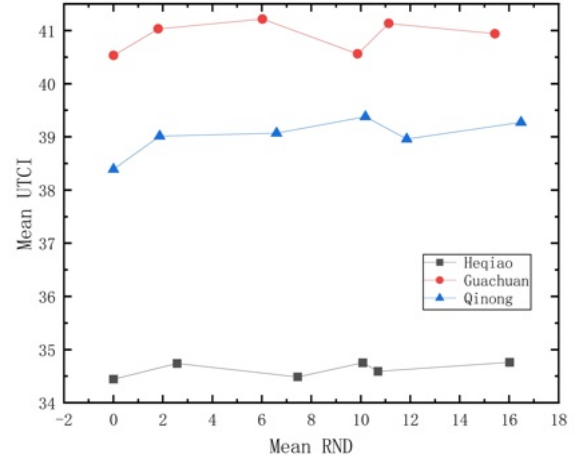
(c) Relationship between AH and UTCI



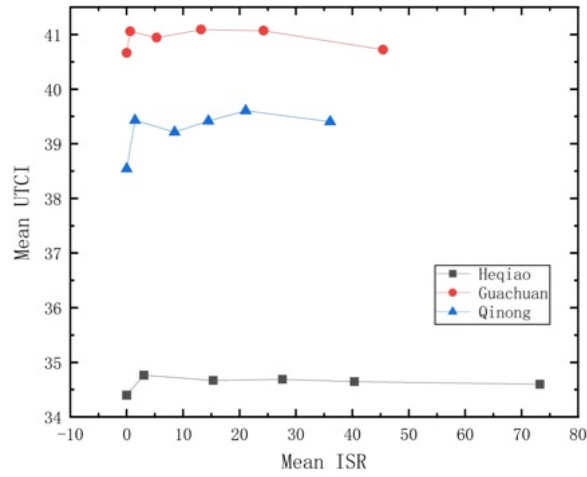
(d) Relationship between GSR and UTCI



(e) Relationship between BHI and UTCI



(f) Relationship between RND and UTCI



(g) Relationship between ISR and UTCI

Fig. 19. Village-specific indicator–UTCI curves for the three representative villages

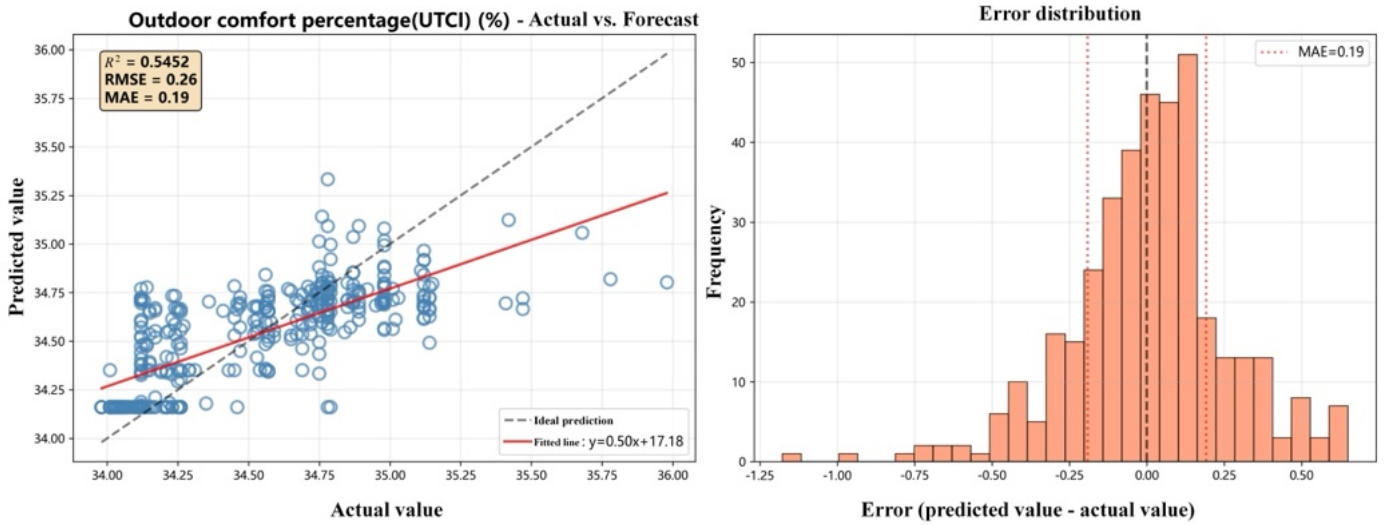
5. Village-wise Predictive Analysis

Building on the village-specific importance rankings derived from a common RMMD candidate pool of 13 morphology indicators, village-wise predictive analyses were conducted for Heqiao, Guachuan, and Qinong. For each village, three feature scopes—Top 5, Top 8, and All—were evaluated using the ANN framework described in Section 3.7. Here, All denotes the full set of retained non-constant and informative predictors for the corresponding village. Because AREA only represents the fixed size of each RMMD grid cell ($10\text{ m} \times 10\text{ m} = 100\text{ m}^2$), it was excluded from predictive modelling. After excluding AREA, the All set contains 12 indicators in Heqiao, 11 in Guachuan, and 12 in Qinong. Specifically, the retained predictors are ANBS, WAR, FAR, AH, ISR, ABA, BHI, GSR, SAR, RND, BDI, and SVF for Heqiao; GSR, BHI, FAR, RND, BDI, SAR, SVF, ABA, ISR, ANBS, and AH for Guachuan; and GSR, FAR, ISR, WAR, ABA, BDI, RND, BHI, AH, ANBS, SAR, and SVF for Qinong. Thus, after

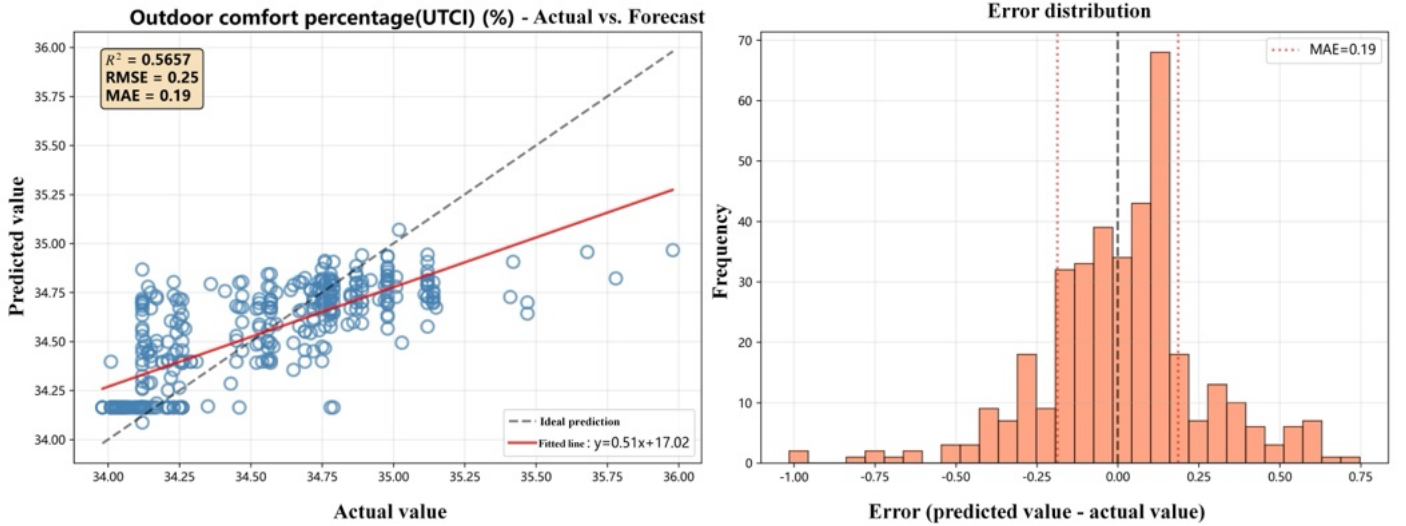
excluding AREA, the only remaining difference in the All set is that WAR is retained in Heqiao and Qinong, but not in Guachuan, indicating weaker predictive relevance of water-related variation in the mountainous village. These differences reflect village-specific predictor relevance under the same modelling workflow, rather than ad hoc manual selection. With predictive modelling detailed in Section 3.7, the following discusses comparative predictive performance and the preferred feature scope in each village.

5.1 Heqiao Village

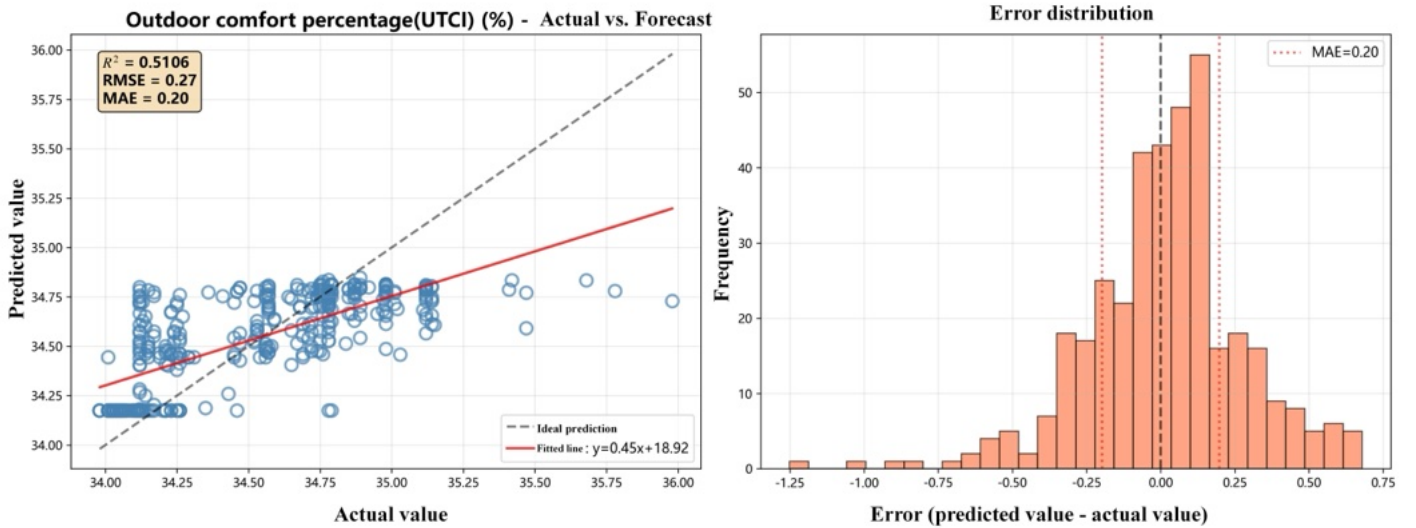
For Heqiao Village, the Top 8 model achieved the best overall performance, with the highest test-set R^2 (0.5657) and the lowest RMSE (0.25), while MAE remained comparable to that of the Top 5 model (Fig. 20). By contrast, the full model showed lower generalization performance, indicating that adding all available predictors did not improve accuracy. This suggests that in Heqiao, a moderately expanded but still compact feature set provides the best balance between predictive performance and model parsimony, and is therefore adopted as the preferred specification.



(a) Top-5 key indicators. (ANBS, WAR, FAR, AH, ISR)



(b) Top-8 key indicators. (ANBS, WAR, FAR, AH, ISR, ABA, BHI, GSR)

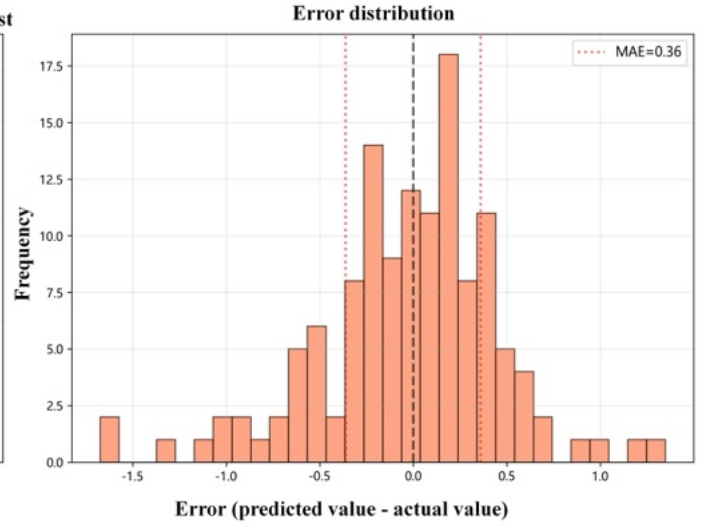
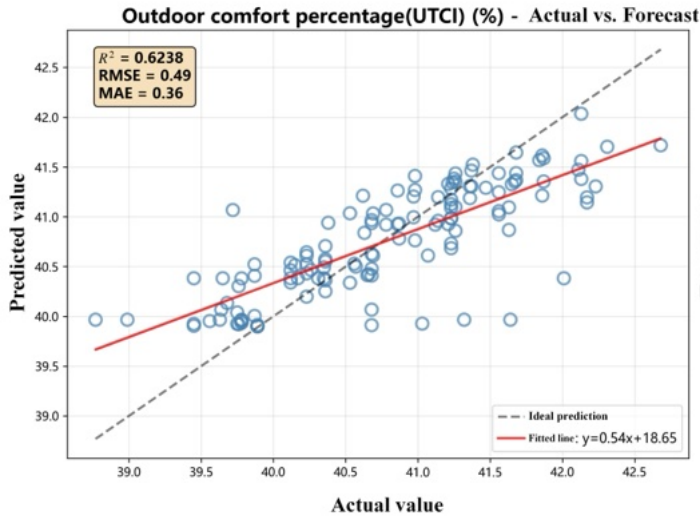


(c) All set (12 indicators).(ANBS, WAR, FAR, AH, ISR, ABA, BHI, GSR, SAR, RND, BDI, SVF)

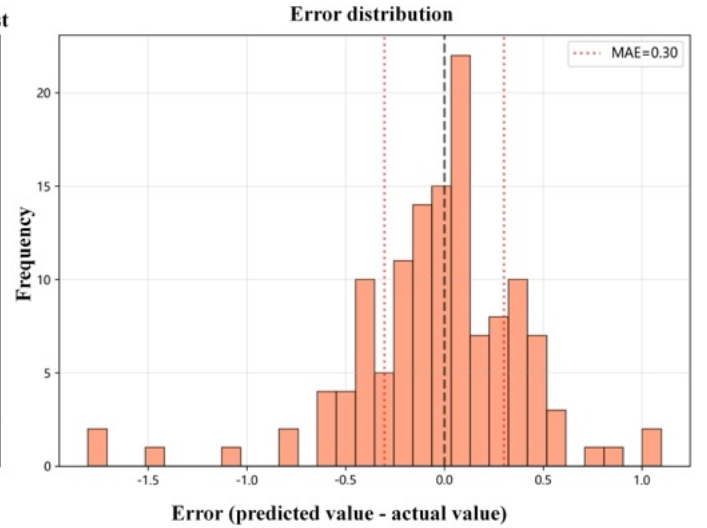
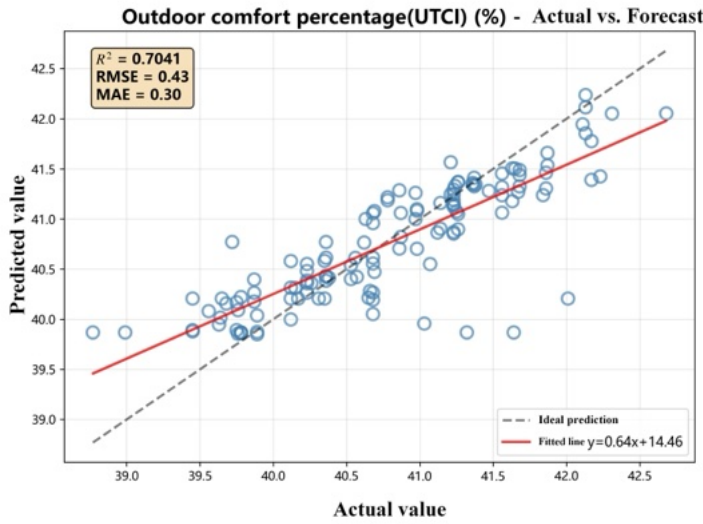
Fig. 20. Heqiao-Predicting UTCI from village morphology under different indicator scopes

5.2 Guachuan Village

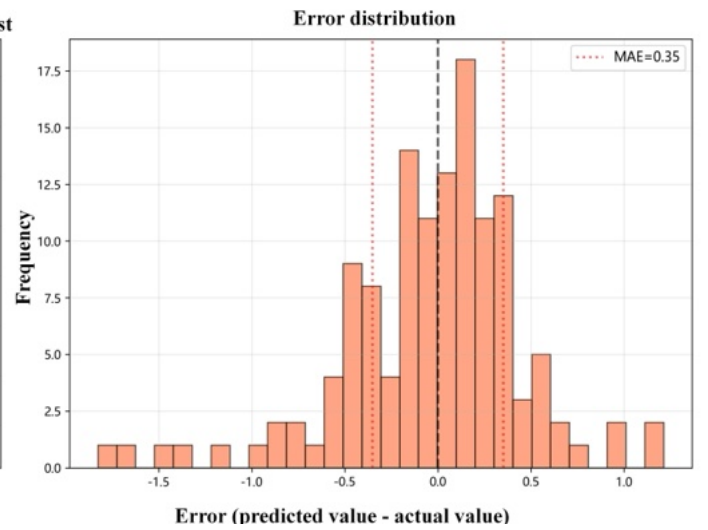
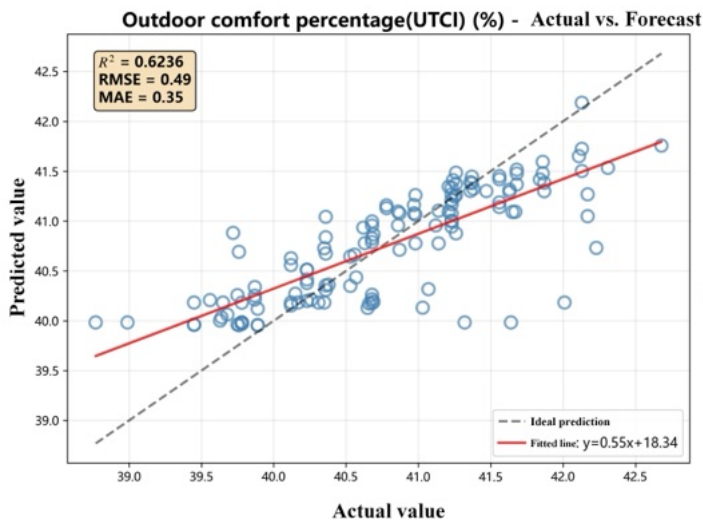
For Guachuan Village, the Top 8 model again achieved the best predictive performance, with the highest test-set R^2 (0.7041) and the lowest RMSE (0.43) and MAE (0.30) (Fig. 21). Both the Top 5 and full models performed less well, indicating that neither an overly compact nor a fully expanded feature set was optimal in this mountainous context. The results suggest that a moderately expanded feature scope is most effective for capturing the morphology-UTCI relationship in Guachuan and is therefore selected as the preferred specification.



(a) Top-5 key indicators. (GSR, BHI, FAR, RND, BDI)



(b) Top-8 key indicators.(GSR, BHI, FAR, RND, BDI, SAR, SVF, ABA)

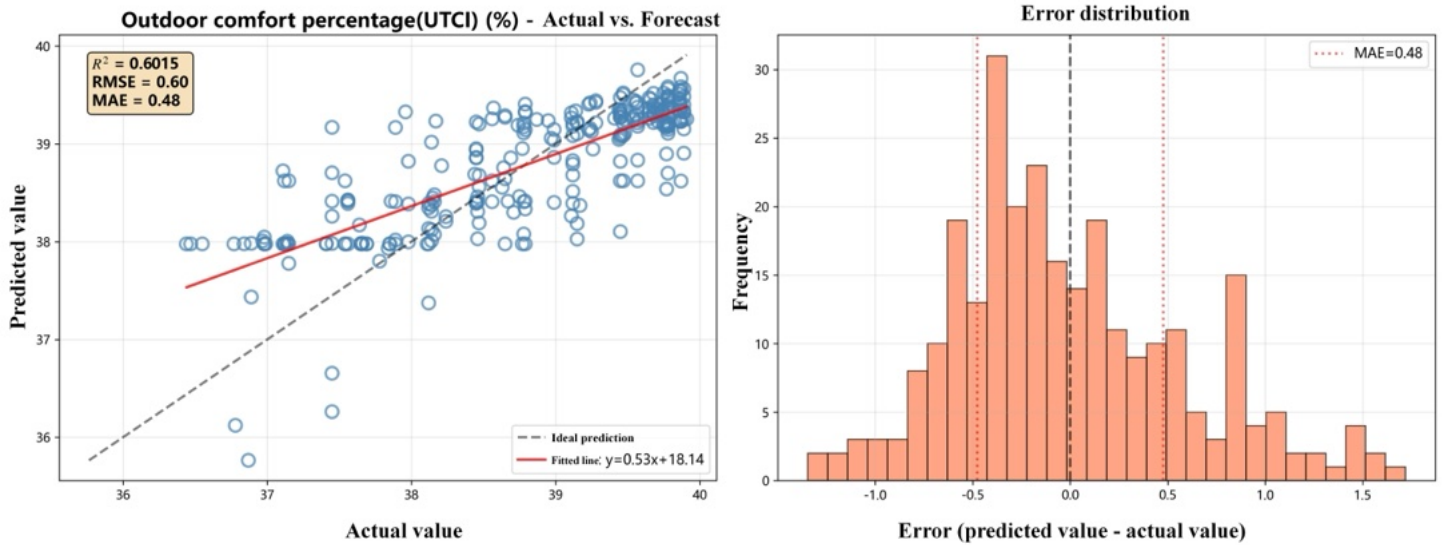


(c) All set (11 indicators). (GSR, BHI, FAR, RND, BDI, SAR, SVF, ABA, ISR, ANBS, AH)

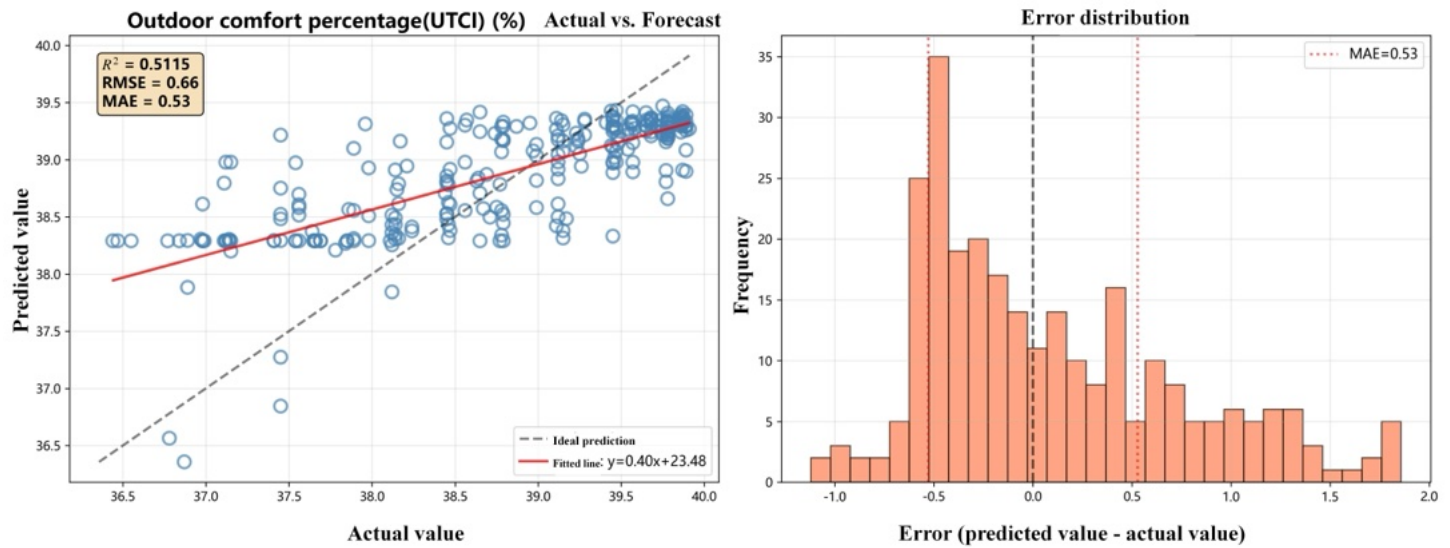
Fig. 21. Guachuan-Predicting UTCI from village morphology under different indicator scopes

5.3 Qinong Village

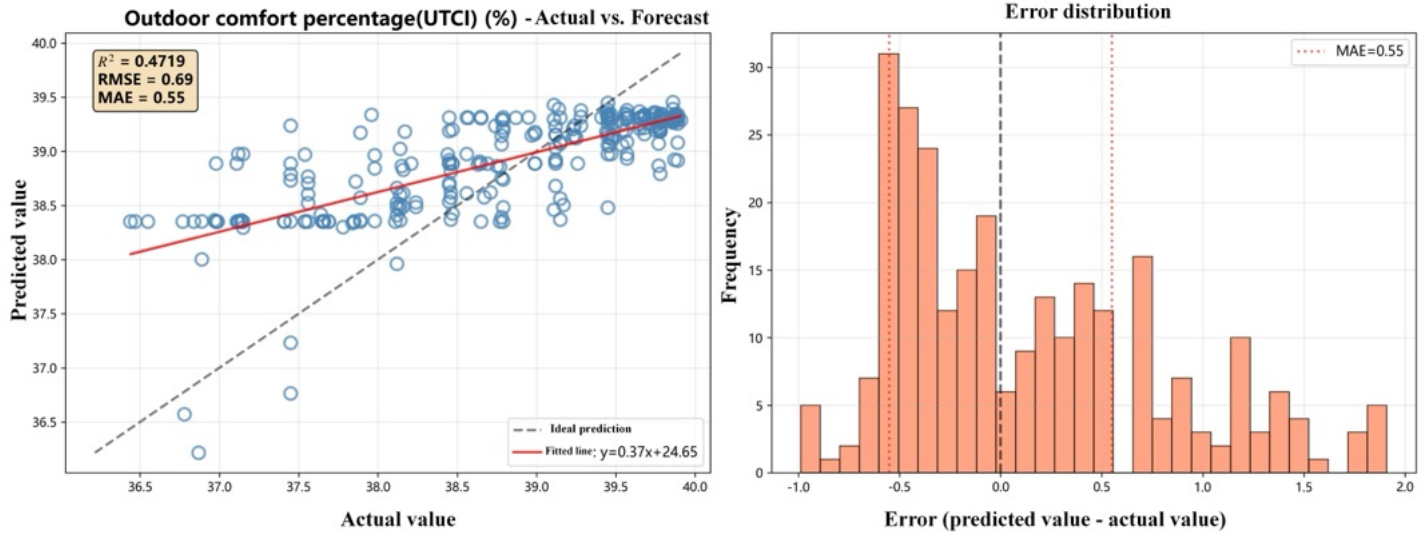
For Qinong Village, the Top 5 model performed best, with the highest test-set R^2 (0.6015) and the lowest RMSE (0.60) and MAE (0.48) (Fig. 22). Both the Top 8 and full models showed weaker generalization, indicating that adding more predictors mainly introduced redundancy rather than improving performance. This suggests that, in the relatively regular plain-village context, a compact feature set is sufficient to represent the dominant morphology-UTCI relationship and is therefore adopted as the preferred specification.



(a) Top-5 key indicators. (GSR, FAR, ISR, WAR, ABA)



(b) Top-8 key indicators. (GSR, FAR, ISR, WAR, ABA, BDI, RND, BHI)



(c) All set (12 indicators). (GSR, FAR, ISR, WAR, ABA, BDI, RND, BHI, AH, ANBS, SAR, SVF)

Fig. 22. Qinong-Predicting UTCI from village morphology under different indicator scopes

Overall, the optimal feature scope varies by village context: Heqiao and Guachuan achieve the best predictive performance with eight indicators, whereas Qinong performs best with a five-indicator set. This suggests that hydro-topographically more complex villages require a moderately expanded but still non-redundant predictor set, while the more regular plain-village context can be represented effectively by a smaller subset.

6. Conclusions and Implications

6.1 Theoretical Implications

This study integrates in-situ field measurements, ENVI-met simulations, and nonlinear statistical analyses within a three-tier indicator framework of spatial layout, spatial form, and spatial elements to examine how rural external morphology influences UTCI in typical villages of Lin'an, western Zhejiang.

The results show that morphology affects UTCI through scale-specific but coupled pathways. At the point scale, street-and-alley organization, SAR, and SVF mainly regulate solar exposure and ventilation. At the block scale, building-depth irregularity, street-space openness, and green-space ratio improve thermal comfort by enhancing airflow, reducing enclosure, and strengthening shading and evapotranspiration. At the settlement scale, FAR and impervious surface ratio reflect overall development intensity and ecological buffering capacity. These findings indicate that rural thermal comfort can be improved by jointly optimizing S–V–H.

The methodological contribution of this study lies in addressing nonlinear spatial–climate responses, weak cross-scale coupling, and limited interpretability in data-driven thermal-comfort research. By combining a structured multi-scale indicator system with interpretable ensemble learning, the study identifies feature effects, threshold-like responses, and geomorphology-dependent heterogeneity through XGBoost and SHAP, thereby improving the explanatory capacity of morphology–UTCI analysis.

The village-specific predictive analysis further shows that compact feature scopes can achieve reliable performance compared with the full indicator set. This suggests that a limited number of key morphology indicators can be used to support efficient, context-sensitive assessment of UTCI changes under alternative rural spatial design scenarios.

6.2 Managerial Implications

For planners and village managers, the results translate into a typology-aware, low-cost, and phased toolkit for microclimate-oriented spatial optimization, supported by grid-based diagnostics and scenario testing. In practice, this entails prioritizing interventions based on spatially explicit UTCI “micro-hotspot” detection, selecting a small set of controllable morphological levers at the appropriate scale (point, block, or settlement), and sequencing actions to maximize near-term benefits while maintaining feasibility under typical budget and construction constraints. Three exemplar applications are:

- (1) Waterfront villages benefit from limiting excessive FAR and improving street-space openness to enhance ventilation corridors while refining shading sequences.
- (2) Mountainous villages should prioritize increasing green-space ratio and adopt layered tree-shrub-lawn assemblages to enhance evapotranspiration and guide airflow along slope corridors.
- (3) Plain villages require coordinated increases in green-space share and controls on impervious surfaces, with interventions targeted at identified micro-hotspots and staged in accordance with the S–V–H principle.

6.3 Outlook

In this study, the findings are typology-oriented and context-dependent based on the selected representative villages in a single climate zone, with varying geomorphological contexts. Results show different emphases in morphology-UTCI regulation across village types: blue-green and water-related factors are more prominent in the riverside village, terrain-related enclosure and spatial heterogeneity are more influential in the mountainous village, and greenness, imperviousness, and development intensity are more important in the plain village. These findings inform the adaptive climate-responsive rural design strategies needed across geomorphological village types. Future research is to incorporate the presented framework with

broader regional samples, more diverse climatic contexts, and year-round simulation scenarios to further enhance its generalizability.

The indicator system may also be refined by incorporating façade reflectance, more detailed vegetation typologies, water-body morphology, anthropogenic heat, and diurnal exposure dynamics, while methodological robustness may be strengthened through deep learning, remote-sensing big data, spatiotemporal modelling, and uncertainty-aware estimation. Ultimately, the present framework can support more targeted rural planning, green-infrastructure design, and heat-risk management.

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