

Article

Exploring the Determinants of Rural Housing Vacancy in Mountainous Regions: Evidence from Jinshan Town, Fujian Province, China

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Abstract

The rational management of vacant rural housing is critical for optimization of Territorial Spatial Patterns. Although the issue of rural housing vacancy (RHV) has attracted widespread attention, systematic investigations in mountainous regions remain limited. This study is based on census data covering 3039 rural houses across six villages in Jinshan Town, Nanjing County, Zhangzhou City, Fujian Province, China. Using binary logistic regression and the XGBoost machine learning model, it systematically identifies the dominant determinants of rural housing vacancy in mountainous areas and evaluates their relative importance. The results show that the relative importance of the influencing factors is ranked as follows: locational conditions, physical housing characteristics, and topographic features. Specifically, among locational factors, the distances to the national road, county government, township government, and village committee centers are the most critical determinants of housing vacancy. In terms of physical attributes, the number of stories, the structural type, the floor area per story, and the orientation of the house are key variables. Regarding topographic factors, slope and aspect have limited overall influence. The two models yielded consistent directions and magnitudes of the key predictors, confirming the robustness and reliability of the results. The findings of this study help address the existing gaps in research regions, influencing factors, and methodological approaches, thereby contributing to the promotion of sustainable rural development.

Keywords: mountainous regions; rural housing vacancy; influencing factors; rural governance



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1. Introduction

Driven by accelerating globalization and rapid urbanization, countries around the world are experiencing varying degrees of RHV, reflecting deeper social, economic, and policy-related challenges. Both the United States and Japan have witnessed sharp rural population declines that have triggered community economic downturns, the contraction of public services, and the entrenchment of poverty [1–3]. Rural areas in several European countries—including Spain and Italy in Southern Europe, Germany in Central Europe, and various nations in Eastern Europe—have been facing growing marginalization due to population decline, accelerated ageing, sluggish industrial development, and stagnant public infrastructure provision [4–10]. This widespread phenomenon has prompted a

number of governments to re-evaluate rural land policies and residential patterns, thereby initiating efforts to promote [11] land reuse and implement rural revitalization strategies.

In China, the issue of rural housing vacancy (RHV) is more complex in both its manifestations and causes, encompassing multiple dimensions. In recent decades, rapid industrialization and urbanization have driven large-scale rural-to-urban migration, leading to an increasingly severe phenomenon of rural hollowing. According to China's Seventh National Population Census, the rural resident population declined to 509.8 million in 2020, a reduction of 164 million compared to 2010, with an average annual outflow rate of 3.2% [12]. During the first decade of the 21st century, China experienced a paradox: while its rural population declined by 133 million, the area of rural residential land paradoxically expanded by 2.03 million hectares. This demographic outflow led to an annual increase of 594 million m² of vacant rural dwellings. By 2017, the total idle and vacant rural residential land in China had reached approximately 2.00 million hectares, while the area of inefficiently utilized rural land exceeded 6 million hectares [13]. In 2019, the national vacancy rate of rural homesteads in China reached 10.7%, with the RHV rate exceeding 35% in some regions [14].

As rural residents migrate out, the issue of “hollow villages” has emerged across many rural areas [15,16]. This phenomenon has led to mismatches in land resource allocation, inefficient use of rural homesteads, a sustained decline in agricultural productivity, and potential threats to food security [17]. In addition, it has triggered a series of challenges including demographic shifts, reduced efficiency in public service provision, and the deterioration of rural living environments [18].

To address this challenge, the Chinese government has carried out a series of institutional arrangements and reform explorations at the national strategic level. Under the overall framework of the Rural Revitalization Strategy, the core initiative is to deepen the “three-tiered rights separation” reform of rural homestead land, namely, on the basis of safeguarding collective ownership and stabilizing household qualification rights, to appropriately relax the use rights of rural homesteads and idle housing, so as to open up an institutional channel for revitalizing idle resources [19]. Complementary policies have included the “linkage between the increase and decrease of urban and rural construction land” and locally piloted mechanisms for the compensated withdrawal of rural homesteads. These initiatives are intended to promote a more efficient allocation of land resources by introducing market-based incentives [20].

Existing research on RHV can be broadly divided into three main categories. The first focuses on estimating vacancy rates and analyzing their spatiotemporal characteristics. Scholars have applied data sources such as drone imagery [21], remote sensing data [22], nighttime light data [23], utility consumption records [24], and social media big data [25] to detect, identify, and estimate the spatial distribution of vacant housing, thereby revealing its macro-level clustering patterns and temporal evolution. The second category centers on the revitalization and governance strategies for vacant rural housing. This line of research emphasizes reforms in property rights and homestead systems [26,27], innovations in land transfer mechanisms [28], land consolidation practices [29], improvements in the legal system [30], and the integration of cultural and tourism industries [31–33]. It highlights the importance of activating idle resources through a combination of policy guidance [34–36], market-based approaches [35,37], and the active participation of rural organizations and farmers [38,39]. The third category of research focuses on the driving factors behind RHV. At the macro and meso levels, existing studies examine the roles of natural conditions [15], economic factors [40], locational attributes [41], policy and institutional frameworks [42], and infrastructure provision [43]. At the micro level, attention is given to household characteristics [44], family attributes [45], and housing conditions [46]. Together, these

studies reveal the dynamic mechanisms underlying RHV, shaped by the interplay of rural–urban migration, resource mismatches, and institutional constraints.

It is worth noting that existing studies lack a unified standard or clear definition of “RHV”. Some define it based on the degree of idleness, while others focus on changes in housing utilization and residential attributes. At the same time, there is a lack of a nationwide and systematic census approach specifically targeting vacant rural housing in China. Existing data are primarily derived from idle land statistics within land use surveys or from academic case-based sampling studies. While a variety of identification methods have been developed in academic practice, these diverse approaches have also led to inconsistencies in the definitional standards and data frameworks adopted across different studies. Although substantial progress has been made in the study of RHV, it remains necessary to further investigate the underlying mechanisms of RHV in the Chinese context. Previous studies have primarily focused on the Northeast China Plain, North China Plain, the Middle–Lower Yangtze Plain, the Pastoral–Agricultural Transitional Zone, the Loess Hilly Region, and metropolitan peripheries, while comparatively little attention has been paid to China’s coastal mountainous regions. Although coastal regions are generally characterized by strong economic performance, rural housing vacancy has also emerged as a prominent issue due to pronounced disparities between urban and rural development and the spatial heterogeneity between mountainous and coastal zones. Most existing studies on RHV have concentrated on macro-level scales such as the national, regional, or provincial levels [16,46], while relatively limited attention has been given to the integration of housing physical characteristics, fine-grained topographic features, and locational factors. Although parametric models have been widely employed, the nonlinear relationships and complex interaction effects among the driving factors of rural housing vacancy (RHV) have often remained insufficiently explored. In light of this, the present study seeks to address the following questions: Which factors are most strongly associated with RHV? And what kinds of nonlinear threshold patterns do these factors exhibit?

This study is organized into six sections. Section 2 reviews the relevant literature and, based on previous research, develops a theoretical framework for the factors influencing rural housing vacancy (RHV). Section 3 introduces the study area, describes the spatial distribution of RHV, and outlines the research methodology. Section 4 presents the results of spatial effect diagnostics and model selection, followed by the outcomes of both parametric and non-parametric models of RHV, as well as a comparative analysis of the two approaches. Section 5 discusses the spatial patterns and heterogeneous responses of RHV, examines its driving factors from three dimensions—locational conditions, topographic features, and housing attributes—and evaluates the applicability of spatial models. This section also highlights the limitations of the study and suggests directions for future research. Finally, Section 6 summarizes the main conclusions.

2. Literature Review and Theoretical Framework

2.1. Literature Review on RHV Determinants

RHV is a typical manifestation of rural transformation, driven by the evolving human–land relationship, shifts in urban–rural structures, and institutional governance mechanisms. Existing studies have explored the driving mechanisms of RHV from multiple dimensions. At the macro level, existing research highlights the dual influence of regional development trajectories and institutional constraints. Geographical endowments and levels of economic development provide the structural foundations for rural transformation [43,47], while land markets, labor mobility, and agricultural modernization mediate the allocation of urban–rural resources [48]. Concurrently, Policies such as the separation of three rights in rural homesteads and the household registration (*hukou*)

system reform have jointly driven rural land-use restructuring, combining binding regulatory frameworks with market-oriented incentives [34,37]. At the meso level, attention is focused on village environments. The natural attributes of land parcels [43,49], physical characteristics of villages [50,51], village social capital [37,48], and community cohesion [48] constitute the fundamental driving forces of population mobility through disparities in living convenience and development opportunities. At the micro level, research has focused on household decision-making, highlighting how family demographic structure [15,41], livelihood strategy choices [40,45], and preferences for rural–urban mobility [42,52] directly influence housing demand. Additionally, emotional attachment to land and the actual condition of homesteads further shape decisions regarding housing utilization [46,53]. Rural homestead vacancy and farmland abandonment, as cumulative outcomes of micro-level household behavior [17], not only constitute a dual withdrawal from rural areas in terms of livelihood spaces but also, in turn, constrain the economic vitality of villages [41]. Furthermore, cognitive factors play a sustained and pervasive role throughout the entire decision-making process. Farmers' evaluations of policy rationality, perceived potential for homestead value appreciation, and adaptability to urban life, and place attachment collectively mediate the translation of external conditions into concrete behavioral choices [54–56]. These four dimensions are not isolated from one another. Micro-level rational choices are conditioned by the opportunities provided at the meso level, while macro-level policies indirectly shape individual behavior by redefining the rules governing resource flows. Meanwhile, cognitive attitudes serve as a critical intermediary between objective constraints and subjective actions in contexts of information asymmetry. Together, they form a complex logical framework for understanding the spatial restructuring of rural areas. Notably, many macro- and meso-level driving factors—such as geographical conditions, regional economic development levels, and the accessibility of village-level infrastructure—are inherently characterized by significant spatial heterogeneity and clustering. The uneven spatial distribution of these influencing factors often results in spatial dependence in rural housing vacancy patterns—that is, whether a particular house is vacant may be associated with the status of neighboring dwellings [57]. Therefore, when investigating the driving factors, it is essential to diagnose potential spatial effects. If the model residuals exhibit significant spatial autocorrelation, this may violate the basic assumption of observational independence in conventional regression models, necessitating the use of spatial econometric methods for correction [58]. However, the effectiveness of these methods heavily depends on the alignment between the spatial structure of the data and the underlying theoretical mechanisms, and their applicability requires careful evaluation.

2.2. Theoretical Framework

This study constructs an integrated system-level framework encompassing macro-, meso-, and micro-level factors (Figure 1), grounded in push–pull theory, human–land relationship theory, and sustainable livelihood theory, to elucidate the transmission mechanisms across different levels. At the macro level, urbanization and the urban–rural income gap generate strong urban pull forces, while institutions such as the hukou and land systems shape the broader migration context by restricting or encouraging factor mobility. At the meso level, locational attributes affect the opportunity cost of remaining in rural areas by determining residents' accessibility to economic opportunities, public services, and infrastructure. Meanwhile, topographic variation shapes the natural foundation for rural production and living conditions by influencing agricultural suitability, infrastructure development costs, and residential safety risks. In coastal mountainous areas, the locational advantage of proximity to cities is often in tension with the topographic barriers of mountainous terrain. These opposing forces jointly constrain and ultimately determine

the actual development potential of villages. At the micro level, based on the sustainable livelihood framework, rural households assess their available livelihood assets and make rational decisions by weighing the expected net benefits of staying versus migrating. When the benefits of migration significantly outweigh those of staying, migration occurs, resulting in the vacancy of original dwellings. Within the above theoretical framework, this study focuses on examining its core components: the effects of meso-level village geo-environmental systems and micro-level housing physical conditions on RHV. Specifically, it quantifies three categories of variables—location, topography and geomorphology, and housing conditions—to verify the internal transmission mechanisms of meso-level factors and the direct effects of micro-level housing attributes.

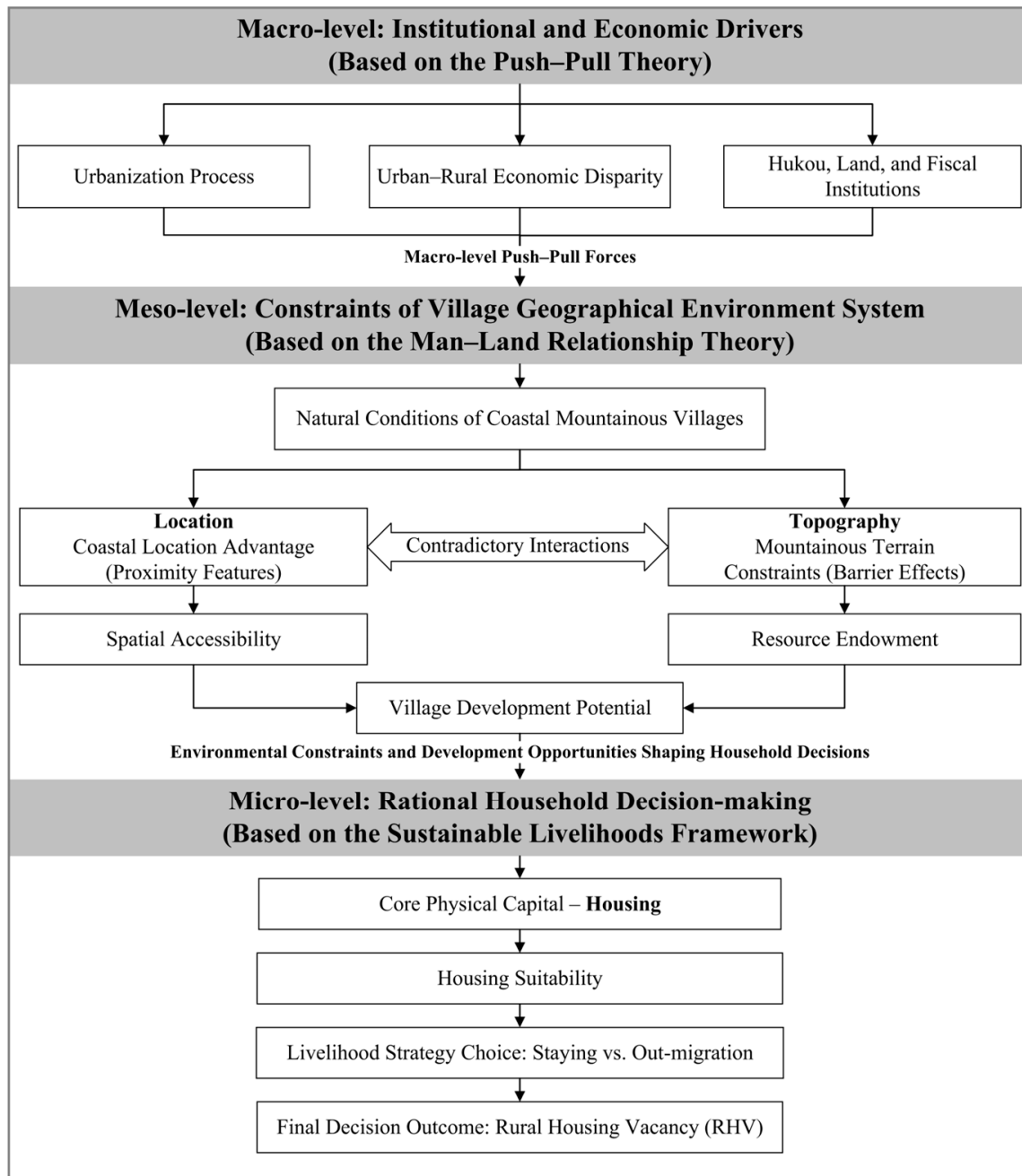


Figure 1. Theoretical Framework of Factors Influencing RHV in Mountainous Regions.

3. Data and Methods

3.1. Study Area and Spatial Distribution of RHV

3.1.1. Research Scope and Data Collection

Jinshan Town is located in the northeastern part of Nanjing County, Zhangzhou City, Fujian Province. Covering a total area of 234.23 km², the town administers one residential community and 19 administrative villages. As of 2022, the total population reached 37,022. The town is predominantly characterized by low mountainous and hilly terrain. As a mountainous township within a coastal city's jurisdiction, Jinshan Town is situated at the intersection of the urban–rural and mountain–sea gradients, embodying the typical characteristics of both types of spatial differentiation. On the one hand, the economically developed coastal cities of Fujian exert a strong siphon effect on the inland mountainous areas; on the other hand, the geographical differentiation between mountains and the sea leads to an uneven spatial distribution of development opportunities.

Against this backdrop, Jinshan Town is simultaneously subject to the population outflow pressures induced by urbanization and the development constraints imposed by its mountainous terrain, making it an ideal case for examining how dual gradients shape rural housing vacancy. Its pronounced “coastal–mountainous” spatial dichotomy exemplifies the broader developmental dilemmas faced by mountainous regions across Fujian and the broader southeastern coastal areas, thereby offering strong regional representativeness [59]. Based on the functional classification of villages outlined in the Rural Revitalization Strategic Plan (2018–2022), this study focuses on three types of villages: those designated for relocation and consolidation, those under heritage protection, and those targeted for agglomeration and upgrading. Following preliminary field surveys and in-depth consultations with local natural resources departments and village committees, six sample villages were selected to represent each planning type with clear distinctions. The study area is shown in Figure 2.

This study conducted a systematic field census in six sample villages of Jinshan Town. Data were collected between July and August 2022. First, all buildings within the study area were manually interpreted and identified based on 0.6 m resolution satellite imagery of Jinshan Town, which was obtained from the ArcGIS REST Services Directory (<https://services.arcgisonline.com/arcgis/rest/services>, accessed on 5 June 2022). Second, the research team conducted field surveys village by village, using the outdoor tracking application Footprint App (known in Chinese as Liuzhijiao, literally “Six Footprints”) to geotag and photograph each house on site, while recording its structural type, number of stories, and orientation. To accurately delineate the status of rural housing vacancy (RHV), this study specifically focuses on its most severe form—namely, “abandoned rural housing,” defined as dwellings that have been entirely deserted, left uninhabited for an extended period, and have largely lost their functional utility.

The identification of such housing integrates two criteria: objective visual assessment and local resident confirmation. (1) Objective indicators include visibly derelict conditions such as serious structural damage, partial collapse, broken doors and windows, and overgrown or untended courtyards. (2) Resident-based confirmation was obtained through interviews with village officials and elderly long-term residents, who verified that the homeowners had relocated to urban areas for many years and expressed no intention of returning. To validate the RHV classification, the research team adopted a participatory mapping approach. Village officials and informed residents were invited to cross-check the preliminary image interpretation and field observations, confirming each dwelling's ownership status, household composition, and actual occupancy condition. Through the integration and cross-validation of multi-source data, a geospatial database was ultimately constructed comprising 3039 housing units across six villages.

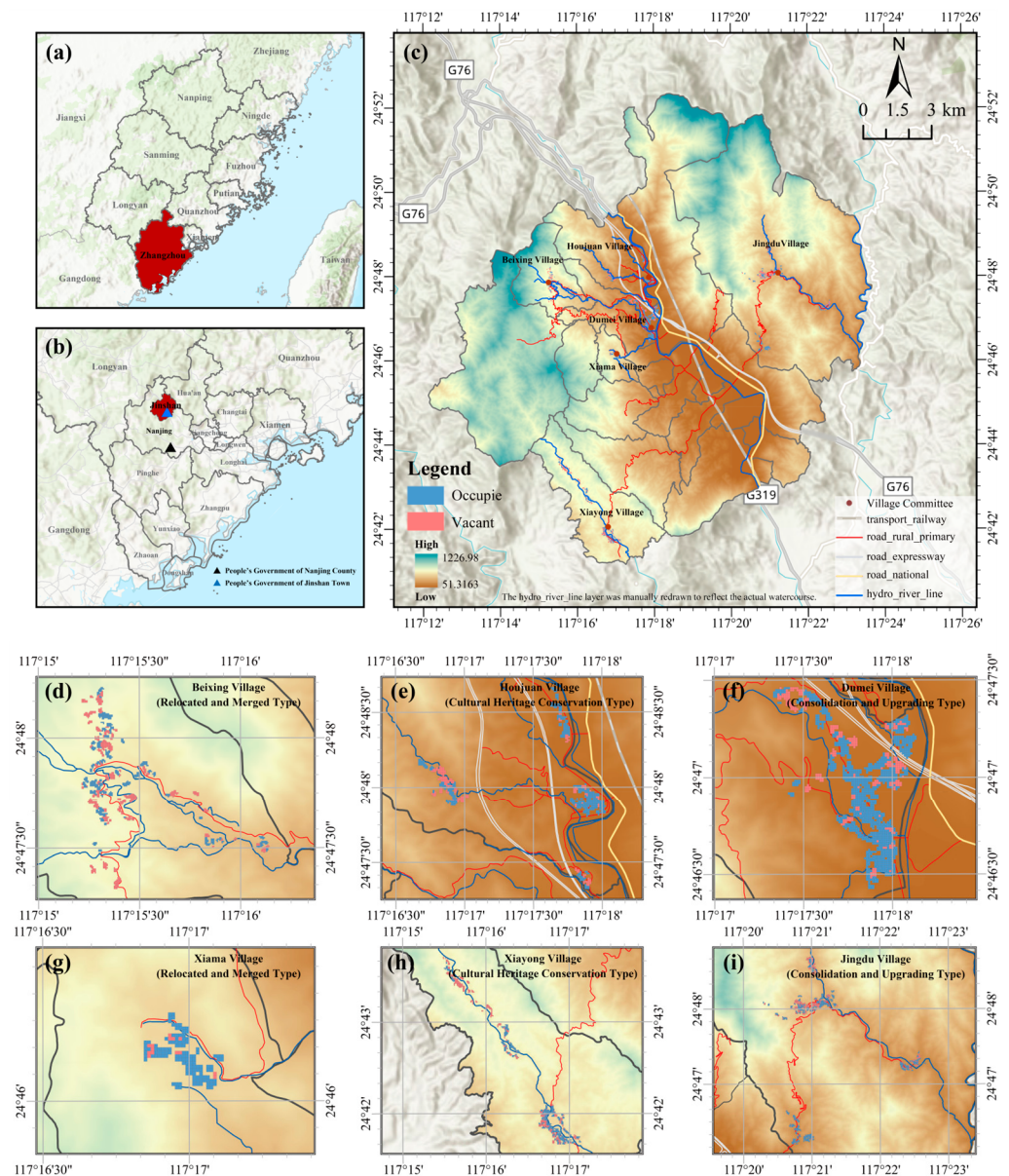


Figure 2. Location of the study area: (a) Zhangzhou City, (b) Nanjing County, (c) Jinshan Town, and (d) Beixing Village, (e) Houjuan Village, (f) Dumei Village, (g) Xima Village, (h) Xiayong Village, and (i) Jingdu Village.

In addition, village-level contextual data were collected from multiple sources, including the Natural Resources Bureau of Nanjing County, the Rural Revitalization Strategic Plan (2018–2022), the Nanjing County Statistical Yearbooks (2014–2022), the Nanjing County Master Plan (2012–2030), the Nanjing County Territorial Spatial Plan (2020–2035), the village plans of the six sampled villages in Jinshan Town, and interviews with local village committees. The municipal and county boundaries, administrative center locations, as well as major road and river data were obtained from the National Geographic Information Resource Catalogue Service Platform. The river data, though a simplified representation of the major hydrological system, effectively conveys the dominant spatial configuration despite not capturing the full morphological complexity of natural waterways. A 12.5-m resolution Digital Elevation Model (DEM) was acquired from NASA's Earth Science Data Portal (<https://search.asf.alaska.edu/#/>, accessed on 3 November 2023), enabling the extraction of topographic variables such as elevation, slope, and aspect for each housing unit. Furthermore, GIS-based nearest-neighbor analysis was employed to compute the

distance from each housing unit to key spatial features, including Nanjing County Government center, Jinshan Township Government center, village committee centers, rivers, and national highways. The overall methodological flow is illustrated in Figure 3.

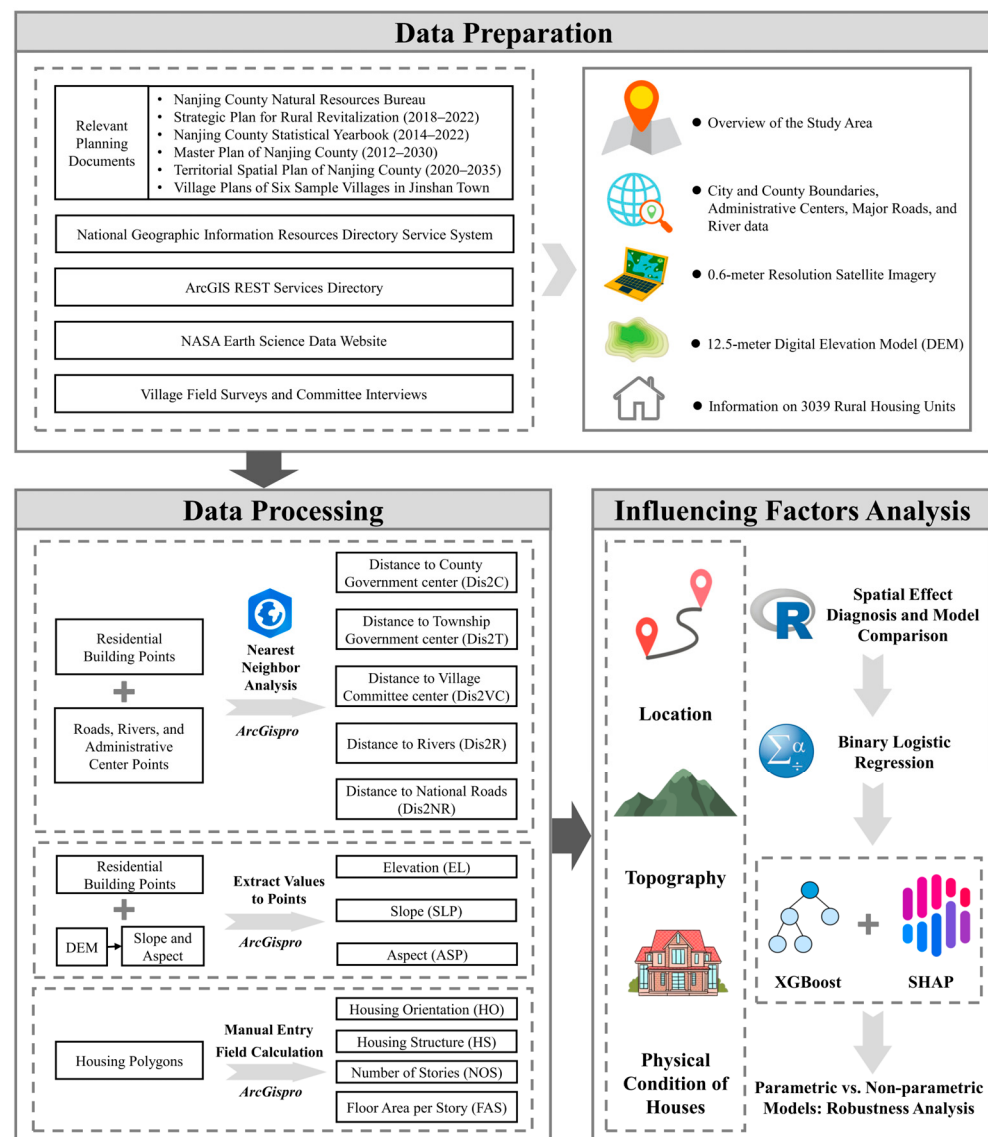


Figure 3. Overall methodological flow of the study.

3.1.2. Overall Distribution Characteristics

Statistical analysis reveals that the average vacancy rate across the six sampled villages reaches as high as 31.39%, with substantial inter-village variation ranging from 15.79% to 53.82%—a difference of more than threefold between the highest and lowest rates. Figure 2 visualizes the spatial distribution of all housing units, differentiating between vacant and occupied dwellings, while Figure 4 presents the on-site conditions of vacant rural housing in the study area. As shown in Table 1, the sample villages also differ markedly in terms of planning classification, population size, economic development level, and resource endowment. For instance, both Beixing Village (53.82%) and Xiayong Village (48.34%) exhibit high vacancy rates, yet they are positioned on distinctly different development trajectories: Beixing is categorized under the “relocation and consolidation” type, whereas Xiayong falls within the “heritage protection” category.



Figure 4. On-site conditions of vacant rural housing.

Table 1. Basic characteristics of the sample villages.

Village Name	Beixing	Xiama	Xiayong	Houjuan	Dumei	Jingdu
Village Type	Relocated and Merged Type	Relocated and Merged Type	Cultural Heritage Conservation Type	Cultural Heritage Conservation Type	Consolidation and Upgrading Type	Consolidation and Upgrading Type
Topography	Hilly Area	Hilly Area	Hilly and Plain Area	Plain Area	Plain Area	Low and Medium Mountains
Village Area (ha)	801.23	281.25	1471.78	1074.47	797.87	5885.21
Village Clinic Staff per 1000 Agricultural Population (persons/1000)	2.24	3.03	0.66	0.61	0.65	0.6
Number of Rural Public Toilets (count)	2	0	4	1	1	1
Per Capita Road Area (m ² /person)	0.022	0.010	0.171	0.383	0.138	0.056
Registered Population (persons)	448	315	1521	1437	2259	1655
Proportion of Resident Population (%)	0.699	0.098	0.414	0.741	1.093	0.447
Total Collective Assets of the Village (10,000 CNY)	2.4	10	11	60	3.6	12
Per Capita Disposable Income of Rural Residents, (CNY)	8000	2000	12,000	10,000	8000	20,000
Proportion of Income from Migrant Work (%)	0.210	0.179	0.148	0.178	0.186	0.130
Land Reclamation Rate (%)	0.029	0.037	0.053	0.062	0.099	0.022
Per Capita Cultivated Land Area (m ² /person)	50.89	61.81	320.7	479.47	250.2	773.29
Number of Distinctive Buildings (count)	1	0	3	4	3	4
Number of Types of Traditional Activities (count)	0	2	2	4	0	0
Overall Housing Vacancy Rate (%)	53.82%	15.79%	48.34%	23.26%	16.83%	30.31%

3.1.3. Spatial Clustering Characteristics

Housing points were aggregated into 300-m hexagonal grid cells, and vacancy rates were calculated for each cell. A hot spot analysis using the Getis-Ord G_i^* statistic [60] was then performed to identify clusters of high and low vacancy rates—namely, hot spots and cold spots. As shown in Figure 5, hot spot areas are primarily concentrated in Beixing and Xiayong villages. In terms of spatial morphology, hot spots in Beixing are distributed in a contiguous pattern along the main road in the southern part of the village, whereas in Xiayong, they extend linearly along the river. These patterns suggest widespread housing abandonment across substantial areas of both villages.

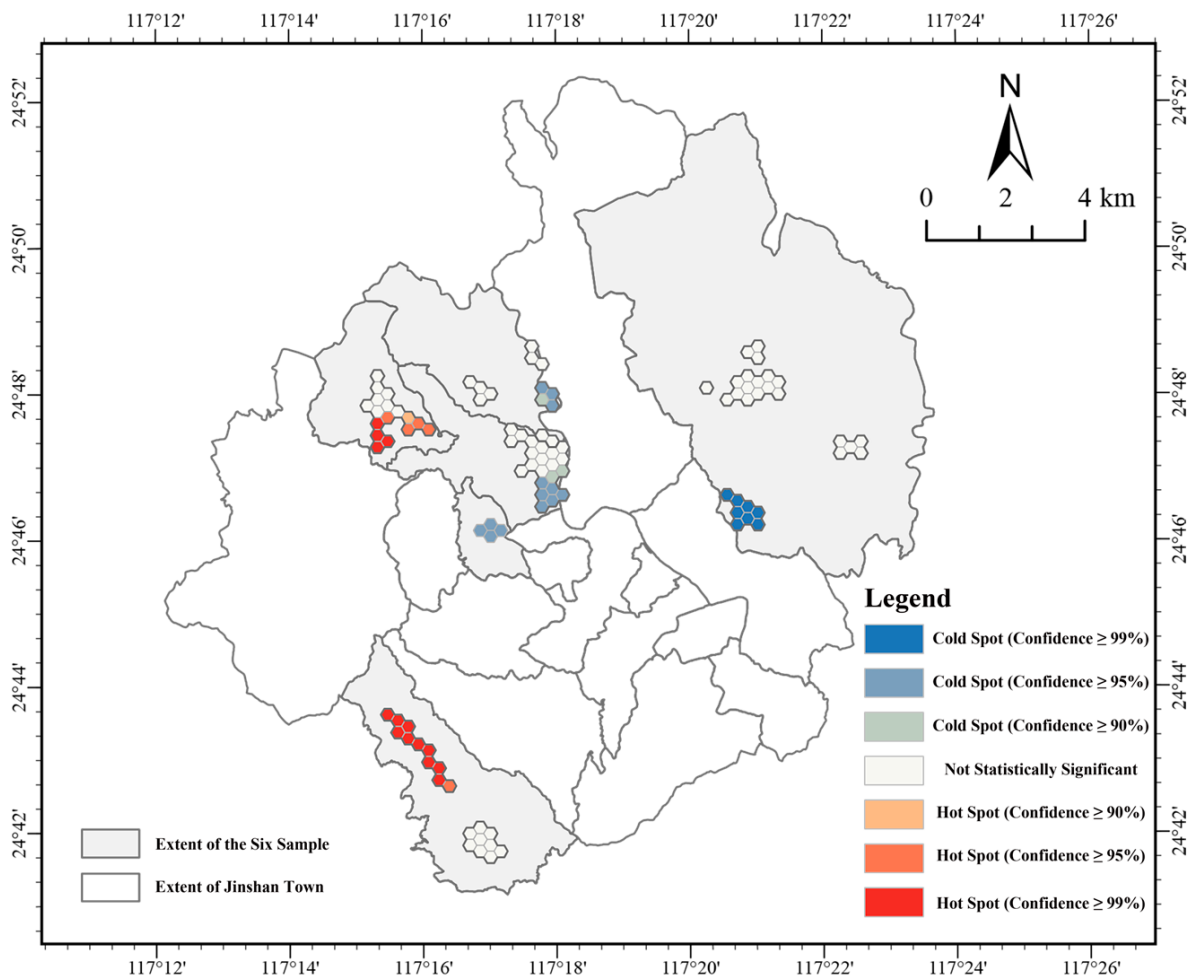


Figure 5. Hot spot analysis (Getis-Ord G_i^*) of RHV based on 300-m hexagonal grids.

3.2. Research Methods

3.2.1. RHV and Its Determinants

This study selects a total of 12 indicators across three categories to measure the factors influencing RHV, as outlined in the variable framework shown in Table 2. Locational variables [48,61] reflect the spatial accessibility of housing; distances to county government, township government, and village committee centers, national highways, and rivers collectively constrain access to public services, employment opportunities, and asset liquidity, forming the structural context that influences vacancy risk. Topographic factors influence agricultural production, residential safety, and living costs through slope [49,62,63] and elevation [64]. This study further incorporates slope aspect to capture its regulatory effects on housing livability in terms of microclimate, sunlight exposure, and energy consumption [65–70]. As the primary form of household physical capital, housing attributes—such as floor area [16,45,51,71], building age [16,53], construction quality [48,55], building materials [55,72], structural type [72,73], and number of stories [74]—influence housing use status through capital investment, residential quality, and maintenance costs. This study further incorporates house orientation and floor area per story to capture their combined effects on physical performance and cultural preferences.

Table 2. Variable Definitions and Descriptive Statistics.

Variable Category	Variable Name	Variable Description	Mean	SD	Min	Max	
Dependent variable	Housing Vacancy Status	0 = Occupied; 1 = Vacant	0.300	0.457	0	1	
	Location	Distance to County Government center (Dis2C)	Distance from housing to county center Government (km)	29.107	3.415	20.745	33.159
		Distance to Township Government center (Dis2T)	Distance from housing to township government (km)	5.796	1.608	2.736	9.250
		Distance to Village Committee center (Dis2VC)	Distance from housing to village committee (km)	0.855	0.896	0.002	3.768
		Distance to Rivers (Dis2R)	Distance from housing to nearest river (km)	0.379	0.533	0.000	2.445
		Distance to National Roads (Dis2NR)	Distance from housing to nearest national road (km)	2.885	2.470	0.133	7.733
	Topography	Elevation (EL)	Elevation derived from DEM (m)	260.421	176.868	78.129	613.539
		Slope (SLP)	Natural terrain slope (°)	8.104	5.934	0.001	31.441
	Physical Condition of Houses	Aspect (ASP)	E; EN; ES; W; WN; WS; N; S	—	—	—	—
		Housing Orientation (HO)	E; EN; ES; W; WN; WS; N; S	—	—	—	—
		Housing Structure (HS)	Earth, Timber, Brick-Concrete, Steel-Concrete, Others.	—	—	—	—
		Number of Stories (NOS)	1 story, 2 stories, 3 stories, 4 stories	1.690	0.829	1	4
		Floor Area per Story (FAS)	Average Floor Area per Story (m ²)	143.824	138.841	20.211	2275.778

Note: A hyphen (–) denotes that the statistic is not applicable or not calculated for the variable.

3.2.2. Diagnosis of Spatial Effects and Model Selection

To identify potential spatial dependence in rural housing vacancy decisions, this study first conducts a diagnostic test for spatial effects prior to constructing the final explanatory models. Specifically, binary logistic regression and XGBoost models are employed as baseline models, and Moran's I tests are performed on their residuals to examine the presence of spatial autocorrelation [57]. If significant spatial autocorrelation is detected, two strategies are adopted: (1) introducing village-level fixed effects via two approaches: FE-Logit with village dummies, and XGBoost based on Frisch–Waugh–Lovell (FWL) residuals [75], to control for village-level heterogeneity. (2) Constructing spatial econometric models, including the Spatial Autoregressive Probit (SAR-Probit) model and the Spatial Error Probit (SEM-Probit) model, to capture endogenous interaction effects and spatially omitted variables, respectively [58]. During model selection, statistical properties such as multicollinearity, goodness of fit, the structural validity of the spatial weight matrix, and its alignment with the data characteristics are comprehensively assessed to ensure that the chosen model aligns with the theoretical framework and data structure of this study.

3.2.3. Parametric Model: Binary Logistic Regression

This study employs a parametric binary logistic regression model to identify the significant driving factors of rural housing vacancy and determine their directions of influence [76]. In the model design, RHV is defined as the dependent variable Y , where a value of 1 indicates a vacant house and 0 indicates a non-vacant house. The influencing factors of vacancy are denoted as X , with individual variables represented as $X_1, X_2, \dots, X_n$. Accordingly, a binary logistic regression model with multiple independent variables is specified as follows:

$$P = \frac{\exp(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)}{1 + \exp(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)} \quad (1)$$

During the regression analysis, a logit transformation is applied to derive the final probability function, resulting in the following linear regression model between the log-odds and the independent variables:

$$\text{Logit}(P) = \ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (2)$$

In Equation (2), represents the probability of housing vacancy, $\beta_1, \beta_2, \dots, \beta_n$ denote the regression coefficients of the influencing factors, and β_0 is the intercept term.

3.2.4. Non-Parametric Models: Machine Learning Models and SHAP Interpretability Method

To reveal potential nonlinear relationships and complex interactions among the driving factors of rural housing vacancy (RHV), this study employs seven classification algorithms—Gradient Boosted Decision Trees (GBDT), K-Nearest Neighbors (KNN), Logistic Regression (LR), Multilayer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)—to construct binary classification models for predicting RHV. To identify the optimal model, this study adopts Accuracy, Precision, Recall, F1 Score, and the Area Under the Curve (AUC) as evaluation metrics. The model with the highest predictive performance and strongest explanatory power was ultimately selected to identify the key driving factors of RHV and to determine their effect thresholds.

SHAP, an additive attribution algorithm grounded in game theory [77], quantifies the contribution of each feature to the model's output by computing SHAP values, thereby

revealing complex associations between predictors and outcomes. The SHAP value is calculated as follows [78]:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f_{S \cup \{i\}}(x_{S \cup \{i\}}) - f_S(x_S)] \quad (3)$$

In Equation (3), ϕ_i represents the SHAP value of feature i , reflecting the weighted average of its marginal contribution to the prediction outcome across all possible feature combinations.

4. Results

4.1. Diagnostic Results of Spatial Effects and Model Comparison

The diagnostic results reveal significant spatial autocorrelation in the residuals of the baseline binary logistic regression (Moran's $I = 0.282$, $p < 0.001$) and XGBoost models (Moran's $I = 0.1819$, $p < 0.001$), indicating the necessity of cautious model specification. To address this, we evaluated two approaches. First, village-level fixed effects were introduced. The residual spatial autocorrelation in the FE-Logit and XGBoost on FWL residuals models showed only a slight decline, with Moran's I values decreasing to 0.274 and 0.178, respectively. The core findings of the FE-Logit model remained highly consistent with those of the baseline model (Tables S1 and S2). However, this adjustment induced severe multicollinearity with key locational variables ($VIF > 70$) (Table S3), rendering parameter estimation invalid. Secondly, spatial econometric models (SAR/SEM) are unsuitable in this study due to the "island-like" geographic distribution of the samples (Table S4), which severely violates the assumption of spatial continuity. Moreover, the neighborhood diffusion mechanism underlying the SAR model is theoretically inconsistent with this study's framework, which emphasizes the vertical transmission of locational endowments at the village level and household migration decisions. Theoretically, the SEM model is suitable for capturing unobserved spatially omitted variables. However, since the locational variables have already adequately represented village effects (as indicated by the FE models), the information the SEM attempts to identify has effectively been absorbed. In addition, deficiencies in the specification of the spatial weight matrix led to model failure, with the residual Moran's I increasing rather than decreasing to 0.288 and 0.413, respectively.

This systematic diagnostic indicates that, given the specific data structure of this study, more complex spatial models not only fail to enhance explanatory power but also introduce new statistical challenges. Accordingly, following the Principle of Parsimony in statistics, this study ultimately adopts binary logistic regression and XGBoost as the core analytical tools—the former for robust identification of key determinants, and the latter for uncovering complex nonlinear relationships. Together, they constitute the optimal analytical framework for this research.

4.2. Causes of Rural Housing Vacancy

4.2.1. Parametric Model Analysis: Identification of Key Influencing Factors

Prior to constructing the binary logistic regression model, all independent variables were subjected to multicollinearity diagnostics. Continuous variables were evaluated using the Variance Inflation Factor (VIF), while categorical variables were assessed using the generalized variance inflation factor adjusted by degrees of freedom ($GVIF(1/(2 \times df))$), with a threshold of 10 applied to both. The diagnostics revealed strong multicollinearity between DEM and variables such as distance to national roads, which stems from the geographic characteristics of coastal mountainous areas. Elevation constrains topographic relief, and major transportation routes are typically constructed along low-lying areas, forming a spatial pattern in which "the higher the elevation, the farther from main roads." In addition,

slope is itself a derivative indicator of elevation. To avoid redundant representation, the DEM variable was excluded, reducing the average VIF of the model to 1.939 (Table S5), which falls within an acceptable range.

Model fit diagnostics indicate that the Hosmer–Lemeshow test yields a p -value of 0.287 (>0.05), suggesting a good agreement between predicted and observed values. The area under the ROC curve (AUC) is 0.809, indicating strong discriminative power. The Nagelkerke R^2 is 0.334, implying that the independent variables explain 33.4% of the variation in the dependent variable. Overall, the model demonstrates credible explanatory power. Regression results are presented in Table A1.

These results show that housing orientations toward east-south (HO_ES) and west-north (HO_WN), brick–concrete structures (HS_BC), two-, three-, and four-story buildings (NOS_2, NOS_3, NOS_4), and slope degree (SLP) were found to significantly reduce the probability of RHV. Conversely, wooden structures (HS_Timber) and earth structures (HS_Earth), floor area per story (FAS), east-north slope aspect (ASP_EN), and the distances to county government centers (Dis2C), township government centers (Dis2T), and national roads (Dis2NR) significantly increased the likelihood of housing vacancy. The remaining variables were not statistically significant in this model and may require further investigation.

4.2.2. Nonparametric Model Analysis: Variable Importance and Nonlinear Relationships

(1) Evaluating the Predictive Accuracy of the XGBoost Model

To provide a scientifically robust interpretation of the mechanisms driving RHV, this study employed a data-splitting strategy consisting of 70% training data, 10% validation data, and 20% test data. Combined with parameter tuning procedures, the predictive performance of seven machine learning models was compared and evaluated. As shown in Table S6, in terms of performance evaluation metrics, the XGBoost model achieved the highest predictive accuracy among all models, with AUC values of 0.93 on the training set and 0.88 on the test set. This indicates that the model effectively meets the analytical need to uncover the nonlinear mechanisms underlying RHV. Table S7 presents the hyperparameter settings of the seven models.

(2) SHAP-Based Variable Importance in Explaining RHV

This study employed the SHAP summary bar plot (Figure 6a), SHAP beeswarm plot (Figure 6b), and SHAP value heatmap (Figure 6c) to preliminarily explore the relative importance and global impact of each variable. These visualizations help interpret the average contribution of each feature and its specific influence on housing vacancy across all samples. In terms of overall importance (bar plot), the distance to national roads (Dis2NR) ranked first, contributing 58%, followed by the distance to township government centers (Dis2T, 39%), number of stories—one story (NOS_1, 33%) and three stories (NOS_3, 31%)—distance to village committee centers (Dis2VC, 28%), and brick–concrete housing structure (HS_BC, 26%). The distance to county government centers (Dis2C) contributed 23%, while earth structure (HS_Earth) and distance to rivers (Dis2R) each accounted for 21%. Slope (SLP) and floor area per story (FAS) contributed 17%, housing orientations toward east–south (HO_ES) and west–south (HO_WS) contributed 13% and 12%, respectively. The remaining 19 features collectively contributed 38%.

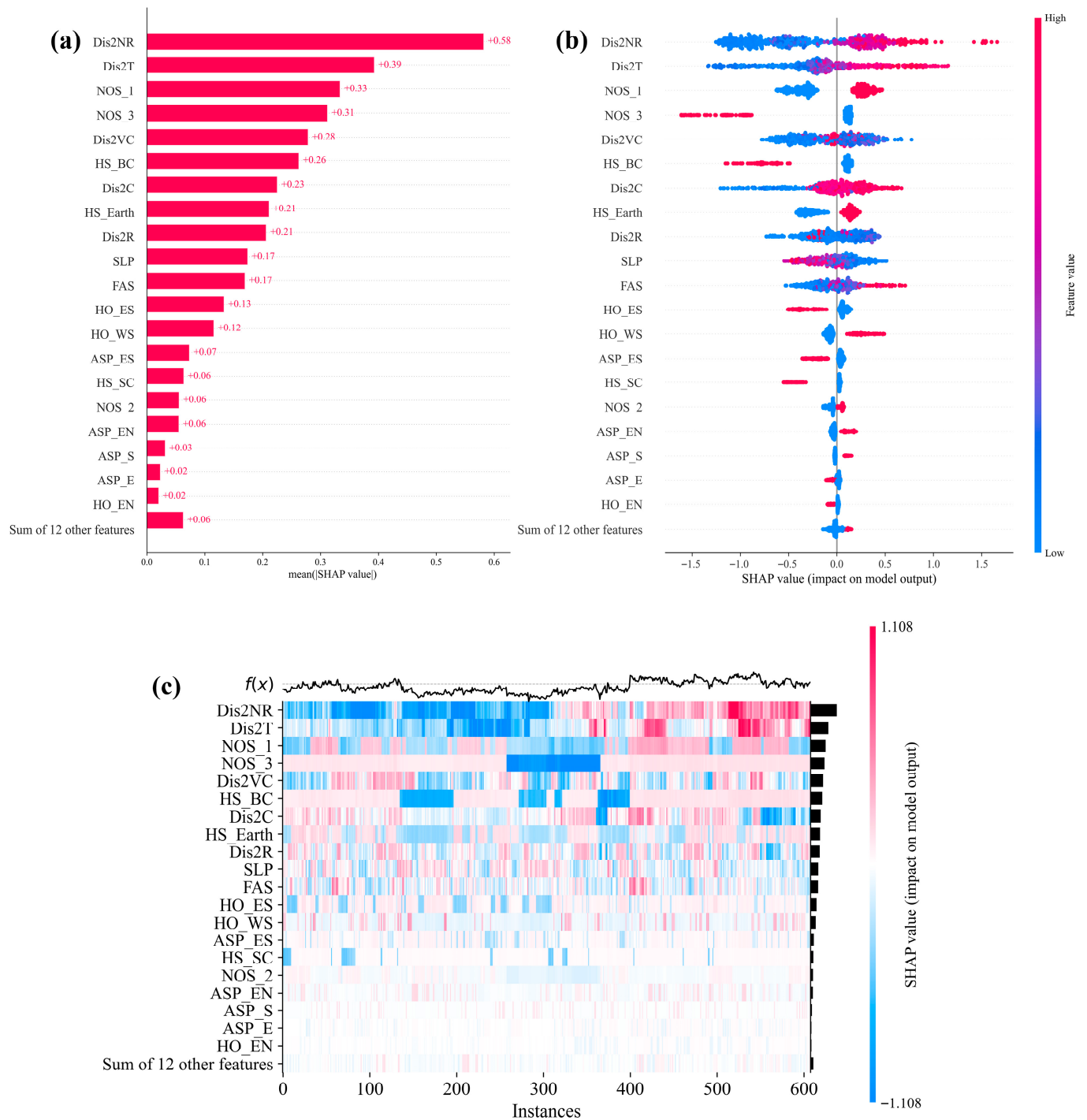


Figure 6. (a) SHAP Summary Bar Plot of RHV Determinants; (b) SHAP Beeswarm Plot of RHV Determinants; (c) SHAP Heatmap of RHV Determinants.

(3) SHAP-Revealed Nonlinear Effects on RHV

This study plotted SHAP feature dependence diagrams for the seven continuous variables in the model and applied LOESS curves (locally weighted regression smoothing) to fit the scatter data, as shown in Figure 7. This method synthesizes information from all samples to provide a global perspective on the impact patterns of each variable. It enables the identification of key thresholds, nonlinear inflection points, and the dynamic effects of variables on housing vacancy status.

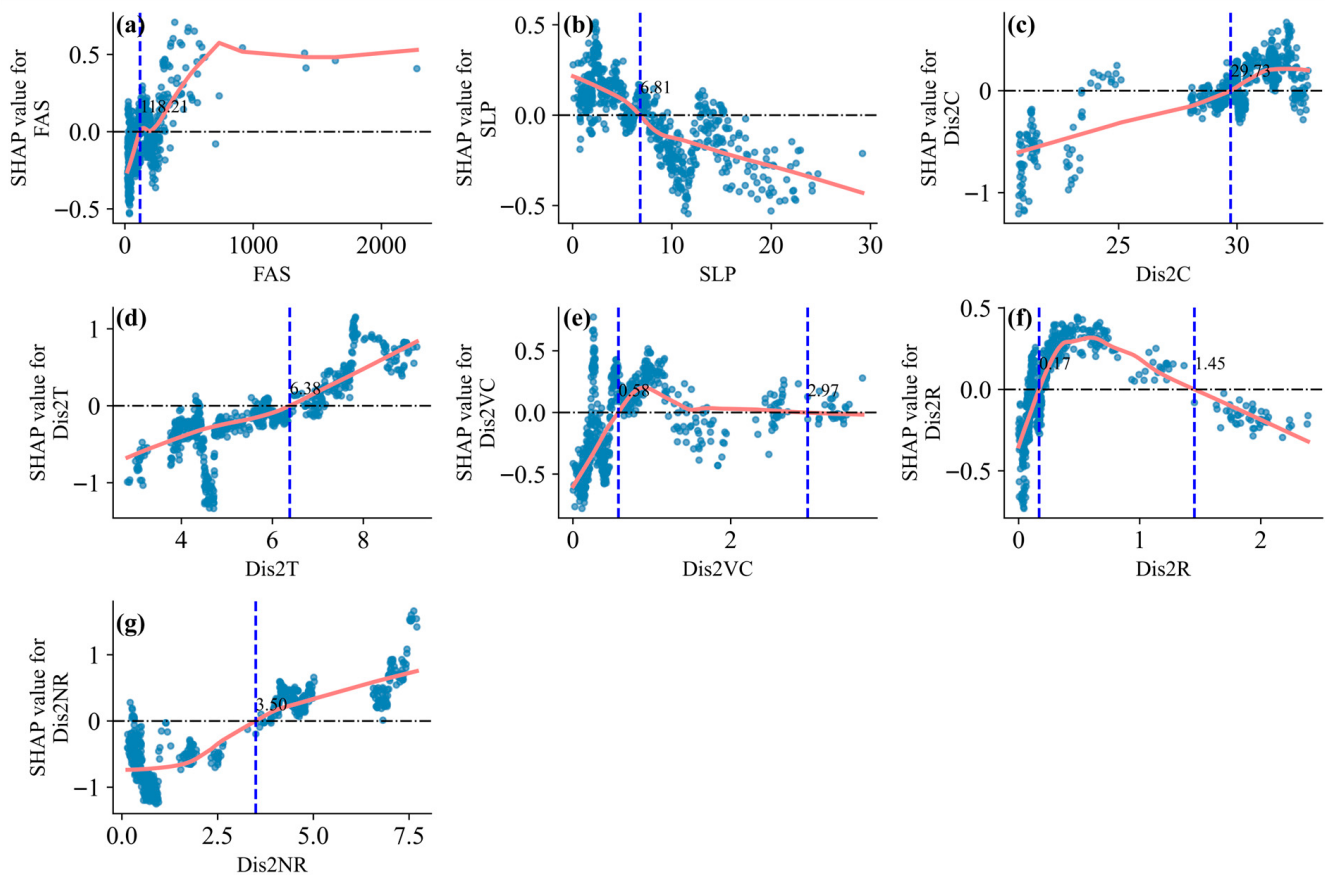


Figure 7. SHAP Dependence Plots of RHV Determinants. ((a): FAS, (b): SLP, (c): Dis2C, (d): Dis2T, (e): Dis2VC, (f): Dis2R, (g): Dis2NR).

SHAP dependence analysis revealed that floor area per story (FAS) exhibited an “accelerated increase–plateau” pattern in relation to vacancy risk. A critical inflection point was observed at 118.21 m²: below this threshold, smaller floor areas were associated with lower risk; above it, the effect became positive, and the rate of increase gradually leveled off after 500 m². Slope degree (SLP), in contrast, showed a “linear decline” pattern, with 6.81° identified as a key threshold. Vacancy risk was higher in low-slope areas and decreased rapidly as slope increased, remaining suppressed beyond 15°.

Among the spatial distance indicators, the risk of housing vacancy gradually increased after a threshold of 29.73 km for distance to county government centers (Dis2C) and rose notably beyond 6.38 km for distance to township government centers (Dis2T). The impact of distance to village committee offices (Dis2V) became neutral after exceeding 0.58 km. Distance to water systems (Dis2R) followed an inverted U-shaped pattern, with the highest vacancy risk occurring within the range of 0.17–1.45 km. In contrast, the risk remained stable within 3.5 km of national roads (Dis2NR), but increased slightly beyond this threshold. Various factors jointly shape the spatial differentiation mechanism of housing vacancy risk through nonlinear thresholds and differentiated response curves.

4.3. Comparison Between Parametric and Non-Parametric Models

This study compares the results of the XGBoost model and binary logistic regression. In the logistic model, the average of standardized regression coefficients with signs retained was used to assess the overall net effect of each category of variables. As shown in Table A2, the results show that locational factors ranked highest in both models, followed by housing physical conditions, while topographic features had relatively weaker effects. The consistency in importance rankings indicates that although the logistic model

had slightly lower predictive performance (AUC = 0.81 vs. 0.88), it captured a similar explanatory structure.

5. Discussion

5.1. *Vacancy Patterns and Heterogeneous Responses Under Dual Gradient Pressures*

This study reveals that the spatial pattern of rural housing vacancy in mountainous areas represents a heterogeneous response of villages to their intrinsic endowments under the systemic pressures imposed by the typical “coastal–mountainous” geographical gradient. China’s rapid urbanization has manifested pronounced regional disparities in spatial patterns. The study area represents a typical microcosm of the coastal–mountainous gradient, subjected to dual development pressures from the “urban siphoning effect” and the “topographic constraints” of mountainous regions. Against this backdrop, rural housing vacancy serves as a concentrated manifestation of the systematic restructuring of human–land relationships under specific geographical and institutional contexts.

This process of systemic restructuring exhibits pronounced path divergence. Spatial analysis of vacancy hotspots reveals that high vacancy rates occur not only in “demolition-and-relocation” villages with weak socioeconomic foundations, such as Beixing, but also in “heritage-conservation” villages with favorable endowments, such as Xiayong. In Beixing Village, a pattern of “systemic decline” is evident, where vacancy represents the ultimate outcome of exhausted development momentum. Vacant dwellings are predominantly traditional structures located on the village periphery, with high maintenance costs. This type of vacancy can be characterized as a “cost–location dual disadvantage.” In stark contrast, the vacancy hotspots in Xiayong Village exhibit a pattern of “internally polarized peripheries.” In this context, overall prosperity coexists with localized abandonment. Vacancy is not a sign of termination, but rather the result of intense internal spatial restructuring triggered by external capital or policy interventions. The selective concentration of development opportunities in specific areas has led to the functional devaluation and rapid marginalization of housing in other areas. This type of vacancy can be characterized as a “function–opportunity mismatch.” Macro-level regional pressures constitute the fundamental driving force behind housing vacancy, whereas the specific pathways and spatial manifestations are shaped by the intrinsic development logic determined by village endowments.

5.2. *Driving Factors of Rural Housing Vacancy*

5.2.1. The Dominant Role of Locational Conditions

The influence of locational conditions on rural housing vacancy in mountainous areas essentially stems from the superposition and interference of multiple spatial radiation systems. This process is jointly shaped by the scale differences in radiation radii, the non-monotonic effects of distance, and the systematic distortion of land rent gradients induced by land-use policies.

The effect of distance to county-level administrative centers remains contested, with existing studies reporting both the suppressive impact of proximity on housing vacancy [74,79] and the expansive effect of homestead development in distant suburban areas [34,80]. This study identified a critical influence radius of approximately 29.73 km to reconcile this contradiction: within this range, advantages in public services and commuting costs lead to lower vacancy risks; beyond it, the influence of county-level centers diminishes, and locally specific factors dominate the spatial pattern, resulting in divergent findings across studies. The influence of the township government delineates a 6.38 km threshold, representing the effective supply boundary of core public services at the township level. Proximity to the township area is associated with lower housing vacancy risk [45,47,74],

while exceeding this distance leads to a sharp increase in vacancy risk. However, some studies have observed higher vacancy rates in areas closer to township centers [72,73]. This discrepancy may be attributed to passive hollowing-out in near-township areas driven by the “linking increase with decrease” policy, as well as the transformation and reuse of vacant housing in remote areas under ecological migration policies. A 0.58 km radius from the village committee delineates the spatial limit for sustaining close-knit rural social capital and mutual aid networks. Beyond this threshold, everyday interactions and caregiving mechanisms based on geographic proximity rapidly break down, leading to the collapse of the community attachment value of housing.

In the dimensions of transportation and natural conditions, the identified thresholds reflect the dynamic transformation of dominant functions. The 3.5 km inflection point from the national highway essentially represents a balance between the forces of “transportation-induced economic impact” and “land regulation policies.” Within this range, rural housing can benefit from non-agricultural employment opportunities and improved logistics brought by road access. Beyond this threshold, areas are often designated as basic farmland protection zones or ecological redlines, subject to strict regulations on non-agricultural development, which restrict economic growth and accelerate the process of abandonment. This mechanism also explains why county and township roads facilitate development [48,64], while national and provincial highways show no significant effects [34,80]. The effectiveness of road infrastructure fundamentally depends on the regulatory flexibility of land policies in the areas it traverses. Similarly, the inverted U-shaped effect of river distance suggests that areas close to rivers maintain a low vacancy risk due to traditional agricultural reliance and social advantages [34,80]. In the mid-range zone, declining irrigation efficiency and increasing water protection policies accelerate agricultural decline and population outmigration. In the distant zone, although water access becomes costly, flood risks are fully avoided. Some housing has been repurposed as rural homestays or ecological monitoring stations. Coupled with ecological resettlement policies, these areas experience a significant decline in vacancy risk.

5.2.2. The Constraining Effects of Topographic Features

The constraints of topography on rural housing vacancy have evolved from a purely physical limitation into a complex process jointly shaped by land-use policies and residential preferences.

Conflicting findings exist regarding the impact of slope on rural housing vacancy, with some studies reporting that vacancy risk increases with steeper slopes [34,79], while others find that it decreases [45,73]. This study reveals a monotonic decreasing relationship with a threshold of 6.81° : the vacancy rate is relatively high below this threshold and declines significantly above it. This contrasts with the conclusion that “steeper slopes lead to higher vacancy risk.” A possible explanation is that low-slope areas ($<6.81^\circ$) in mountainous regions are constrained by farmland protection policies, face higher flood risks due to low elevation, and experience greater population outflow, resulting in higher vacancy rates. In contrast, mid- to high-slope areas ($>6.81^\circ$) typically have limited housing stock due to traditional residential preferences and strict development controls, and are more likely to be used for actual residence, leading to generally lower vacancy rates. In terms of aspect, this study finds that rural houses on southeast-facing slopes exhibit lower vacancy risks, while those on northeast-facing slopes show higher risks. This is primarily because southeast-facing slopes benefit from better sunlight and ventilation, whereas northeast-facing slopes are constrained by prolonged damp and shaded conditions.

5.2.3. The Selective Effect of Housing Physical Conditions

While locational conditions define the macro framework for village development, the physical attributes of housing perform a more refined “screening” function at the micro level. The risk of vacancy is shaped by the interplay among capital characteristics, functional utility, and residential quality.

Building structure and number of stories serve as the primary filters of “capital and modernity.” Existing studies have confirmed that rural houses with reinforced concrete structures have the highest utilization rates [72], whereas those with brick–wood structures are more likely to be abandoned, aligning with the broader trend of structural modernization [74]. This study shows that single-story houses are more likely to be vacant due to their reliance on traditional materials, inadequate functional layout, and high maintenance costs. In contrast, three-story houses, typically built with brick–concrete structures, feature more rational spatial organization and reflect greater household economic investment, significantly reducing the risk of vacancy. Housing size reflects an “economic rationality” filter. Empirical results reveal a pattern of “accelerated increase–high-level plateau” between housing size and rural housing vacancy. Below the threshold of 118.21 m², the vacancy risk remains low due to affordable costs and suitability for smaller households. Beyond the threshold, rising maintenance costs and policy constraints jointly elevate vacancy risk, resulting in the phenomenon of “built but unused,” consistent with previous studies [48,51]. As for oversized houses exceeding 750 m², most are legacy buildings from the past, and their vacancy risk has nearly reached saturation. Housing orientation serves as the final screening layer of “residential quality,” reflecting climatic adaptability and cultural preferences. Southeast-facing houses have the lowest vacancy risk due to their superior lighting and ventilation. Southwest-facing houses exhibit higher vacancy risks due to intense west-facing sunlight in summer, which reduces residential comfort and significantly increases maintenance costs.

5.3. Applicability of Spatial Models

Spatial diagnostics in this study indicate that, in mountainous rural settings, locational variables essentially serve as high-dimensional proxies for village-level spatial effects. Those village characteristics that are not directly observed but exhibit spatial clustering—such as infrastructure, public services, and social networks—are effectively captured by locational variables. This finding enriches the theoretical connotation of “location”—it is not only an exogenous geographical attribute, but also a comprehensive carrier of village-level socio-economic characteristics.

From a methodological perspective, accurately characterizing key locational variables may offer greater explanatory power than introducing complex spatial models. In rural studies, conventional spatial econometric methods face clear applicability boundaries. First, these models assume a relatively continuous and adjacent geographic distribution of sample units. However, rural surveys often adopt stratified sampling strategies, resulting in highly scattered sample points and “island-like” spatial patterns, which challenge the fundamental premise of spatial dependence required by such models [81]. Secondly, the theoretical mechanism underlying spatial econometric models must align with the intrinsic logic of the studied phenomenon. For rural housing vacancy, which is primarily driven by rational household migration decisions, the indiscriminate application of spatial models may lead to misleading policy implications [82]. Therefore, under limited data conditions, accurately characterizing the theoretical mechanism and robustly identifying core variables should take precedence over the perfect fitting of residual distributions. Overemphasis on the latter may lead to model over-parameterization, ultimately undermining the internal validity of the research.

5.4. Limitations and Future Prospects

This study, through a data-driven approach, identifies how spatial elements and physical attributes of housing influence vacancy in the mountainous areas of southeastern coastal China, though certain aspects still warrant further improvement. First, at the data level, there are limitations related to sampling bias and temporal validity. Although purposive sampling effectively captures the representative characteristics of different village types, its capacity for regional statistical inference may be limited. Furthermore, the cross-sectional nature of the data constrains the ability to capture population mobility dynamics and the lagged effects of policy interventions, especially the intergenerational evolution of long-term migration trends, potentially weakening the robustness of the inference. Therefore, the drivers and thresholds identified in this study are more applicable to understanding coastal mountainous areas undergoing similar rapid urbanization shocks, and caution should be exercised when generalizing the findings to regions with distinctly different vacancy patterns. Secondly, the measurement of key sociocultural variables remains insufficient. Residents' subjective attitudes toward housing—such as place attachment and urban adaptability—were not directly measured. Moreover, in the Minnan region, clan ideologies and the tradition of ancestral house preservation exert implicit regulatory effects on housing vacancy. However, this study lacks direct measurement of socio-ecological variables such as clan networks and village-level governance capacity, which limits a deeper understanding of how cultural traditions and collective action shape spatial governance in the context of population outmigration [83,84]. In addition, the depiction of spatial relationships still leaves room for improvement. The current analysis relies solely on Euclidean distance. In the future, if data on actual travel time based on road networks or social network connections can be obtained to construct spatial weight matrices grounded in real accessibility, it would provide a more robust foundation for the application of spatial econometric methods and potentially reveal more nuanced intra- and inter-village spatial interaction mechanisms. Moreover, it is worthwhile to further investigate spatial heterogeneity using tools such as multilevel models or geographically weighted regression, which do not rely on traditional adjacency matrices [85].

Future research may develop panel data models and integrate policy text mining to analyze the phased impacts of dynamic policy adjustments on vacancy risk. It could also incorporate social capital indices and space syntax to quantify the spatiotemporal regulatory pathways through which cultural practices influence housing utilization. Introducing more direct proxy variables (e.g., village committee allocation, village-level fiscal revenue, and collective income) would enable a more precise assessment of service accessibility and social capital gradients, thereby deepening the understanding of variations in village governance capacity and community cohesion. Furthermore, adopting mixed-method approaches may help reveal the complex mechanisms linking sociocultural structures and spatial patterns.

6. Conclusions

This study demonstrates that the spatial pattern of rural housing vacancy in mountainous areas is predominantly shaped by the systematic interaction of three categories of factors, locational conditions, topographic features, and housing physical attributes, with their relative importance ranked as follows: locational conditions > housing physical attributes > topographic features. Among locational factors, distances to national highways, county and township governments, and village committees drive the macro-level differentiation of vacancy through spatial accessibility. Regarding housing physical conditions, the structural type, the number of floors, the floor area per level, and building orientation influence micro-level decisions through cost and functional utility. Although topographic factors such as slope and aspect exert weaker overall effects, they generate synergistic

interactions with other variables at the local scale. The core contribution of this study lies in constructing an explanatory framework that integrates multidimensional factors to uncover the transmission mechanism of “macro-level pressure–village-level path–micro-level selection” behind housing vacancy. This offers a new analytical perspective for understanding rural spatial restructuring in mountainous coastal regions under urbanization.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land14112187/s1>, Table S1: Spatial autocorrelation tests of residuals across models; Table S2: Significance comparison between FE-Logit and baseline Logit models; Table S3: Results of multicollinearity diagnostics for the FE-Logit and baseline Logit models; Table S4: Connected component counts by k-nearest neighbors (k); Table S5: Multicollinearity diagnostics before and after excluding the DEM variable; Table S6: Comparison of Machine Learning Model Performance in Predicting RHV; Table S7: Hyperparameter settings for the seven non-parametric models.

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Data Availability Statement: The data that support the findings of this study are not publicly available due to confidentiality agreements and privacy restrictions. Data are available from the corresponding author upon reasonable request and with permission from the data providers.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Results of binary logistic regression (Unstandardized Coefficients).

Variables	B	SE	Wald χ^2	df	p-Value	OR	95% CI
HO_EN	−0.25	0.172	2.108	1	0.147	0.779	0.556–1.091
HO_ES	−0.633 ***	0.176	12.934	1	<0.001	0.531	0.376–0.75
HO_N	−0.21	0.284	0.549	1	0.459	0.81	0.464–1.414
HO_S	0.223	0.2	1.238	1	0.266	1.25	0.844–1.85
HO_W	−0.065	0.269	0.058	1	0.809	0.937	0.553–1.587
HO_WN	−0.473 *	0.224	4.448	1	0.035	0.623	0.402–0.967
HO_WS	0.265	0.172	2.392	1	0.122	1.304	0.932–1.825
HS_Timber	0.756 **	0.275	7.554	1	0.006	2.131	1.242–3.654
HS_Earth	1.088 ***	0.232	21.985	1	<0.001	2.969	1.884–4.678
HS_BC	−0.574 *	0.278	4.256	1	0.039	0.563	0.326–0.972
HS_Oth	0.922 **	0.288	10.221	1	0.001	2.515	1.429–4.426
ASP_EN	0.364 **	0.138	6.931	1	0.008	1.439	1.098–1.888
ASP_ES	−0.076	0.149	0.257	1	0.612	0.927	0.692–1.242
ASP_N	0.076	0.213	0.127	1	0.722	1.079	0.711–1.636

Table A1. Cont.

Variables	B	SE	Wald χ^2	df	p-Value	OR	95% CI
ASP_S	0.173	0.16	1.176	1	0.278	1.189	0.869–1.627
ASP_W	0.131	0.244	0.291	1	0.589	1.14	0.708–1.838
ASP_WN	0.41	0.367	1.247	1	0.264	1.506	0.734–3.092
ASP_WS	−0.268	0.179	2.245	1	0.134	0.765	0.539–1.086
NOS_2	−0.58 ***	0.112	26.611	1	<0.001	0.56	0.449–0.698
NOS_3	−2.256 ***	0.226	99.563	1	<0.001	0.105	0.067–0.163
NOS_4	−1.265 *	0.616	4.221	1	0.040	0.282	0.084–0.943
FAS	0.001 **	0	8.684	1	0.003	1.001	1–1.002
SLP	−0.032 **	0.01	10.572	1	0.001	0.969	0.951–0.988
Dis2C	0.081 ***	0.02	16.69	1	<0.001	1.084	1.043–1.127
Dis2T	0.297 ***	0.053	31.244	1	<0.001	1.346	1.213–1.494
Dis2VC	0.057	0.061	0.862	1	0.353	1.058	0.939–1.193
Dis2R	−0.187	0.113	2.756	1	0.097	0.829	0.665–1.034
Dis2NR	0.164 ***	0.044	14.133	1	<0.001	1.178	1.082–1.284

Note: (1) $p < 0.05$ *, $p < 0.01$ **, $p < 0.001$ ***. (2) Coefficients are estimated using a binary logistic regression model, where the dependent variable is rural housing vacancy status (0 = Occupied, 1 = Vacant). (3) Wald χ^2 statistics test the significance of each coefficient. (4) Exp(B) represents the odds ratio (OR): values > 1 indicate a positive association with vacancy, while values < 1 indicate a negative association. (5) Model fit statistics (Cox & Snell $R^2 = 0.235$, Nagelkerke $R^2 = 0.334$) and significance levels were obtained using SPSS 26.0; AUC = 0.809 was calculated in R (version 4.4.1).

Table A2. Comparison of results between parametric and non-parametric models.

Variables	XGBoost			Binary Logistic Regression			
	Relative Importance	Rank	Average	Standardized Coefficient (β)	p-Value	Rank	Average
Physical condition of houses							
Housing Orientation (HO)							
HO_E	0.01	23		Reference category	<0.001		
HO_EN	0.02	20		−0.25	0.147	17	
HO_ES	0.13	12		−0.633 ***	<0.001	6	
HO_N	0	27		−0.21	0.459	19	
HO_S	0.01	25		0.223	0.266	18	
HO_W	0	27		−0.065	0.809	26	
HO_WN	0.01	26		−0.473 *	0.035	10	
HO_WS	0.12	13		0.265	0.122	16	
Housing Structure (HS)			0.096				−0.160
HS_SC	0.06	15		Reference category	<0.001		
HS_Timber	0.01	24		0.756 **	0.006	5	
HS_Earth	0.21	8		1.088 ***	<0.001	3	
HS_BC	0.26	6		−0.574 *	0.039	8	
HS_Oth	0.02	21		0.922 **	0.001	4	
Number of Stories (NOS)							
NOS_1	0.33	3		Reference category	<0.001		
NOS_2	0.06	16		−0.58 ***	<0.001	7	
NOS_3	0.31	4		−2.256 ***	<0.001	1	
NOS_4	0	27		−1.265 *	0.040	2	
Floor Area per Story (FAS)	0.17	11		0.128 **	0.003	23	

Table A2. Cont.

Variables	XGBoost			Binary Logistic Regression			
	Relative Importance	Rank	Average	Standardized Coefficient (β)	p-Value	Rank	Average
Topography							
Slope (SLP)	0.17	10		−0.187 **	0.001	20	
Aspect (ASP)							
ASP_E	0.02	19		Reference category	0.015		
ASP_EN	0.06	17	0.040	0.364 **	0.008	13	0.020
ASP_ES	0.07	14		−0.076	0.612	24	
ASP_N	0	27		0.076	0.722	25	
ASP_S	0.03	18		0.173	0.278	21	
ASP_W	0	27		0.131	0.589	22	
ASP_WN	0	27		0.41	0.264	11	
ASP_WS	0.01	22		−0.268	0.134	15	
Location							
Distance to county government center (Dis2C)	0.23	7		0.276 ***	<0.001	14	
Distance to township government center (Dis2T)	0.39	2		0.478 ***	<0.001	9	
Distance to village committee center (Dis2VC)	0.28	5	0.338	0.051	0.353	28	0.232
Distance to rivers (Dis2R)	0.21	9		−0.1	0.097	24	
Distance to national roads (Dis2NR)	0.58	1		0.406 ***	<0.001	12	

Notes: (1) SHAP importance is the mean absolute SHAP value from the summary bar plot. (2) Logistic β are standardized regression coefficients (z-score); reference categories are listed in “Variables”. (3) $p < 0.05$ *, $p < 0.01$ **, $p < 0.001$ ***. AUC: XGBoost = 0.88, Binary logistic regression = 0.81.

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