

Article

Amplified by Heat: Modeling the Spatially Varying Impact of Thermal Environment on Urban Noise Complaints

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Abstract

Urban noise complaints reflect not only perceived acoustic disturbance, but also complaint behaviour shaped by thermal conditions and the built environment. Using Sanya, China, as a case study, this study integrated Landsat-derived land surface temperature data with the spatial distribution of noise complaints to examine how thermal environment and urban contextual factors jointly influence complaint patterns. An interpretable modeling framework combining eXtreme Gradient Boosting (XGBoost) and Multiscale Geographically Weighted Regression (MGWR) was employed to assess the associations of urban heat island intensity (UHI), road density, point of interest (POI) count, and population density on complaint occurrence and intensity, while also generating spatial predictions of complaint distribution. The results revealed a weak but statistically significant spatial association between the thermal environment and noise complaints, with urban heat island intensity showing nonlinear and spatially heterogeneous associations with complaint counts. POI count emerged as the strongest global predictor, while road density, population density, and thermal environment exhibited substantial spatial heterogeneity in their associations with complaint patterns. The integrated model outperformed both individual models alone, achieving the highest prediction accuracy. Overall, the findings suggest that urban noise complaint patterns reflect not only perceived acoustic disturbance, but also context-dependent social perception and reporting behaviour, providing empirical support for more place-sensitive and people-centered urban noise governance.

Keywords: thermal environment; MGWR; XGBoost; machine learning; noise complaints



Academic Editor: Siu-Kit Lau

Received: 22 June 2026

Revised: 12 July 2026

Accepted: 17 July 2026

Published: 22 July 2026

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1. Introduction

Urbanization has intensified multiple environmental stressors, among which noise pollution and the urban heat island (UHI) effect are particularly prominent, posing growing challenges to public health and sustainable urban development [1]. In this context, creating an optimal acoustic environment has become a critical issue for enhancing residents' quality of life and promoting healthy urban development [2]. However, urban noise should not be understood solely as a physical exposure, but also as a perceptual and behavioral response shaped by multiple environmental conditions [3–5]. Classical community-noise research established systematic exposure–annoyance relationships, while also demonstrating that personal and situational factors contribute to variations in annoyance beyond physical noise levels. Research indicates that long-term exposure to noise significantly increases

the risk of cardiovascular diseases [6,7] and induces psychological stress and cognitive impairment [8,9].

Existing studies have examined urban noise mainly from two perspectives: the physical effects of the built environment on sound distribution, and the perceptual dimension of noise shaped by multisensory environmental interactions. At the physical level, urban morphological elements—such as building form, vegetation structure, street layout, and land use—have been confirmed to significantly shape the spatial distribution of sound fields [10,11]. The effects of these factors exhibit distinct spatial heterogeneity and scale dependence; for instance, complex correlations exist between noise complaint rates and variables like building density and road proximity [12]. At the perceptual level, noise evaluation is not solely determined by sound pressure levels; non-acoustic factors, including the visual landscape [13] and the thermal environment [3], are equally critical. In particular, growing evidence suggests that the thermal environment may modify noise perception: elevated temperatures can intensify noise-related discomfort, while extreme thermal conditions may further reshape auditory sensitivity and behavioral tolerance [4,14]. This suggests that examining the acoustic or thermal environment in isolation is insufficient to fully explain residents' noise perception and behavioral feedback.

Despite increasing attention to built environment characteristics, thermal conditions, and noise perception, an integrated framework linking the built environment, thermal environment, and residents' noise complaints remains underdeveloped [5,15,16]. Specifically, there is a lack of integrated exploration regarding the spatial association mechanisms among these three dimensions. Furthermore, traditional acoustic assessment methods, such as noise mapping and numerical simulation, often fail to fully incorporate the social differentiation of human perception [17]. In contrast, noise complaint data provide a socially responsive indicator of publicly reported noise-related problems, reflecting residents' behavioral responses to perceived acoustic disturbance rather than directly measured acoustic exposure. Therefore, such data capture the spatial pattern of reported noise annoyance and offer an important bridge between the built environment and public complaint behavior.

To address these gaps, this study investigates how built-environment characteristics and the thermal environment are associated with the spatial distribution of urban noise complaints. Specifically, it aims to: (1) compare the relative predictive contributions of built-environment factors to complaint occurrence and intensity; (2) assess whether the thermal environment exhibits a nonlinear association with complaint counts and characterize the form of this association; and (3) evaluate the extent to which these associations vary spatially across different urban contexts.

To achieve these objectives, this study employs Multiscale Geographically Weighted Regression (MGWR) and eXtreme Gradient Boosting (XGBoost) models. MGWR is capable of effectively capturing the spatial non-stationarity and scale differences of variable associations, making it suitable for analyzing the spatially differentiated relationships between urban morphology, thermal environment factors, and noise complaints across different regions. Meanwhile, XGBoost excels at handling complex nonlinear relationships and variable interaction effects, helping to identify nonlinear associations in noise complaint patterns under the joint action of multiple factors. In addition, the predictive performance of the integrated XGBoost–MGWR model is compared with that of the individual models to evaluate whether model integration improves prediction robustness. By integrating explainable machine learning with spatially explicit regression, this study seeks to provide both empirical evidence and methodological support for people-centered urban noise governance.

2. Methodology

2.1. Study Area

Sanya, located in Hainan Province, China, is situated at the southernmost tip of Hainan Island, between latitudes $18^{\circ}09'34''$ N– $18^{\circ}37'27''$ N and longitudes $108^{\circ}56'30''$ E– $109^{\circ}48'28''$ E (Figure 1). The city encompasses a total land area of 1921.40 km^2 and a sea area of 3226 km^2 (Sanya Municipal Government). Administratively, it consists of four districts: Haitang, Jiyang, Tianya, and Yazhou. In 2024, the average daytime equivalent sound level in Sanya was 53.3 dB. Noise during daytime hours was predominantly generated by social activities (85.9%), with traffic noise (5.6%) and construction noise (8.5%) contributing to a lesser extent. The daytime compliance rate for acoustic environmental quality in functional zones reached 100%, while the nighttime compliance rate was 83.3%, representing a 5.6-percentage-point decrease from 2023 (2024 Sanya Ecological Environment Status Bulletin). Sanya is a typical tropical island city. In 2024, the average annual temperature reached 26.7°C , with average monthly maximum and minimum temperatures of 32°C and 17°C , respectively (Sanya Meteorological Bureau). The city's strong solar radiation significantly intensifies the urban heat island effect [18].

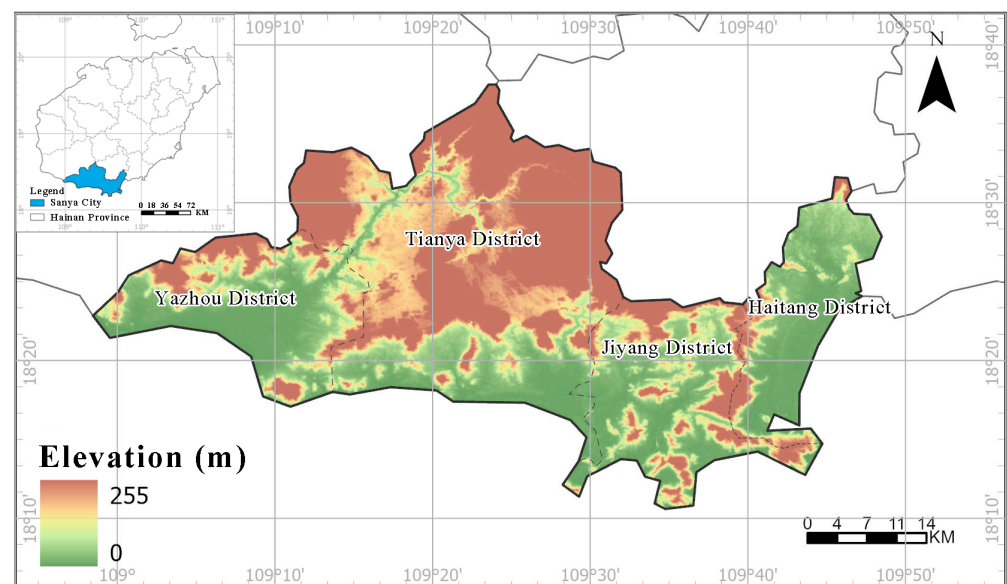


Figure 1. Geographic location, administrative divisions, and elevation of Sanya, Hainan Province, China, with an inset showing its location within the province.

Noise, particularly traffic noise, typically attenuates within 200–300 m (following the ISO 9613-2 standard [19]). Accordingly, the study area was divided into 3461 grids of $250 \text{ m} \times 250 \text{ m}$, a scale that effectively links noise complaint hotspots and aligns with the spatial range of residents' daily activities, and captures neighborhood-level road-noise exposure around residential complaint locations. Kernel Density Estimation was employed to identify complaint hotspots, and grid cells within the extracted boundaries were retained, resulting in 724 analytical units. The full set of 3461 grids was used for spatial visualization, zero-inflation diagnosis, and hotspot identification. Consistent with the spatially clustered nature of complaint-based social-sensing data [8,13], a large proportion of the full-domain grids contained zero complaints, directly applying regression models to all grids would substantially increase zero-inflation and sparsity, thereby reducing the ability of the models to identify associations within complaint-concentrated areas. Therefore, after hotspot extraction, the 724 hotspot grid cells were used as the unified analytical dataset for all subsequent models, including MGWR, XGBoost, and the integrated XGBoost–MGWR

model. This design ensured consistency across models and focused the analysis on the spatial associations within complaint-concentrated areas (Supplementary Table S1).

2.2. Data Preprocessing

2.2.1. Metric System Construction

POI data refer to geospatial datasets that identify specific locations within a geographic area. These locations may be natural or man-made features and typically include attributes such as name, category, address, and geographic coordinates [20]. POI data reflect plot-level functions and, to a certain extent, represent the spatial distribution of different urban functional areas. A substantial body of literature has demonstrated that POI count [10,12], road density [5,12], population density [21], and temperature [3,22,23] significantly influence noise complaints. Based on these findings, POI, roads, population, and temperature were selected as independent variables to investigate their mechanisms of influence on noise complaints. The datasets used in this study were obtained from publicly accessible government or institutional data sources. Specifically, noise complaint data for 2024 were acquired from the Sanya Municipal Government website to characterize publicly reported noise-related complaint behaviour. Surface temperature data were retrieved and inverted using Landsat 8–9 OLI/TIRS C2 L2 satellite remote sensing imagery from the Geospatial Data Cloud. The road network dataset was extracted from OpenStreetMap, while POI data were compiled from 2024 Autonavi (Amap) data.

2.2.2. Complaint Data

Noise complaint records were collected from the Sanya Municipal Government website (<https://www.sanya.gov.cn/>, accessed on 21 June 2026), covering the period from March 2024 to June 2024. The complaint dataset included textual descriptions of complaint events, specifically their time and location. After semantic parsing, complaint addresses were extracted and geocoded into latitude–longitude coordinates using Baidu Geocoding (<https://www.piliang.tech/geocoding>, accessed on 21 June 2026). The geocoded results were subsequently converted into point data within ArcGIS pro.

2.2.3. Geographic Predictors

Temperature: Data were derived from the Geospatial Data Cloud (<https://www.gscloud.cn/>, accessed on 21 June 2026). Landsat 8–9 OLI/TIRS Collection 2 Level-2 remote sensing images from March to June 2024 (one scene per month) were used to retrieve land surface temperature (LST). For missing pixels caused by cloud cover, a bilinear interpolation method was applied to fill the gaps, thereby improving spatial continuity and reducing the impact of data loss on the results. Subsequently, the multi-temporal retrieval results were averaged to characterize the overall thermal conditions during the study period. Since L2 data includes thermal radiation calibration, an approximate linear simulation of Planck's law was applied: $0.00341802 * B1$ (radiative luminance value of TIRS Band 10) + 149–273.15, to calculate surface temperature.

Then, the following formula was used:

$$UHI = \frac{T_s - T_m}{SD}, \quad (1)$$

where T_s means Surface temperature; T_m means Average surface temperature of the study area; SD means Standard deviation. UHI was classified into five levels: weak, medium, strong, very strong, and extremely strong heat island effect.

Road network: Data were obtained from OpenStreetMap (<https://download.geofabrik.de/>) as of 25 March 2024. After acquiring the road shapefile, road segments were processed and assigned to the study fishnet to generate road density.

Population density: Data were sourced from LandScan Global 2023, with a spatial resolution of approximately 1 km, and were used to represent the population distribution pattern during the 2024 complaint observation period. The LandScan population surface was spatially matched to the 250 m fishnet, and a population-density value was assigned to each analytical grid.

POI count: Data were sourced from 2024 Amap data, with records updated as of 25 July 2024. POI data, marked and uploaded by map users [17], include names, categories, and coordinate information, effectively associating human activities with plot functions. POI kernel density was divided into three concentration areas, all within the central urban area of Yalong Bay. POI count in Sanya were classified into 17 categories. First, Pearson correlation analysis was used to calculate the linear correlation strength and statistical significance between POI count and noise complaint count ($p < 0.05$). Categories were sorted by correlation strength with the dependent variable. A multiple linear regression model was built by sequentially adding POI categories to identify the point where marginal returns sharply decline:

$$Y = \beta_0 + \sum \beta_i X_i + \varepsilon, \quad (2)$$

where Y is the complaint count, X_i are the POI variables, and β_i are the regression coefficients. Model significance (F-test) and variable coefficient significance were tested.

2.3. Study Steps

2.3.1. Visualization of Study Variables

Noise complaint count, POI count, road density, population density, and temperature information were spatially matched and imported into ArcGIS Pro's research fishnet. Each study unit was assigned the corresponding variable attribute information. Variable distribution maps were generated using ArcGIS Pro's visualization features, and attribute data were exported to Excel as input for the model. The overall research framework is illustrated in Figure 2.

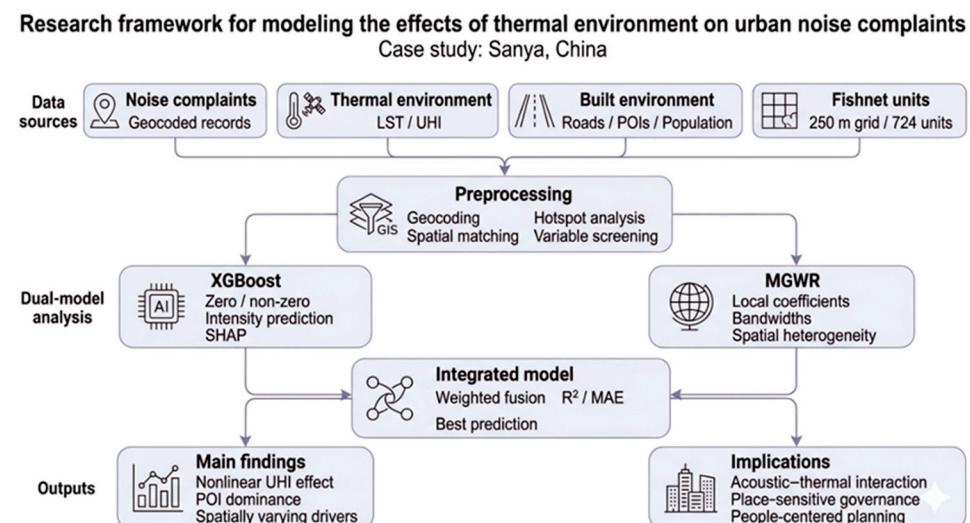


Figure 2. Research framework for modeling the effects of this study.

2.3.2. Research Model Construction

Training and Evaluation of Machine Learning XGBoost Models

Because many hotspot grid cells still contained zero complaints, the outcome variable exhibited a zero-inflated distribution, which may reduce the performance of conventional single-stage regression models. To address this issue, a two-stage XGBoost framework was developed to separately model complaint occurrence and complaint intensity based on

the 724 hotspot analytical units. In Stage 1, all training samples within the hotspot dataset were used to train the classification model, with the binary label defined by whether the complaint count was greater than zero. In Stage 2, only the non-zero complaint samples within the hotspot training set were used to train the regression model for complaint intensity. During prediction, both the classification and regression models generated outputs for all hotspot grid cells, and the final two-stage XGBoost prediction was obtained by multiplying the complaint-occurrence probability by the regression output.

The dataset was randomly split into 80% training and 20% testing sets with stratification based on complaint occurrence (random seed fixed at 42). Five-fold stratified cross-validation was adopted to validate model performance and ensure the robustness of the evaluation results. The hyperparameters of the XGBoost classifier and regressor were set empirically. SHapley Additive exPlanations (SHAP) values were computed separately for the classification and regression stages to interpret the impact of each feature on complaint occurrence probability and complaint counts.

Compared with a single regression model, the two-stage (classification + regression) approach effectively handles zero-inflated data by separately modeling the processes of “whether a complaint occurs” and “how many complaints occur,” thereby improving overall predictive accuracy and interpretability.

Stage 1 (Classification model): The classification model, based on XGBoost, predicts whether noise complaints occur (i.e., complaint count > 0) to mitigate the zero-inflation issue. The model outputs continuous probability values representing the likelihood of complaint occurrence, which are subsequently used as inputs for probability-weighted regression. Due to class imbalance in the classification task, F1-score and Area under the precision–recall curve (AUC-PR) were adopted as evaluation metrics. The F1-score represents the harmonic mean of precision and recall, while AUC-PR is more sensitive to the predictive performance on the positive class.

Stage 2 (Regression model): The regression model was configured with 300 trees, a maximum tree depth of 3, and a learning rate of 0.1. It was trained exclusively on non-zero samples (i.e., grid cells with observed complaints) to avoid the dilution effect caused by excessive zero values in error estimation. However, during the prediction phase, the model generates outputs for all study units. Model performance was evaluated on the subset of samples with non-zero observed complaint counts, using Mean Absolute Error (MAE) and the coefficient of determination (R^2) to assess predictive accuracy and goodness of fit for complaint intensity.

Probability-weighted integration of Stages 1 and 2: In this study, probability weighting was employed to couple the outputs of the classification and regression models. The final predicted value is expressed as:

$$\hat{y} = P(y > 0|X) \times \hat{y}_{reg}, \quad (3)$$

where $P(y > 0|X)$ denotes the probability of complaint occurrence predicted by the classification model, and $\hat{y}_{reg}$ represents the potential complaint intensity estimated by the regression model.

This mechanism preserves the regression model’s ability to predict the intensity of positive samples, while effectively suppressing zero-value samples through probabilistic weighting. Compared with threshold-based methods that directly classify samples near the threshold as zero—thereby causing information loss—the proposed approach yields smoother predictions and better reflects the underlying generation process of noise complaints.

Training and Evaluation of MGWR Models

The Multiscale Geographically Weighted Regression (MGWR) model was employed to capture the spatial non-stationarity of complaint-driving factors by estimating location-specific coefficients and variable-specific bandwidths across the study area, which allowed for a detailed understanding of the strength and direction of different factors at the local scale. The analysis used “Fishnet_ID” as the spatial unit identifier and a Gaussian distribution assumption. The dependent variable was the “number of complaint count,” with independent variables including temperature, POI count, population density, and road density. An adaptive bisquare kernel was utilized, and optimal bandwidths were determined via the golden section search method based on the corrected Akaike information criterion (AICc). The model output comprised both an overall statistical summary and local parameter estimates for each spatial unit. Model performance was evaluated using the mean absolute error (MAE) and coefficient of determination (R^2) to ensure predictive accuracy and explanatory robustness.

Baseline Model

To further evaluate the added value of the proposed framework, an ordinary least squares (OLS) regression model was included as a simple global linear baseline. The OLS model used the same predictor variables and the same 8:2 train–test split as the XGBoost and MGWR–XGBoost models. Since complaint counts cannot be negative, negative OLS predictions were truncated to zero before model evaluation.

Model Weighting

An integrated modeling framework and weight optimization procedure were implemented in the Python environment. First, the prediction outputs of the XGBoost and MGWR models were combined. By adjusting the weighting coefficients, a series of integrated predictions were generated from the two model outputs.

To evaluate the performance of the integrated model under different weight allocations, the relationships between the XGBoost weight and model performance metrics—namely the coefficient of determination (R^2) and Mean Absolute Error (MAE)—were analyzed. The optimal MGWR weight (w_{MGWR}) was determined by selecting the weight combination that produced the highest R^2 , while MAE was also calculated for comparison. Accordingly, the XGBoost weight was defined as $(1 - w)$. That is:

$$\hat{y} = w \cdot \hat{y}_{MGWR} + (1 - w) \cdot \hat{y}_{XGB}, \quad (4)$$

where w denotes the weight assigned to the MGWR model, and $(1 - w)$ represents the weight of the XGBoost model. $\hat{y}_{MGWR}$ denotes the predicted values from the MGWR model, and $\hat{y}_{XGB}$ denotes the predicted values from the XGBoost model.

A convex linear combination was adopted instead of a more complex stacking approach because it provides a transparent and directly interpretable balance between the predictive contributions of the two component models while avoiding an additional meta-learner that could increase the risk of overfitting given the limited hotspot sample.

2.3.3. Visualization and Evaluation of Results

A six-panel graph compared complaint distributions predicted by the MGWR model, XGBoost model, the combined model, and complaint residuals, visually assessing prediction accuracy and guiding subsequent model improvement.

2.4. Statistical Analysis Methods

2.4.1. Spatial Pattern Identification

To identify hotspot areas and spatial aggregation characteristics of noise complaints, this study employs Kernel Density Analysis. As a non-parametric method for estimating the probability density function of continuous spatial point data, Kernel Density Analysis is primarily used in ArcGIS Pro to generate a continuous density surface from discrete point features, visually illustrating the clustered distribution patterns of point-based geographic events in space. Since both noise complaint data and POI count are in point format, applying Kernel Density Analysis allows for an intuitive understanding of data distribution and provides preliminary clustering analysis results.

2.4.2. Correlation Analysis

To preliminarily identify urban functional elements that may be correlated with the spatial distribution of noise complaints, this study employed Spearman's rank correlation analysis. This method calculates the correlation coefficients between various relevant socioeconomic factors and noise complaint density, supplemented by significance testing ($p < 0.001$). Spearman's rank correlation effectively quantifies the strength and direction of monotonic associations between variables, with the results presented in the form of a correlation matrix. This analysis aimed to provide a preliminary basis for including statistically relevant variables in subsequent models.

In addition, to explore the relative contribution of different POI categories to complaint counts, this study further employed the Pearson correlation coefficient as an exploratory ranking tool within the POI-category screening procedure. Pearson correlation was used to calculate the linear association between each POI category and complaint count. The absolute value of the correlation coefficient was used only as an initial ranking indicator, providing a preliminary basis for the subsequent evaluation of POI categories in multivariate regression models.

2.4.3. Variable Screening

To reduce dimensionality while limiting potential overfitting, Pearson correlation was used only to provide an initial exploratory ranking of the 17 POI categories. The number of retained categories was subsequently evaluated using repeated five-fold cross-validation with 10 repetitions. Within each training fold, the POI categories were re-ranked using only the training data, and regression models containing the top 1–17 categories were evaluated on the corresponding held-out fold. The one-standard-error rule was then applied to select the smallest model whose mean RMSE was within one standard error of the minimum cross-validated RMSE. This procedure emphasized out-of-sample performance and model parsimony rather than relying solely on in-sample increases in R^2 .

2.4.4. Model Interpretability Analysis

To reveal the key factors influencing noise complaints and their mechanisms of action, this study introduces SHAP values for post hoc model interpretation based on the constructed XGBoost prediction model. SHAP, based on a unified game-theoretic framework, quantifies the magnitude and direction of each feature variable's contribution to the model's predictions, thereby visualizing the decision-making process of the "black-box" model and ultimately explaining the influence of various driving factors on the spatial distribution of noise complaints.

The above analytical processes were primarily implemented using the following software platforms: spatial analysis and kernel density calculations were performed in ArcGIS Pro 3.4; MGWR modeling was conducted using MGWR 2.2 software; and machine

learning model construction, variable screening, and correlation analysis were carried out in PyCharm Community Edition 2022.3.2 using Python 3.12.9. The main Python packages included XGBoost 3.2.0, SHAP 0.51.0, scikit-learn 1.8.0, pandas 3.0.2, and NumPy 2.4.4.

3. Results

3.1. Characteristics of Built Environment and Social Perception Data

3.1.1. POI Data Screening Results

The exploratory sequential regression results (Table 1) showed substantial initial gains after the inclusion of Life Services, Catering Services, and Commercial Residence, with the adjusted R^2 reaching 0.4875. The robustness analysis further supported retaining these three categories. Although the minimum mean cross-validated RMSE occurred with eight POI categories (RMSE = 0.5030), the three-category model produced a nearly identical RMSE of 0.5042 and remained within one standard error (0.0073) of the minimum. According to the one-standard-error rule, the more parsimonious three-category model was therefore retained. Moreover, Life Services, Catering Services, and Commercial Residence were consistently ranked among the top three categories in all 50 cross-validation training partitions, indicating high selection stability. To examine potential multicollinearity among the retained POI variables, variance inflation factor (VIF) values were calculated. The VIF values were 3.37 for Life Services, 3.05 for Catering Services, and 1.68 for Commercial Residence, all below the commonly used threshold of 5, indicating that no severe multicollinearity existed among the selected POI indicators.

Table 1. POI category screening results based on Pearson correlation and marginal R^2 gains.

Sort	POI Categories	Pearson Correlation Coefficient	Adjusted R^2	Marginal Returns
1	Life services	R = 0.64	0.41	+0.41
2	Catering services	R = 0.61	0.43	+0.02
3	Business residence	R = 0.60	0.49	+0.06
4	Healthcare services	R = 0.51	0.49	+0.00
5	Shopping services	R = 0.49	0.49	+0.00
6	Transportation facilities services	R = 0.44	0.50	+0.01
7	Government agencies and social groups	R = 0.42	0.50	+0.01
8	Sports leisure	R = 0.41	0.50	+0.00
9	Science, education, culture and services	R = 0.38	0.50	+0.00
10	Financial insurance services	R = 0.35	0.50	+0.00
11	Companies and enterprises	R = 0.33	0.50	+0.00
12	Public facilities	R = 0.23	0.50	+0.00
13	Motorcycle service	R = 0.20	0.50	+0.00
14	Car service	R = 0.16	0.50	+0.00
15	Scenic spots	R = 0.09	0.50	+0.00
16	Car repair	R = 0.02	0.50	+0.00
17	Automobile sales	R = 0.01	0.50	+0.00

3.1.2. Spatial Distribution Characteristics of Relevant Factors

Based on the ArcGIS Pro platform, this study visualized the spatial distribution of noise complaints and their relevant influencing factors in the central urban area of Sanya (Figure 3), which represents the core analytical area extracted from the broader city-level study area shown in Figure 1. The results reveal marked spatial clustering and differentiation across all variables, although the specific patterns vary by factor.

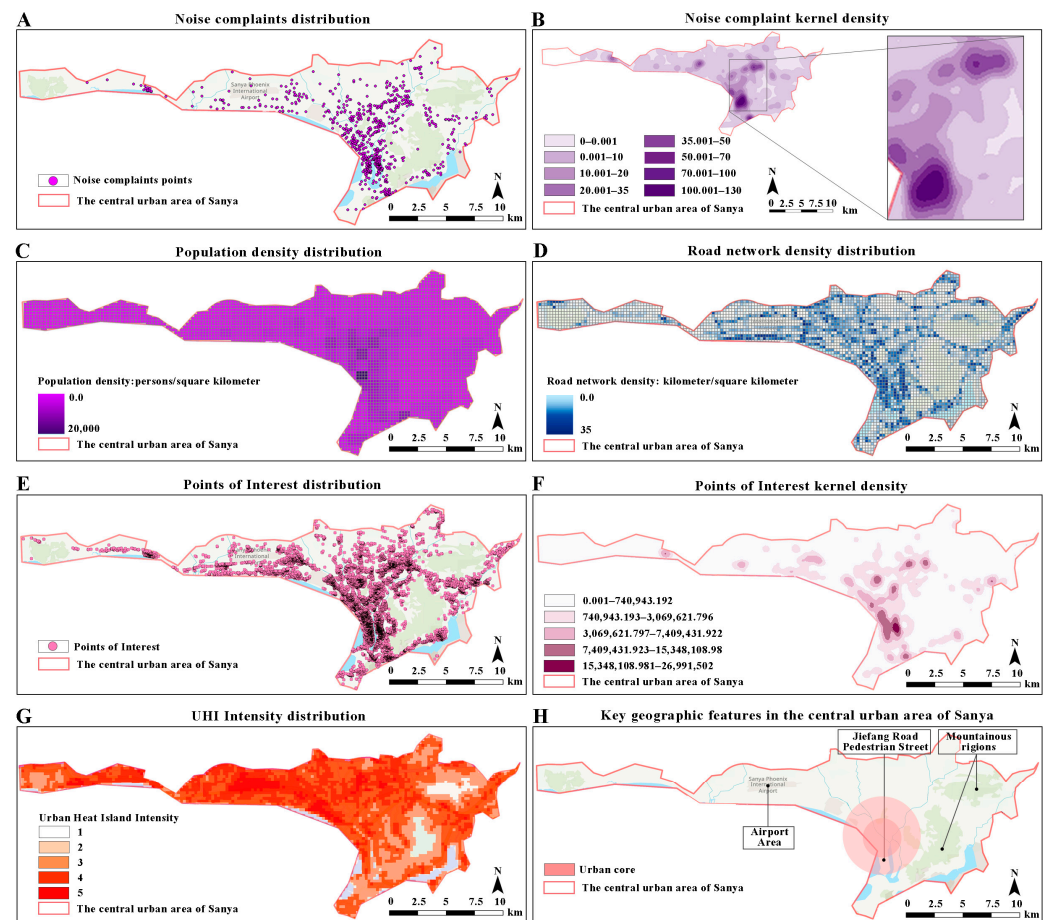


Figure 3. Spatial distributions of noise complaints, built-environment characteristics, and UHI levels in central Sanya, with key geographic features shown for reference.

The spatial distribution of various factors exhibits clear patterns across the study area. Noise complaints were strongly concentrated in the urban core, with the Jiefang Road Pedestrian Street area (Figure 3H) emerging as the most prominent hotspot (Figure 3A). Kernel density estimation further revealed significant spatial heterogeneity in complaint hotspot areas, and the noise complaint hotspot regions were selected as the target areas for subsequent model prediction (Figure 3B). Population density shows a similar spatial trend, with residents primarily concentrated in the central urban districts and gradually decreasing toward the periphery (Figure 3C). The road network displays a relatively uniform distribution across the city, except in mountainous regions (Figure 3H) where road density visibly declines (Figure 3D). POI counts are likewise strongly clustered within urbanized areas, reflecting functional concentration and activity intensity (Figure 3E,F). Considering the nonlinear and threshold-dependent nature of temperature effects on noise complaints, the urban heat island intensity in Sanya was classified into five grades for model analysis. Regarding thermal conditions, UHI level was particularly high around Sanya Phoenix International Airport, whereas mountainous terrain was associated with lower UHI level (Figure 3G,H).

3.1.3. Relationship Between Social Perception Data and Built Environment Data

Variance Inflation Factor (VIF) analysis was conducted to assess multicollinearity among the independent variables. The commonly accepted thresholds of $VIF < 5$ (satisfactory) and $VIF < 10$ (acceptable) were adopted for evaluation. The VIF values for UHI level, population density, road density, and total POI count were 1.1, 1.2, 1.4, and 1.3, respectively. These values were all well below the conservative threshold of 5, indicating that

multicollinearity was negligible and that these variables could be included in regression modeling without severe multicollinearity concerns.

Furthermore, the Spearman correlation coefficient matrix (Table 2) revealed significant positive correlations among all variables, albeit with varying strengths. Population density showed the strongest correlation with total POI count ($r = 0.585$), while the remaining coefficients ranged from 0.196 to 0.574, indicating weak to moderate correlations. All correlations were statistically significant at $p < 0.001$. Specifically, although the correlation between UHI level and complaint count was weak ($r = 0.196$), the corresponding p -value was 1.0512×10^{-7} , confirming statistical significance at the $p < 0.001$ level.

Table 2. Correlation coefficient matrix and statistical significance of key variables.

	Complaint Count	POI Count	Urban Heat Island Level	Population Density	Road Density
complaint count	1.000	0.654 ***	0.196 ***	0.437 ***	0.456 ***
POI count		1.000	0.453 ***	0.585 ***	0.574 ***
Urban Heat Island Intensity			1.000	0.366 ***	0.280 ***
Population density				1.000	0.506 ***
Road					1.000

Notes: *** means $p < 0.001$.

3.2. Model Predictions

3.2.1. Effects of UHI Level on Noise Complaints

In the MGWR model, the association between UHI level and noise complaints showed clear spatial heterogeneity: coefficients were positive in southwestern Sanya, gradually weakened toward the northeast, and became negative in some northeastern areas (Figure 4A). This pattern indicates that the strength and direction of the association varied across the study area. In the classification model (Figure 5A), UHI level was not a dominant predictor of complaint occurrence. By contrast, SHAP results from the regression model revealed a nonlinear association of intensity (Figure 5B): moderate UHI level tended to contribute positively to complaint count, whereas very high UHI level were associated with negative contributions. This suggests that moderate UHI levels were positively associated with complaint counts, whereas very high UHI levels were negatively associated with complaint counts, possibly due to reduced outdoor activities or increased window closure during extreme heat conditions.

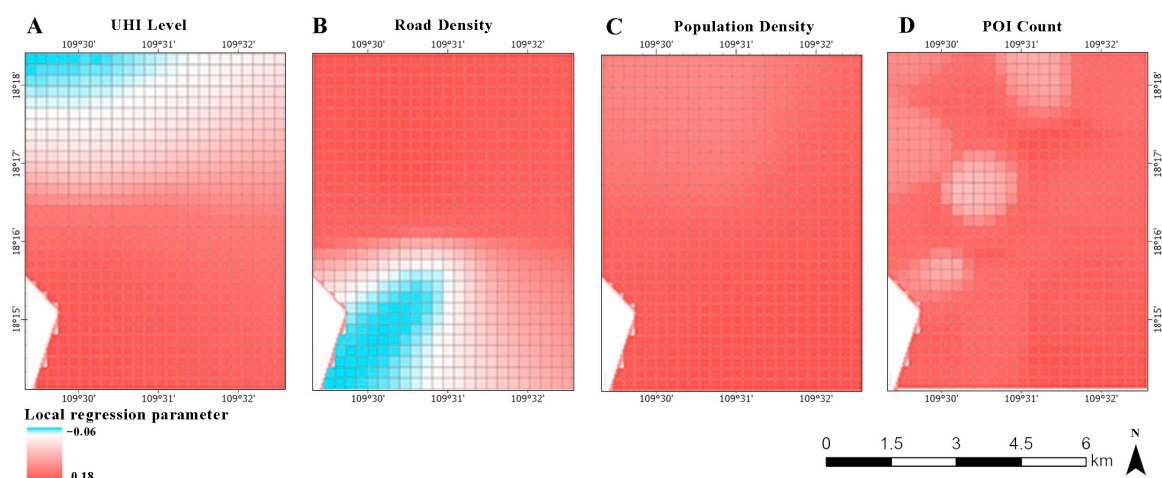


Figure 4. Spatial distribution of local regression parameters for relevant factors estimated by MGWR.

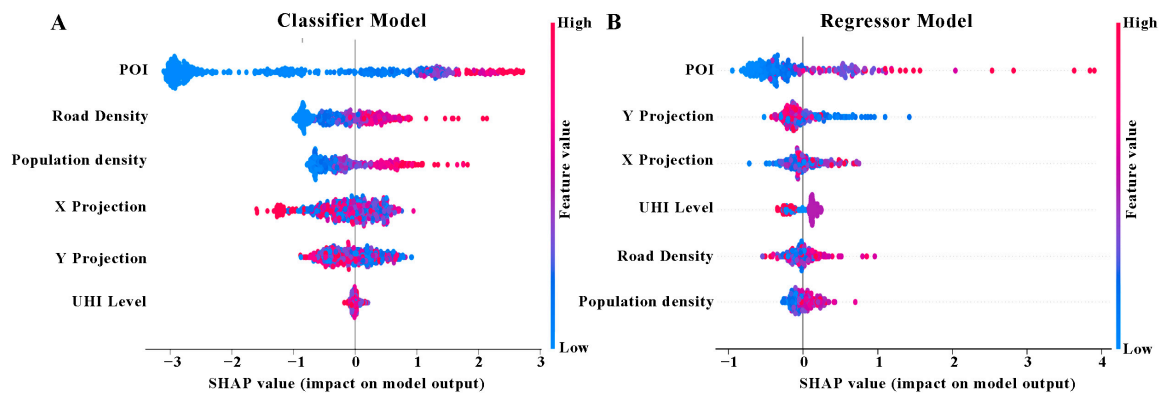


Figure 5. SHAP summary plots for the XGBoost model.

In summary, UHI level showed a nonlinear and spatially heterogeneous relationship with complaints: spatially, positive in the southwest and negative in the northeast; nonlinearly, positive only at moderate intensities, while both low and very high intensities were negatively associated.

3.2.2. Effects of Road Network Density on Noise Complaints

Road network density also exhibited pronounced spatial heterogeneity in the MGWR model (Figure 4B). In the central urban area of Sanya, high road network density was negatively associated with complaint counts in the central urban area, whereas it was positively associated with complaint counts in peripheral areas. This pattern runs counter to intuition—central urban areas have dense road networks but fewer complaints, which may be attributed to more standardized traffic management and more comprehensive acoustic environment optimization measures in these areas. In contrast, the increase in complaint count associated with high road network density in peripheral areas may reflect issues such as the passage of heavy vehicles and inadequate traffic organization.

Both the XGBoost classification and regression models (Figure 5A,B) indicated an overall positive association between road network density and noise complaints across the entire study area. In contrast, the MGWR results showed that this association varied locally, being negative in the central urban area and positive in peripheral areas. These findings are not contradictory: XGBoost captures the overall relationship across the entire study area, whereas MGWR reveals location-specific relationships within different parts of the study area.

3.2.3. Effects of Population Density on Noise Complaints

In the MGWR model, the relationship between population density and noise complaints generally exhibited a positive effect, with weak spatial heterogeneity (Figure 4C). In the central urban area of Sanya, population density showed a consistently positive association with complaint counts, as high density may correspond to greater noise exposure and social friction. In the central urban area, the increase in population density often coincides with the agglomeration of commercial activities, increasing exposure to commercial-related noise and leading to more complaints, where the effect of population density is stronger. In contrast, in some low-density communities, an increase in population density may be accompanied by more comprehensive residential environment planning and noise reduction facilities, thereby partially mitigating the generation of complaints.

Both the XGBoost classification model (Figure 5A) and the regression model (Figure 5B) were consistent with the observations from the MGWR model. They showed a positive correlation between population density and the occurrence rate of complaints, indicating

that population density was also positively associated with complaint occurrence at the global level.

3.2.4. Effects of POI Count on Noise Complaints

In the MGWR model, the effect of POI count exhibited certain spatial heterogeneity (Figure 4D), showing a positive influence across different urban areas but with varying intensities. This indicates that the association between POI count and complaints is closely related to local functional characteristics and other environmental and built-environment factors.

In the XGBoost classification model, POI count ranked as the most important predictor of complaint occurrence (Figure 5A). In the XGBoost regression model (Figure 5B), POI count remained the most influential variable among the retained variables and was positively correlated with complaint count, indicating that POI count was strongly associated with noise complaint patterns (Figure 6A,B).

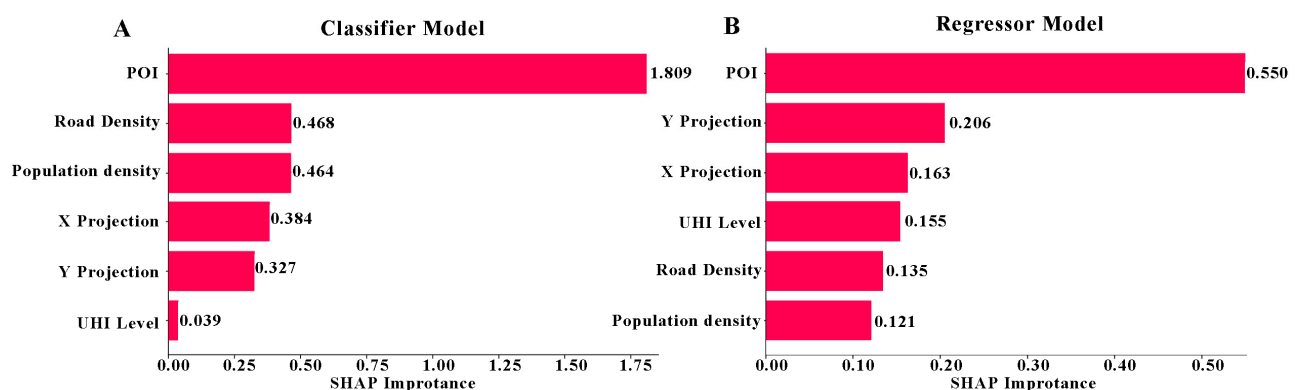


Figure 6. SHAP-based feature importance rankings for the XGBoost model: (A) Classifier Model SHAP Feature Importance and (B) Regressor Model SHAP Feature Importance.

3.3. Analysis of Model Accuracy

Unless otherwise stated, the model performance metrics reported in Section 3.3 were calculated on a held-out 20% test set comprising 145 samples. This dataset was used both to select the ensemble weight and to report the performance of the selected integrated model. Therefore, these metrics should be interpreted as conditional performance estimates rather than as results from a fully independent final evaluation.

3.3.1. XGBoost + MGWR Combined Model

Among the evaluated weight combinations, the highest observed R^2 was obtained with an MGWR weight of 0.35 and a corresponding XGBoost weight of 0.65 (Figure 7A,B). As a robustness check, the five-fold analysis yielded mean weights of 0.342 ± 0.129 for MGWR and 0.658 ± 0.129 for XGBoost, broadly consistent with the selected weight allocation. Within the current hotspot sample, the larger XGBoost weight suggests that global nonlinear patterns contributed more strongly to predictive performance, while MGWR provided a complementary spatial adjustment for local heterogeneity. Although the numerical balance may vary across urban contexts, the weighting framework provides a transferable approach for comparing the relative predictive contributions of global nonlinear patterns and local spatial heterogeneity across cities.

The integrated model produces prediction values ranging from 0 to 7.3, with high-value clusters (dark yellow) remaining concentrated in the southern central portion of Sanya (Figure 8E). The residuals show a random spatial pattern (Figure 8F), indicating no significant spatial bias.

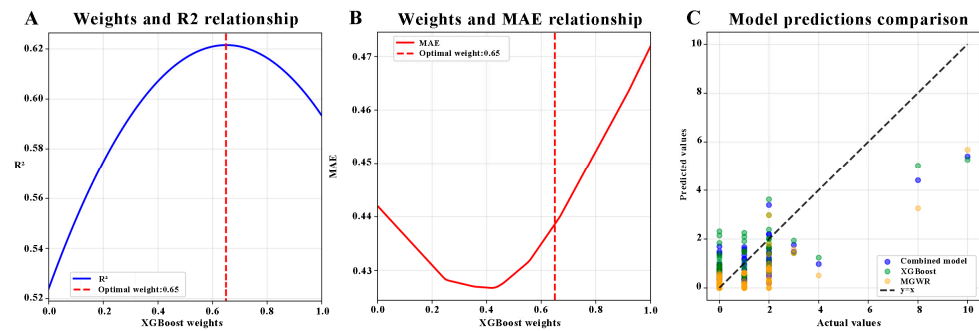


Figure 7. Model performance under different XGBoost weights and comparison of observed and predicted complaint counts.

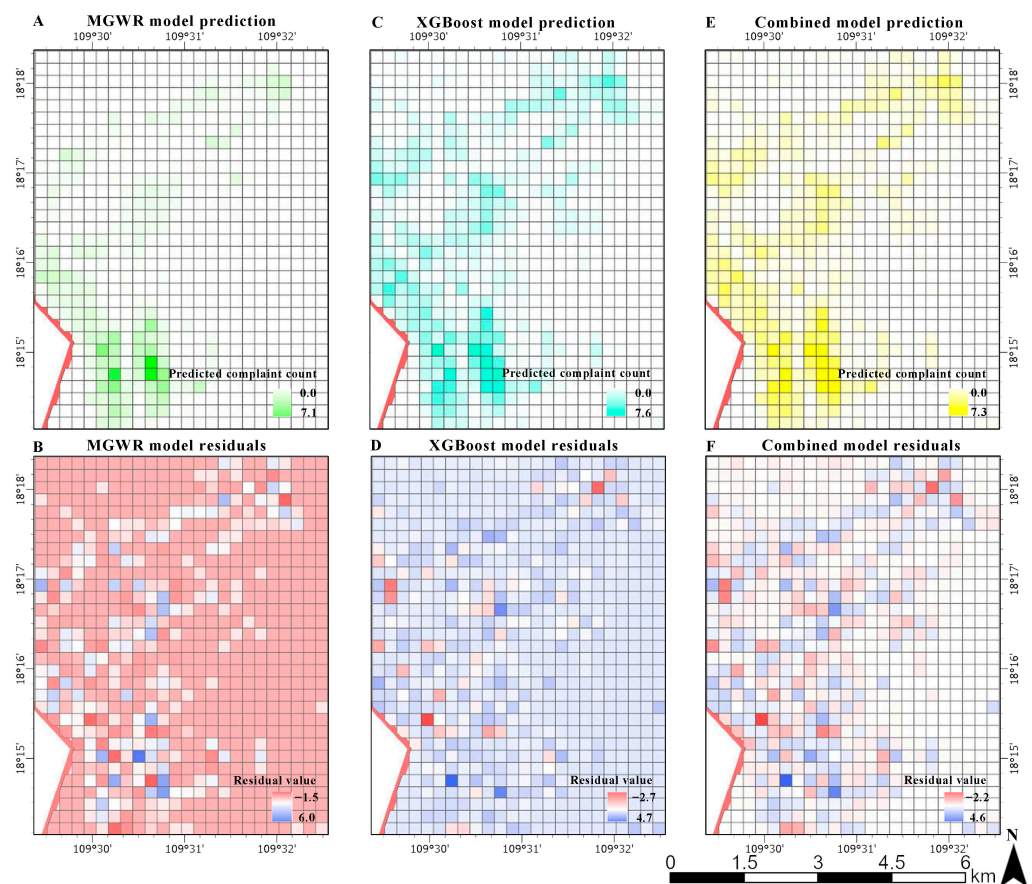


Figure 8. Spatial distribution of model predictions and residuals.

In isolation, the XGBoost model tends to underestimate complaint values, whereas the MGWR model exhibits a tendency toward overestimation. The integrated model combined the nonlinear predictive capacity of XGBoost with the spatially adaptive explanatory power of MGWR, resulting in the best overall performance among the tested models.

Compared with the individual models, the combined model demonstrates notable improvements in predictive accuracy, achieving an MAE of 0.44 and an R^2 of 0.62. By assigning greater weight to XGBoost while retaining the MGWR component, the integrated model partially corrected the overall overestimation of MGWR while reducing the irregular residual fluctuations of XGBoost. This complementary interaction results in a more balanced and robust model that effectively minimizes overall prediction bias.

Compared with the OLS baseline, the proposed MGWR–XGBoost model showed improved predictive performance on the held-out test set. The OLS baseline achieved an MAE of 0.5278 and an R^2 of 0.5699, whereas the integrated model reduced the MAE to

0.4386 and increased the R^2 to 0.6215. This indicates that the proposed framework provides additional predictive value beyond a simple global linear model.

3.3.2. MGWR Model Accuracy

Since the MGWR outputs were standardized, they were transformed back to the original complaint-count scale using the mean and standard deviation of the dependent variable. This inverse transformation was necessary to enable direct comparison and weighted integration with the XGBoost predictions. As it involved only a linear rescaling, it did not materially affect the model fit, and full numerical precision was retained throughout the calculation to minimize potential rounding errors. The MGWR predictions ranged from 0 to 7.1 (Figure 8A), with high-value clusters (dark green) concentrated in the south-central area of Sanya, indicating significant clustering of noise complaints. The residuals (representing the differences between observed and predicted values) indicate that red areas correspond to overestimations, while blue areas correspond to underestimations. The spatially dispersed pattern of the residuals (Figure 8B) suggests that although the model successfully captures the broader trend of elevated noise levels in the noisy southern urban areas, it tends to overestimate overall (Figure 7C) and exhibits local fitting deviations at smaller scales.

The MGWR model achieved an MAE of 0.44, meaning an average absolute deviation of 0.44 from the actual complaint count. The R^2 value of 0.52 indicates that the model explains 52% of the variance in noise complaints. Overall, these results suggest that MGWR effectively captures the main driving mechanisms of complaint distribution.

3.3.3. XGBoost Model

The high predicted values of the XGBoost model (dark cyan) were also concentrated in the south-central area of Sanya, consistent with the hotspot pattern identified by MGWR (Figure 8C). The prediction range was from 0.0 to 7.6. Although the model incorporated X and Y projection variables to capture some spatial trends, it is inherently a global aspatial model that cannot explicitly model local spatial dependence. Consequently, the residuals were irregularly scattered throughout the study area (Figure 8D), showing no clear spatial structure. Although this pattern suggests no obvious systematic spatial bias, it also limits the use of the residual map for identifying geographically coherent areas of persistent overestimation or underestimation.

Classification performance: The model achieved an F1-score of 0.6364 for binary (0/1) complaint occurrence and an AUC-PR of 0.7508, indicating a strong ability to capture nonlinear interactions among predictors.

Regression performance: The regression model achieved an MAE of 0.76 and an R^2 of 0.54, which is comparable to the performance of MGWR, suggesting that the XGBoost regression model has a similar capability to MGWR in predicting complaint magnitude. Nevertheless, MGWR still holds a theoretical advantage in capturing local spatial heterogeneity.

Overall, the two-stage fused XGBoost model achieved a final MAE of 0.47 and an R^2 of 0.59, significantly outperforming the single regressor (which achieved an R^2 of only 0.54), validating the effectiveness of this architecture in handling zero-inflated data. The core advantage of this method lies in decoupling the “occurrence mechanism” and the “magnitude mechanism” of complaints, thereby avoiding the interference of numerous zero samples with the regression task and significantly improving prediction accuracy.

4. Discussion

4.1. Interaction Between Social Sensing and Physical Space: Spatial Heterogeneity of Urban Noise Complaints

This study highlights that the distribution of noise complaints is not spatially uniform, but varies substantially across urban contexts. Unlike traditional acoustic measurements, noise complaints can be regarded as a form of social-sensing data that captures residents' subjective dissatisfaction with the acoustic environment, which may in turn be shaped by both built environment conditions and thermal stress.

Road density shows a spatially heterogeneous association with noise complaints. MGWR analysis reveals a non-uniform spatial pattern: in the innermost central urban area, road network density is negatively correlated with noise complaints, whereas in sub-central and other peripheral areas, it exhibits a positive correlation. Previous research in New York noted a global positive correlation between noise complaint rates and road density or intersection proximity, suggesting that denser road networks imply greater noise source exposure [13]. Our findings refine this perspective. This resonates with findings that planning variables have a significant scale effect on traffic noise, where the direction of impact may reverse at different spatial scales [24]. In the innermost central urban area, higher road network density may reflect a more mature traffic dispersion system, which may be associated with fewer congestion-related noise complaints. In sub-central areas, dense road networks combined with high-rise buildings create a “canyon effect” that traps and amplifies traffic noise, exacerbating residents' annoyance and increasing complaints [25]. In other peripheral areas, road network density is also positively correlated with complaints, but for a different reason—here, higher road density is associated with increased traffic volumes and a lack of the acoustic optimization measures found in central areas, which may correspond to higher complaint levels.

At the perceptual level, the cumulative exposure associated with population concentration may offset part of the physical shielding effect of dense urban form. Physical simulations have shown that high-density building layouts (such as high Ground Space Index (GSI) can significantly reduce regional noise levels (particularly L70-L90) through physical shielding [25]. However, our results indicate that at the perceptual level, complaint rates in high-density areas remain high. From the perspective of exposure science, although high-density buildings may physically block sound propagation, extreme population density implies an exponential increase in the population base exposed to noise events. As observed with the high concentration of complaints in Manhattan, the cumulative effect of social sensing data outweighs the benefits of physical noise reduction [13]. By incorporating UHI level into the analytical framework, this study suggests that thermal stress may alter residents' tolerance to urban noise, thereby extending conventional acoustics-oriented interpretations of complaint behavior.

4.2. Urban Noise Planning Strategies Based on Exposure Science

The findings suggest that urban noise governance may benefit from moving beyond source-oriented control toward a broader exposure-management perspective. Based on the spatial heterogeneity analysis of how POI count and the thermal environment are associated with noise complaints, we recommend differentiated strategies.

Layouts in city centers should be rationally arranged based on plot functions. In city centers, land use mix is high, with residential and commercial activities closely interwoven. Studies indicate a significant positive correlation between the proportion of commercial land and noise complaints [13]. The importance of land use for noise control at finer scales has also been emphasized [24]. In highly mixed-use urban centers, noise-sensitive residential spaces should, where possible, be buffered from high-intensity commercial

functions such as dining and entertainment. Additionally, the green space ratio has been confirmed to have a significant effect on reducing peak noise (L10) [25].

Urban fringe areas require a greater focus on traffic noise control. In these areas, noise primarily stems from arterial traffic interference. A significant positive correlation has been found between the Total Road Length Index (TRLI) and regional noise levels [25]. Multi-scale analyses further note that road factors dominate in larger spatial units [24]. The MGWR results further confirm that noise complaints in urban fringe areas are associated with increased road density. Therefore, planning strategies should focus not simply on road expansion, but on optimizing secondary road connectivity and traffic organization to reduce concentrated exposure along major corridors. This echoes the spatial threshold and spillover effects of urbanization on ecological resilience [26].

4.3. Methodological Implications: The Synergistic Effect of Machine Learning and MGWR

A key methodological contribution of this study lies in integrating explainable machine learning with MGWR to jointly capture nonlinear effects and spatial heterogeneity. This overcomes the limitations of previous studies in capturing complex urban dynamic features, balancing global accuracy in noise complaint prediction with local interpretability.

Machine learning excels at capturing complex global nonlinear effects. Traditional noise complaint studies rely primarily on Spearman rank correlation coefficients or linear regression models [13]. While effective in identifying general trends, these methods implicitly assume a monotonic linear relationship between urban morphology and noise perception. However, as our machine learning screening process reveals, built environmental elements often exhibit significant nonlinear threshold effects (e.g., UHI level shows a nonlinear threshold-like association with complaint counts). Such nonlinear and threshold-dependent relationships may be difficult to identify within conventional linear modeling frameworks. By introducing machine learning for feature importance screening, we can identify key nonlinear associations that might be underestimated in traditional regression, more accurately reconstructing the interaction processes among urban factors.

MGWR helps address spatial non-stationarity and scale issues. Although MGWR has been applied to reveal the spatial heterogeneity of noise-related factors [25], traditional MGWR faces computational and collinearity bottlenecks when handling high-dimensional feature screening. By pre-screening features using Spearman correlation and multivariate regression equations, this study not only improved the operational efficiency of the MGWR model but also enhanced its interpretability. Resonating with the emphasized multi-scale effects [24], our hybrid model identifies not only the operational scale (bandwidth) of variables via MGWR but also quantifies the intensity differences of variable associations across different locations. Combining machine learning for nonlinearity identification with MGWR for spatial analysis achieves a shift from “black-box” prediction to “interpretable spatial inference,” providing a more robust analytical paradigm for urban noise research.

Furthermore, differences in optimal model weights across cities or datasets may provide useful information for comparing the relative roles of global nonlinear regularities and local spatial heterogeneity in explaining complaint patterns. A higher XGBoost weight may indicate that complaint patterns are more strongly associated with citywide nonlinear relationships among variables, such as threshold effects or interactions between POI concentration, road density, population density, and thermal conditions. In contrast, a higher MGWR weight may suggest that complaint patterns are more strongly conditioned by local spatial contexts, where the same built-environment or thermal factor may show different association directions or strengths across urban areas. Therefore, the weighting structure itself can be interpreted as an indicator of whether complaint patterns are mainly

better characterized by broadly shared nonlinear relationships or by locally differentiated spatial processes.

4.4. Limitations and Future Prospects

Despite deepening the understanding of noise complaint mechanisms, this study has limitations.

Bias in complaint behavior: Noise complaints do not directly represent objective acoustic exposure or measured sound pressure levels. Complaint records reflect publicly reported noise-related behavior and may vary with residents' awareness, willingness to complain, access to reporting platforms, trust in authorities, local governance responsiveness, and social norms [27], as well as socio-demographic characteristics such as age and income [28]. However, the complaint records used in this study contained the time, location, and brief textual descriptions of noise events, but did not include individual-level socio-demographic or behavioral information. Future studies should combine complaint data with measured or modeled acoustic indicators, such as LAeq and Lden, and questionnaire-based field surveys covering socio-demographic and behavioral variables. By including residents who experience noise annoyance but do not file complaints, future research could better distinguish objective noise exposure from reporting-related biases and improve the interpretability and robustness of the findings.

Absence of temporal dynamics: The spatial analyses and visualizations in this study represent a static cross-sectional period from March to June 2024 and therefore do not capture seasonal fluctuations, weekday–weekend differences, or daytime–nighttime variations in noise complaint patterns. This limitation is particularly relevant to Sanya, where tourism-related population and activity levels may vary substantially over time. Previous studies have documented seasonal and weekly variations in noise complaints [13], as well as substantial differences between daytime and nighttime complaint patterns [8]. The available complaint records in the present study were limited in size, and further temporal subdivision could reduce the robustness of the statistical analysis. Future studies should incorporate longer-term and higher-temporal-resolution complaint data or alternative social-sensing data sources to examine how the associations between urban environmental factors and noise complaints vary across different temporal contexts. As the 2023 Land-Scan dataset was the closest available population surface to the 2024 study period, it was used to represent the broader population distribution; nevertheless, the one-year temporal difference and its original approximately 1 km resolution may introduce some uncertainty and smooth fine-scale population variations.

Limited variable coverage: The predictor set was limited to road density, population density, POI count, and temperature, which may introduce omitted-variable bias. Land Use Regression (LUR) models have shown that incorporating land-cover and land-use features can improve the explanatory power of traffic noise distribution [29], while recent research has identified scale-dependent associations between multidimensional urban morphology indicators, such as sky openness and building-height variation, and noise distribution [30]. Future studies should build on these findings by incorporating additional built-environment indicators, such as sky openness, building-height variation, street-canyon morphology, and green-space configuration, together with socio-economic variables including income and education and objective acoustic indicators such as LAeq and Lden. Appropriate variable-selection procedures could then be applied to reduce potential omitted-variable bias.

Spatial scope and methodological refinement: The two-level analytical design used all 3461 grids to identify the citywide spatial concentration of complaints and the 724 hotspot grids to examine environmental associations and spatial heterogeneity within

complaint-concentrated areas. Accordingly, the regression results primarily explain variations within hotspot areas. Future full-domain analyses using hurdle or zero-inflated count models could further examine whether these associations also apply to grids with sparse or no complaints.

As this study was based on cross-sectional observational data, the associations identified by MGWR should not be interpreted as causal relationships. In particular, the results cannot establish that thermal conditions directly cause changes in noise complaints, because both may be simultaneously associated with other unobserved spatial or social factors. In addition, the MGWR 2.2 implementation used in this study adopts a Gaussian framework. Although this framework was useful for both spatial prediction and the identification of spatially varying associations, noise complaint counts are discrete and zero-inflated. Furthermore, although MGWR employs adaptive bandwidths, highly uneven complaint distributions—characterized by dense clustering in the center and extreme sparsity at the urban fringe—may require the bandwidths in sparse areas to include geographically distant observations. This may result in over-smoothed local coefficients and greater uncertainty in local estimates. In addition, because the same held-out dataset was used to compare candidate ensemble weights and report the performance of the selected model, the reported MAE and R^2 may slightly overestimate performance on entirely unseen data. Future studies should use an internal validation set or nested cross-validation for weight selection while reserving a separate test set for final evaluation. Future work could conduct comparative studies across multiple cities, including other tropical coastal tourism cities and cities with different climatic and morphological contexts, to further examine the transferability of the spatial heterogeneity patterns found in this study, particularly the contrasting associations of road density between central and peripheral urban areas, while also exploring Poisson, negative binomial, or zero-inflated spatial regression models and coupled models capable of adaptively adjusting weights to better accommodate the distributional characteristics and spatial sparsity of complaint count data.

5. Conclusions

This study integrated XGBoost and MGWR to examine the associations between built-environment characteristics, population density, thermal conditions, and the spatial distribution of noise complaints in Sanya. POI count was the strongest predictor of both complaint occurrence and intensity. UHI level was not a dominant predictor of complaint occurrence, but showed nonlinear and spatially varying associations with complaint intensity, with positive associations at moderate levels and negative associations at very high levels. Road density showed an overall positive association across the study area but a locally negative association in the central urban area, while population density was generally positively associated with complaint patterns.

Taken together, these findings reveal that different factors are associated with different dimensions of noise complaint patterns. Urban functional concentration was most strongly associated with where complaints occurred, whereas thermal conditions were more closely associated with variations in complaint intensity than with complaint occurrence. Meanwhile, the locally reversed association of road density demonstrates that an overall citywide relationship may conceal different or even opposite relationships in particular urban contexts. Noise complaints therefore cannot be interpreted as a simple response to a single environmental stressor or as a direct proxy for acoustic exposure. Instead, they should be understood as context-dependent social-sensing data whose spatial patterns are associated with urban activities, thermal conditions, and local spatial characteristics, while also potentially being influenced by residents' reporting behavior. Methodologically, the integrated model achieved the best observed performance among the evaluated models

on the held-out dataset ($MAE = 0.4386$; $R^2 = 0.6215$), suggesting that global nonlinear prediction and local spatial analysis provide complementary rather than competing information. This complementarity is important not only for improving prediction but also for distinguishing broadly shared patterns from locally specific relationships. Accordingly, complaint-based noise governance should avoid uniform interventions: central urban areas require greater attention to mixed urban functions and thermal conditions, whereas peripheral areas require more targeted traffic organization and noise control. These conclusions remain specific to the present cross-sectional study of Sanya and should be further tested using multi-city comparisons, objective acoustic measurements, and individual-level socio-demographic and behavioral data.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18147478/s1>, Supplementary Table S1: Aggregated grid-level analytical dataset used for model construction.

Author Contributions: L.G.: writing—review and editing, writing—original draft, visualization, software, methodology, formal analysis, and conceptualization. W.-Z.X.: writing—review and editing. J.L.: supervision, resources, and funding acquisition. X.-C.H.: writing—review and editing, supervision, resources, project administration, methodology, funding acquisition, and conceptualization. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant numbers 52208052, 52378049 and 52308055; and the Natural Science Foundation of Fujian Province, China, grant number 2023J05108.

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The noise complaint data used in this study are not publicly available due to privacy and administrative restrictions. The remote sensing and spatial datasets used for deriving environmental and urban variables are available from the corresponding public data platforms described in the manuscript. The processed data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to data-use restrictions.

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

Abbreviations

The following abbreviations are used in this manuscript:

AICc	Corrected Akaike information criterion
AUC-PR	Area under the precision–recall curve
GIS	Geographic information system
KDE	Kernel density estimation
LST	Land surface temperature
MAE	Mean absolute error
MGWR	Multiscale geographically weighted regression
OLI/TIRS	Operational Land Imager/Thermal Infrared Sensor
POI	Point of interest
R^2	Coefficient of determination
SHAP	SHapley Additive exPlanations
UHI	Urban heat island
VIF	Variance inflation factor
XGBoost	eXtreme Gradient Boosting

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