

Bridging Gaps between Subjective and Objective Urban Resilience under Extreme Rainstorms: A

Localized Spatial Machine Learning Approach

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Abstract

Aligning residents' subjective perceptions of recovery with objective infrastructure restoration is critical for effective disaster management. A persistent gap between these two dimensions can undermine community well-being and lead to inequitable resource allocation. However, recovery strategies are often hampered by a failure to understand the spatially heterogeneous drivers of this gap and how they evolve across different recovery phases. Addressing this gap, the study develops a localized analytical framework that integrates a Geographically Weighted Random Forest (GWRF) model to quantify and bridge gaps between subjective and objective urban resilience. We validated the proposed methodology and framework using multi-source urban block scale data from the 2023 Beijing extreme rainstorm. The results reveal that: (1) The framework identified 306 vulnerable communities, and simulated interventions predicted gains 7.9% in subjective resilience, 6.2% in objective resilience, narrowing the overall gap by 10.8%. (2) Socio-economic factors dominated in highly urbanized areas, while environmental variables were more influential in less urbanized zones. (3) These factors exhibited significant nonlinear and spatially varying effects, with key thresholds including impervious surface coverage $\leq 54\%$ and land use diversity index between 0.8 and 1.2. (4) The GWRF model (local $R^2 > 0.80$ and global $R^2 > 0.90$) validates the framework's reliability. By providing localized evidence, this framework empowers policymakers to move beyond one-size-fits-all solutions, enabling targeted strategies that bridge gaps between subjective and objective urban resilience.

Keywords

Urban Resilience; Residents' Needs; Spatial Heterogeneity; Enhancement Strategies

1. Introduction

Recent years have seen an acceleration of global climate change, altering urban systems and increasing the threats of extreme disasters across cities worldwide (Adger et al., 2022; Rajput et al., 2024). Urban resilience, defined as the capacity of urban systems to absorb shocks, adapt, and recover (Meerow et al., 2016), involves both the restoration of physical infrastructure and the recovery of residents' psychological and social well-being (Dargin & Mostafavi, 2020; Zhao et al., 2025). However, traditional approaches often prioritize physical aspects, overlooking the interplay between subjective perceptions and objective physical realities (Cardoso et al., 2022; Haque & Fatema, 2022). The gap between subjective and objective resilience often results in misaligned recovery efforts, where physical infrastructure is restored but residents' perceptions remain underestimated, leading to inefficient resource allocation and social trust (Gu et al., 2025; Zhao et al., 2025). Narrowing this gap is crucial for urban resilience, as it ensures that recovery addresses

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both physical recovery and human experiences, promoting equitable and sustainable development.

Prior research has extensively emphasized the effects of socio-demographic characteristics and environmental attributes on recovery outcomes (Bhattarai et al., 2020; Mouratidis, 2021a). However, three key limitations undermine these efforts. many studies assess global factor importance under the assumption of spatial stationarity, offering little insight into the localized relevance of specific drivers (Wang et al., 2024; Yue & Chen, 2025; Y. Zhang et al., 2025a). Without local R^2 -based validation, areas with poor model performance may go undetected, leading to biased interpretations of resilience drivers in highly heterogeneous contexts. Second, recovery processes are phase-dependent, with dominant factors varying across the emergency window, short-term stabilization, and long-term rebuilding phases (Birkmann et al., 2023; Z. Zhao et al., 2022). Third, the relationships between factors and outcomes are frequently nonlinear and threshold-driven, rendering linear or globally pooled models inadequate for capturing critical intervention ranges (Liu et al., 2023; Yang et al., 2021). Consequently, uniform strategies often fail to address the most acute needs in specific locations and stages, highlighting the need for targeted approaches.

To address these gaps, we develop a localized spatial machine learning framework that analyzes subjective and objective resilience and models their determinants with a Geographically Weighted Random Forest (GWRF). GWRF model combines the ability of Random Forests to capture complex, nonlinear interactions with geographically weighted estimation that allows coefficients and variable importance to vary over space (Brunsdon et al., 1996; Grekousis et al., 2022; Gu et al., 2023; Zhang et al., 2025b). This delivers three decision-relevant outputs for each community and each recovery phase: (i) the top local drivers of subjective and objective resilience, (ii) post-disaster recovery phase effect magnitudes, and (iii) optimal adjustment ranges derived from local partial dependence profiles. The framework moves from identifying “what matters” to prescribing “how much to change, where, and when”.

This study contributes to the urban resilience literature and practice in four ways. (1)The study develops a localized analytical framework that bridges gaps between subjective and objective urban resilience under extreme rainstorms. (2) This study advances localized, phase-specific diagnosis by coupling the GWRF model with human needs-based metrics, revealing where and when particular factors dominate. (3) This study extracts nonlinear, community-level prescriptions (optimal ranges and thresholds), translating analytics into implementable guidance for resource allocation.

The remainder of the paper is organized as follows. Section 2 reviews the literature on subjective and objective resilience, highlighting gaps in spatial and temporal modeling. Sections 3 introduces the analytical framework. Section 4 presents GWRF-based methodological framework. Section 5 reports empirical results, offers enhancement strategies and simulation-based policy implications. Section 6 concludes with limitations and directions for future research.

2. Literature review

2.1 Subjective and Objective Urban Resilience Measurement

The measurement of urban resilience has increasingly recognized the importance of both subjective and objective dimensions, reflecting the multifaceted nature of recovery in disaster-affected communities (Chumo et al., 2022; Haque & Fatema, 2022). Subjective resilience research aims to capture socio-psychological dimensions that underpin a community's capacity to cope with and adapt

to disturbances, encompassing social perceptions, subjective satisfaction, and risk awareness that often overlooked by objective metrics (Qiu et al., 2022). Methodologically, this field relies on qualitative and quantitative tools designed to measure human perception and social capital. For instance, Likert scales and structured questionnaires are frequently employed to quantify indicators such as social trust, community cohesion, risk perception, and institutional faith (Lim et al., 2021; Lwin et al., 2020). These quantitative instruments are often complemented by qualitative methods like semi-structured interviews and textual analysis, which provide deeper context on cultural values and lived experiences (Pan et al., 2022; Zhao et al., 2022). Despite their strength in illuminating the "soft" components of resilience, these methods face significant limitations. They often provide a static snapshot, struggling to capture the dynamic evolution under different stages of crisis. In contrast, the study of objective resilience has seen rapid advancements through the integration of computational models and multi-source data. A prominent trend is the move from static vulnerability assessments to dynamic process simulations (Wang et al., 2025). Precision is further enhanced by fusing diverse datasets, such as integrating nighttime light (NTL) remote sensing with population data to model post-disaster recovery speeds (Yin et al., 2025), or triangulating evidence from policy documents and social media to create comprehensive indicator frameworks (Wu et al., 2024; Zhao et al., 2025). These innovations signify a clear progression towards more dynamic, evidence-driven, and spatially explicit analyses of urban resilience.

A critical gap emerges from the methodological and conceptual divergence between subjective and objective resilience. To narrow the gap, a robust understanding of both dimensions is essential. However, Existing studies on socio-spatial inequality typically analyze these dimensions under disparate indicator systems, which makes direct comparison challenging and hinders the development of strategies. Bridging these gaps by integrating the "why" from subjective research with the "how" from objective analysis remains a crucial frontier for advancing the science and practice of urban resilience.

2.2 Factors Influencing Subjective and Objective Urban Resilience

A substantial body of research demonstrates that urban resilience is shaped by a multifaceted interplay of natural environment, built environment, and socioeconomic factors (Bhattarai et al., 2020; Gu et al., 2025). Yet two critical gaps persist. First, most existing studies assess factor importance at a global scale, overlooking spatial heterogeneity in how these factors operate across diverse urban contexts (Lu et al., 2023; Wang et al., 2024; Yue & Chen, 2025). This constrains the development of localized strategies for resilience enhancement. Second, the post-disaster recovery process operates through distinct mechanisms in emergency versus long-term phases (Huang & Wang, 2024; Yang et al., 2024), but current spatial machine learning models fail to differentiate these temporal dynamics.

Addressing the first gap requires understanding how the same resilience determinants exert different influences in different locations. Natural environment attributes, for example, exhibit highly localized impacts: precipitation intensity is a primary driver of drainage system overload (Li et al., 2024), with maximum daily rainfall serving as a critical indicator of recovery challenges (Munpa et al., 2022a). High river network density can accelerate flood peaks in downstream, densely populated districts (Chen et al., 2020), disproportionately affecting riverside communities. Land cover heterogeneity further shapes resilience patterns, as green spaces and water bodies mitigate flood impacts more effectively than impervious transport surfaces (Liu et al., 2023; Wang et al., 2023). Built environment features such as road network density and land use diversity also reveal spatially contingent effects;

mixed-use neighborhoods typically enjoy superior access to emergency resources compared to single-function areas, whereas unchecked expansion of impervious surfaces can exacerbate local flooding (Ibrahim et al., 2024; Qi et al., 2025). Socioeconomic factors—such as population density, public service availability, and community networks—likewise operate in context-dependent ways. While high-density communities may experience resource strain during disasters (Jeong & Yoon, 2018a), they often cultivate stronger mutual aid networks (Zahnow et al., 2019a).

Crucially, the spatially varied effects of these determinants are not constant over time but shift across the disaster lifecycle, bringing us to the second gap. In the emergency phase, rapid physical access and immediate resource availability tend to dominate resilience outcomes. In contrast, the long-term recovery phase increasingly depends on sustained social infrastructure, environmental quality, and economic revitalization capacity (Finucane et al., 2020). Current decision-support systems often fail to capture these nonlinear, time-dependent relationships. Addressing this gap calls for localized, stage-sensitive models capable of informing decision-making across the entire resilience timeline.

2.3 Modeling Approaches for Resilience Analysis

To bridge the identified gap, resilience modeling requires approaches that simultaneously account for spatial heterogeneity and non-linear interactions, enabling localized insights into post-disaster recovery. Traditional statistical and global machine learning models generate factor importance values for an entire study area (Agonafir et al., 2022; Cheng et al., 2020), assuming uniform effects across space (Chen & Ji, 2021). GWR model offers a promising solution by integrating the interpretability of Geographically Weighted Regression with the non-linear predictive capacity of Random Forests (Wu et al., 2024b; Yi et al., 2024; Zhang et al., 2024). Unlike conventional RF, which estimates factor importance at a global scale, GWR model computes locally weighted decision trees for each spatial unit (Grekousis et al., 2022), allowing the relative influence of variables to vary across locations (Ma et al., 2025). This enables the identification of location-specific top drivers of recovery disparities. For example, that drainage density may be the dominant determinant in low-lying flood-prone districts, while road network connectivity or healthcare facility accessibility may exert greater influence in inland areas.

Beyond ranking local factors, GWR model also extract optimal value ranges for each determinant within a given location (Ma et al., 2025; Wu et al., 2024a; Yue & Chen, 2025), thereby offering actionable guidance. For instance, in a community where road network density is the most influential variable during the emergency phase, the model can indicate the threshold density above which marginal improvements yield minimal gains. Similarly, for green space ratio or maximum daily rainfall tolerance (Munpa et al., 2022a; Wang et al., 2019), GWR-derived partial dependence profiles can quantify the local spot for resilience optimization. By providing such localized prescriptions, policy-makers can prioritize investments that deliver the highest returns for specific neighborhoods, rather than applying uniform strategies that may underperform in certain contexts. By incorporating spatially varying relationships, the GWR approach captures spatial heterogeneity in both the magnitude and direction of factor impacts, while also producing local R^2 values that reveal where the model fits well and where resilience determinants remain unexplained.

Through this combination of spatial adaptivity and non-linear modeling, GWR model narrows the current methodological gap and enhances the practical relevance of resilience analysis. It enables decision-makers to answer three critical questions for each location: (1) Which factors matter most for recovery here? (2) How strongly do they influence outcomes in different recovery phases? (3) To what extent should each factor be improved to maximize resilience gains? This capacity to move from

global averages to place-based, quantitatively optimized recovery strategies.

3. Methodology

This study follows a three-step methodology to bridge subjective and objective resilience. As shown in Fig. 1, the process involves measuring resilience disparities, modeling local determinants using GW-RF, and conducting optimization analysis to predict targeted improvements. First, the baseline GWRF models are applied to identify communities with low resilience scores, forming the set of vulnerable communities. Second, for each vulnerable community, the locally dominant factor is extracted from the model's variable importance ranking. Third, Partial Dependence Plots (PDPs) are generated to explore non-linear effects and to determine the optimal value range for the dominant factor. Finally, the framework simulates adjustments of the dominant factor within its optimal range and forecast post-intervention resilience improvements.

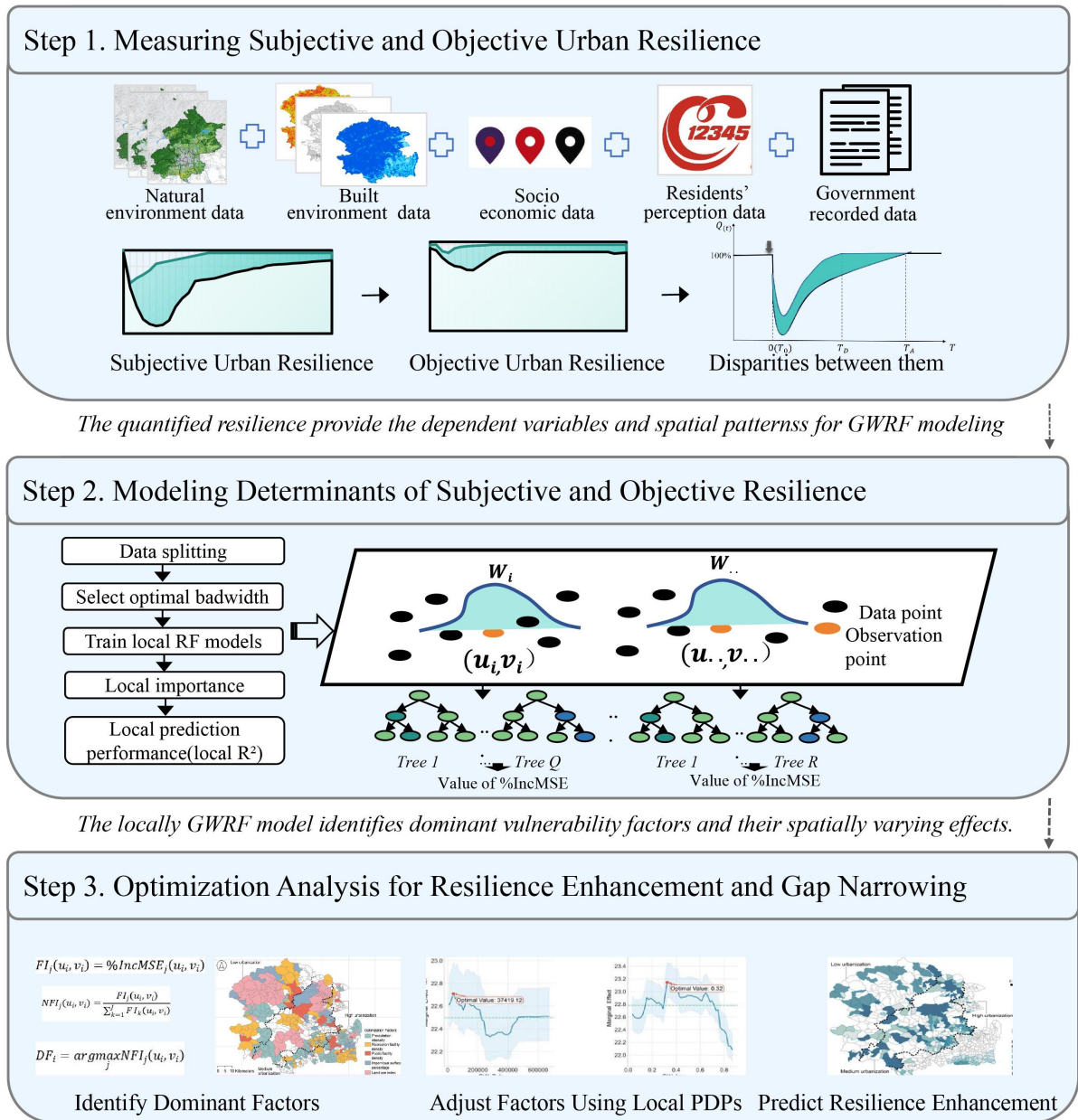


Fig.1. Analytical Framework

补充：关于主客观韧性因子的具体评估方法。

3.1 Measuring Subjective and Objective Urban Resilience

The subjective city performance curve evaluates residents' subjective resilience by capturing how effectively post-disaster service restoration meets their needs over time. Unlike conventional approaches that rely on static satisfaction surveys, this study uses a needs-fulfillment performance curve (Pan et al., 2022a; Zhao et al., 2025), which traces the progressive resolution of residents' demands. The area under the curve serves as a quantitative indicator of resilience (Bruneau et al., 2003), reflecting both the timeliness and completeness of recovery efforts from the residents' perspective. The objective city performance curve quantifies objective resilience by measuring the functional restoration of urban infrastructure using the same demand categories as in the subjective analysis, ensuring direct comparability. Service restoration is defined as the ratio of restored capacity to total demand at each time point.

(1) Data collection and preprocessing. High-resolution, post-disaster resident demand data were compiled from multiple channels, including smart city management platforms, municipal service hotlines, official social media accounts, and mobile applications. Each record contains street-level geographic coordinates and minute-level timestamps, enabling fine-grained spatiotemporal analysis. A multi-step preprocessing pipeline ensures data reliability: (i) duplicate and irrelevant entries are removed; (ii) natural language processing converts unstructured complaints into structured fields capturing demand type, municipal responses, and resolution details; (iii) time series track the interval from request submission to resolution; (iv) spatial information is standardized via GIS-based geocoding. Objective data are obtained from IoT-enabled infrastructure monitoring systems and GIS-based service coverage models, capturing real-time operational status for electricity, water, gas, transportation, communication, and public services. Preprocessing includes (i) removal of erroneous or missing sensor records, (ii) normalization of service status to percentage capacity restored, and (iii) alignment with the demand categories identified in the subjective analysis. AUC values for each category serve as objective resilience scores.

(2) Demand categorization. Latent Dirichlet Allocation (LDA) topic modeling is employed to group complaints into semantically coherent categories, including: infrastructure restoration (e.g., electricity, water, transportation), provision of essentials (e.g., food, medical supplies), public service restoration (e.g., healthcare, education), environmental cleanup, and psychological support. Preprocessing steps such as tokenization, stop-word removal, and stemming ensure model accuracy, and expert validation aligns categories with real-world disaster contexts.

(3) Curve construction. For each category, the needs fulfillment ratio—resolved demands divided by total demands—is calculated at each time point. Performance curves are plotted with time on the x-axis and needs fulfillment on the y-axis, and the integrated area is computed as the subjective resilience score. Integrating these curves with GIS reveals spatial disparities, pinpointing communities with low perceived recovery performance..

3.2 Modeling Determinants of Subjective and Objective Resilience

3.2.1 Geographically Weighted Random Forest (GWRF) Model

The Geographically Weighted Random Forest (GWRF) model integrates the spatial adaptiveness of Geographically Weighted Regression (GWR) with the nonlinear predictive power of Random Forest (RF), making it suitable for resilience modeling in spatially heterogeneous urban contexts. Unlike conventional global models that assume spatial stationarity, GWRF calibrates localized RF sub-models for each spatial unit using geographically weighted data, enabling the derivation of *location-*

specific feature importance scores. In this study, GWRF was implemented via the SpatialML package in R to predict subjective and objective resilience using nine pre-disaster attributes.

(1) Geographically weighted regression (GWR).

GWR extends global regression by estimating location-specific coefficients, weighted by the proximity of neighboring observations within a predefined bandwidth. The GWR model can be expressed as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^k \beta_j(u_i, v_i)x_{ij} + \epsilon_i \quad (1)$$

Where y_i represents the dependent variable for community i , (u_i, v_i) denotes the coordinates of community i , $\beta_j(u_i, v_i)$ signifies the local coefficient estimate for independent variable x_j at community i , and ϵ_i represents the residual error.

Location-specific parameter estimates are achieved by considering neighboring observations within a selected bandwidth for each community. The estimation of parameters at a specific location (u_i, v_i) is formulated as:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y \quad (2)$$

Where $\hat{\beta}(u_i, v_i)$ represents the estimated location-specific parameters, X and Y are matrices of independent and dependent variables, respectively, for neighboring communities within a predefined bandwidth. The bandwidth can be categorized into two types: adaptive bandwidth and fixed bandwidth. Adaptive bandwidth selects neighbors based on a specified number, while fixed bandwidth chooses neighbors within a certain distance range. W represents the spatial weight matrix.

(2) Random Forest (RF)

RF is an ensemble of decision trees trained on bootstrap samples, with random feature selection at each split to enhance generalization. Each tree is trained on a random subset of the dataset, created through bootstrap sampling, and uses a randomly selected subset of features at each node split. In the aggregation phase, RF averages the predictions of all trees to produce a continuous output, making it suitable for regression tasks. This can be expressed as:

$$\hat{Y} = \frac{1}{N_{tree}} \sum_{k=1}^{N_{tree}} T_k(X) \quad (3)$$

Where $\hat{Y}$ is the final predicted value, N_{tree} is the number of trees in the forest, and $T_k(X)$ is the prediction of the k^{th} decision tree for input X .

(3) Geographically Weighted Random Forest (GWRF) model

GWRF model combines these two approaches by training a separate RF model for each location using geographically weighted subsets of the data. GWRF extends global RF by incorporating a spatial weight matrix, which calibrates local RF model for each sub-area based on neighboring observations. This decomposition into local sub-models accounts for spatial variations in the relationships between input variables and resilience outcomes, addressing limitations of global models that assume spatial stationarity. GWRF model captures both nonlinear effects and spatial autocorrelation, making it well-suited for high-dimensional, multi-source datasets. The regression equation for the GWRF model is given by:

$$Y_i = RF(X_i, (u_i, v_i)) + \epsilon_i \quad (4)$$

Where Y_i is the dependent variable value for the i^{th} observation, $RF(X_i, (u_i, v_i))$ is the prediction from the RF model calibrated at location i , and ϵ_i represents the error.

The widely used adaptive bi-square kernel function was adopted as the distance-weighting function:

$$w_{ij} = \begin{cases} \left[1 - (d_{ij}/b)^2\right]^2 & \text{if } d_{ij} < b \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Where w_{ij} denotes the weight between community i and community j , d_{ij} represents the distance between these two communities, and b is the critical distance from regression point i to its M^{th} nearest neighbor. The distance weighting function assigns greater weight to data points closer to the regression point, with weights decreasing for data points further away.

In this study, GWRF model predicts subjective and objective resilience, measured as the population coverage ratio of satisfied demands across three recovery stages, using the nine pre-disaster attributes as inputs. The model generates location-specific feature importance scores, revealing how the influence of each attribute—such as precipitation intensity or social vulnerability—varies geographically. For instance, one variable may have a stronger impact on resilience in flood-prone areas. By integrating spatial weighting with ensemble approach, GWRF mitigates spatial instability and enhances predictive accuracy. The outputs are visualized as spatially varying performance curves, enabling comparative analysis of subjective and objective resilience across communities.

3.2.2 Model Parameter Settings

Four key parameters of GWRF model were tuned via spatial cross-validation: the *bandwidth*, the number of features considered at each node split (*mtry*), the number of trees (*n_estimators*), and the maximum tree depth (*max_depth*). These parameters are tuned to balance local and global model stability, as validated by R^2 metrics. The bandwidth determines the spatial range of the local neighborhood used to calibrate each RF sub-model at a given community with coordinates (u_i, v_i) . An adaptive bandwidth is employed, selecting a fixed number of nearest neighbors to ensure consistent sample sizes across subregions with varying spatial densities. The *mtry* specifies the number of features randomly selected at each node split in the decision trees. The *n_estimators* in each local RF sub-model is adjusted to achieve sufficient ensemble diversity while maintaining computational efficiency.

Parameter tuning is conducted using a grid search over a range of *bandwidth*, *mtry*, *n_estimators*. For each combination, the GWRF model is trained and evaluated using the validation metrics (local R^2 , global R^2 , RMSE, and MAE), with spatial cross-validation to account for spatial autocorrelation. The selection process evaluates model performance using local R^2 , which measures subregional ability, and global R^2 , which assesses overall fit.

3.2.3 Model Validation

(1) Local Fit (Local R^2)

local R^2 is calculated to evaluate the GWRF model's explanatory power at individual communities. Unlike global R^2 , which assumes spatial homogeneity, local R^2 accounts for spatial heterogeneity by focusing on data within a spatially weighted neighborhood defined by the adaptive bi-square kernel function. Local R^2 reflects the model's explanatory power within each subregion's specific context, avoiding bias from global variance that may not represent local conditions, particularly in areas with high spatial heterogeneity. The local R^2 is computed as:

$$R_i^2 = 1 - \frac{RSS_i}{TSS_i} \quad (6)$$

Local RSS_i , the local Residual Sum of Squares, measures the total squared difference between observed and predicted resilience outcomes in the local neighborhood.

$$RSS_i = \sum_{j \in N_i} w_{ij} (y_j - \hat{y}_j)^2 \quad (7)$$

Local TSS_i, the local Total Sum of Squares, measures the total variance of observed resilience outcomes relative to the local mean ($\bar{y}_{N_i}$) within the neighborhood (N_i):

$$TSS_i = \sum_{j \in N_i} w_{ij} (y_j - \bar{y}_{N_i})^2 \quad (8)$$

$$\bar{y}_{N_i} = \frac{\sum_{j \in N_i} w_{ij} y_j}{\sum_{j \in N_i} w_{ij}} \quad (9)$$

Where $\bar{y}_{N_i}$ is the spatially weighted mean of observed resilience outcomes in (N_i). w_{ij} is the spatial weight from the adaptive bi-square kernel. N_i is the set of observations within the adaptive bandwidth centered at i .

(2)Global Fit (Global R²)

Global R², RMSE, and MAE were computed on a held-out test set to assess overall model generalization. These metrics evaluate the model's performance on a held-out test set. The global R² measures the proportion of total variance explained across all communities:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (10)$$

Where y_i is the observed resilience outcome, $\hat{y}_i$ is the predicted outcome, $\bar{y}$ is the global mean, and N is the number of communities. A higher R² indicates better overall fit. In addition, the Root Mean Squared Error (RMSE) quantifies the average magnitude of prediction errors:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (11)$$

The Mean Absolute Error (MAE) measures the average absolute difference between observed and predicted values:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (12)$$

3.3 Optimization Analysis for Resilience Enhancement and Gap Narrowing

3.3.1 Defining Optimization Rules for Key Factors

(1) Identifying dominant Factors Based on Feature Importance

In the GWRF model, feature importance is divided into global importance, which reflects the average influence of a variable across the entire study area, and local importance, which captures the variable's contribution to resilience predictions within specific communities. Local importance is particularly

valuable because a factor that appears insignificant at the global scale may exert substantial influence in certain subregions due to spatial heterogeneity.

For each community, the local feature importance of variable (j) at location (u_i, v_i) is calculated using the Percentage Increase in Mean Squared Error (%IncMSE) within the local RF sub-model:

$$FI_j(u_i, v_i) = \%IncMSE_j(u_i, v_i) = \frac{1}{T} \sum_{t=1}^T \left(\frac{MSE_{t,perm,j} - MSE_{t,base}}{MSE_{t,base}} \times 100 \right) \quad (13)$$

Where $MSE_{t,base}$ is the out-of-bag mean squared error for tree (t) before permutation, and $MSE_{t,perm,j}$ is the MSE after permuting variable (j). Averaging over trees ensures a stable estimate by accounting for variability across the ensemble. This permutation-based approach ensures that the contribution of each variable is assessed relative to the local data context, accounting for spatial heterogeneity. To standardize comparisons across each sub-area, importance scores are normalized:

$$NFI_j(u_i, v_i) = \frac{FI_j(u_i, v_i)}{\sum_{k=1}^J FI_k(u_i, v_i)} \quad (14)$$

Where $NFI_j(u_i, v_i)$ is the normalized feature importance for variable (j), and J is the total number of input variables. This normalization ensures that the sum of importance scores for all variables at each location equals one, facilitating the identification of **dominant factors**.

(2) Ranking Dominant Factors

For each community, variables are ranked by their normalized local importance scores. The variable with the highest score is designated as the primary dominant factor, followed by the second- and third-most important variables. This ranking is conducted separately for subjective resilience (based on resident needs fulfillment) and objective resilience (based on service restoration) to highlight differences in their drivers.

$$DF_i = \underset{j}{argmax} NFI_j(u_i, v_i) \quad (15)$$

Where DF_i is the dominant factor for community i , and the $argmax$ function returns the variable j with the highest normalized feature importance. This approach ensures that the most influential factor is identified locally for each subregion, reflecting spatial variations in the drivers of resilience. To summarize the prevalence of each variable across the study area, the proportion of communities where variable j is the primary dominant factor is calculated:

$$P_j = \frac{\sum_{i=1}^N I(DF_i = j)}{N} \quad (16)$$

where (P_j) is the proportion of communities where variable j is the primary dominant factor, N is the total number of communities, and $(I(\cdot))$ is an indicator function returning 1 if the condition is true and 0 otherwise.

3.3.2 Guiding Adjustments to Dominant Factors Using Local PDPs

Optimization rules are derived from Partial Dependence Plots (PDPs), which visualize the marginal effect of a single variable on predicted resilience while holding all other factors constant. The global PDP assumes spatial homogeneity and is calculated as:

$$PDP_s(x_s) = \frac{1}{n} \sum_{i=1}^n f(x_s, x_{-s,i}) \quad (17)$$

Where $(f(\cdot))$ is the global RF model trained on the entire dataset, and each observation is assigned equal weight. Unlike local PDPs, global PDPs do not account for spatial heterogeneity, providing a baseline average effect across the study area.

For a specific geographic location (u_i, v_i) , the local PDP for variable (x_s) is calculated to quantify its effect on resilience predictions within the local context:

$$PDP_s(u, x_s) = \sum_{i=1}^n w_i(u) f_i(x_s, x_{-s,i}) \quad (18)$$

Where u is the target geographic location, x_s is the target feature, $x_{-s,i}$ represents the values of all other features for the i observation, $f_i(\cdot)$ is the prediction function of the local RF model at location u , calibrated using the spatially weighted dataset, and $w_i(u)$ is the geographic weight for observation i relative to location u , derived from the adaptive bi-square kernel function with the optimized bandwidth.

For each community, the local PDP for the primary dominant factor is analyzed to formulate optimization rules. The PDP curve is examined to identify the value that maximizes predicted resilience within practical constraints (e.g, policy or infrastructure feasibility). The slope and shape of the curve guide the direction and magnitude of adjustments: a steep slope indicates high sensitivity to changes, while a plateau suggests diminishing returns. Optimization rules are defined separately for subjective and objective resilience to account for differences in their response to factor adjustments.

3.3.3 Predicting Resilience Enhancement with GWRF Model

(1) Adjusting dominant factors and predicting resilience outcomes

For each community at coordinates (u_i, v_i) , the primary dominant factor (DF_i) is adjusted based on optimization rules derived from Partial Dependence Plots. The PDP for the dominant factor, $PD_{DF_i}(x_{DF_i}; u_i, v_i)$, is used to select a target value $(x_{DF_i}^*)$ that maximizes the predicted resilience outcome within practical constraints. The adjustment is applied by setting the value of DF_i to $x_{DF_i}^*$ in the local dataset, while keeping other variables unchanged. The GWRF model, calibrated with the optimal parameters, is used to re-predict resilience outcomes for both subjective and objective dimensions. The prediction function for the local RF sub-model at community generates updated resilience values:

$$\hat{y}_i^* = f(X_{DF_i} = x_{DF_i}^*, X_{-DF_i}; u_i, v_i) \quad (19)$$

Where $\hat{y}_i^*$ is the predicted resilience outcome after adjustment, $X_{DF_i} = x_{DF_i}^*$ is the adjusted value of the dominant factor, and X_{-DF_i} represents the unchanged values of other variables. This process is repeated for each community to generate a spatially varying set of enhanced resilience predictions.

(2) Quantifying enhancement and analyzing drivers

Enhancement is calculated separately for subjective and objective resilience to evaluate the effectiveness of factor adjustments in each dimension. The enhancement is defined as the relative change in predicted resilience outcomes before and after adjustment. This metric is computed separately for subjective and objective resilience to assess the effectiveness of factor adjustments in each dimension. The calculation accounts for the local context by using the spatially weighted dataset and model parameters, ensuring that enhancements reflect subregion-specific conditions.

Finally, a comparative driver analysis is conducted across short-term (infrastructure-focused), mid-term (social service-focused), and long-term (land use-focused) recovery stages. This involves comparing normalized local feature importance scores across the two resilience types to identify stage-specific patterns in resilience determinants.

4. Results and Discussion

4.1 Study area and Data description

The study area encompasses 779 disaster-affected communities in southwestern Beijing, a region characterized by diverse topography, land use, and socioeconomic conditions, as shown in Fig.2. The July 31, 2023, rainstorm serves as the case study event, providing a critical context for assessing resilience across pre-disaster preparedness, disaster response, and post-disaster recovery stages. The area covers 3,467 km² with a population of 1.707 million, impacting over 1.31 million residents. Communities are represented as a spatial grid, enabling geographically explicit analysis of resilience drivers. The dataset integrates independent variables, grouped into natural environment, built environment, and socioeconomic categories. Data were compiled from remote sensing, government records, and resident surveys, covering July 31 to November 1, 2023. The independent data encompass three categories.

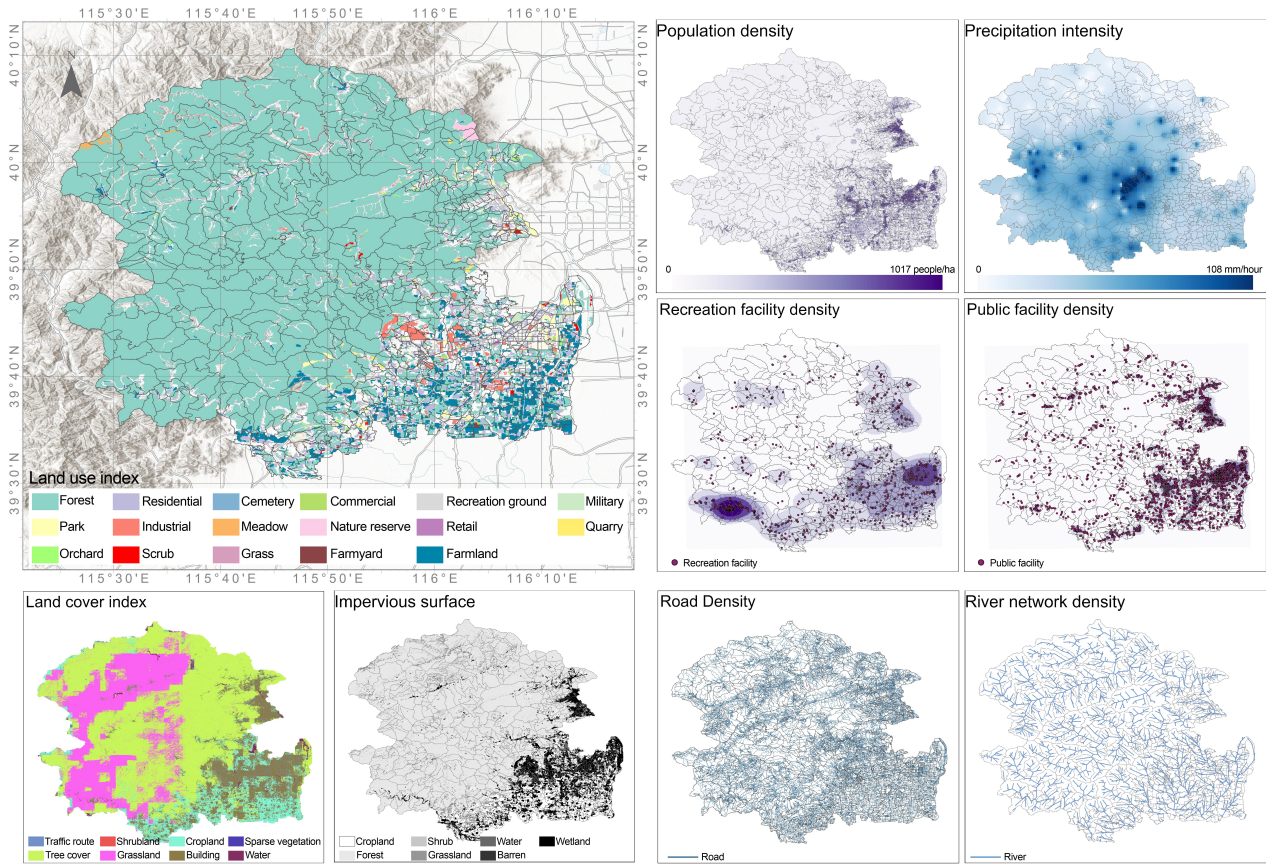


Fig.2. Study area and dataset in each block

(1) Natural Environment: Includes average precipitation, river network density, land cover diversity, and terrain slope. Average precipitation (mm) reflects hydrological conditions, derived from raster data using zonal statistics. River network density (km/km²) measures water system distribution, calculated from a Digital Elevation Model (DEM) via watershed and line density analyses. Land cover diversity, quantified using the Shannon Diversity Index (SHDI), captures the variety of cover types (e.g., forests, water bodies), with higher values indicating greater diversity. Terrain slope (degrees) describes topographic variation, derived from DEM-based slope analysis.

(2) Built Environment: Comprises impervious surface ratio, land use diversity, road network density, service facility density, and commercial facility density. Impervious surface ratio (%) quantifies non-

permeable surfaces (e.g., roads, roofs) from remote sensing imagery. Land use diversity, also measured via SHDI, reflects socioeconomic functions (e.g., residential, commercial). Road network density (km/km²) assesses transportation infrastructure, weighted by road type. Service and commercial facility densities (points/km²) capture urban functionality, derived from Point of Interest (POI) data (e.g., public services, businesses) using kernel density analysis.

(3)Socioeconomic Factors: Includes population density and nighttime light intensity. Population density (people/km²) indicates population distribution, interpolated using Inverse Distance Weighting (IDW). Nighttime light intensity (radiance units) reflects economic activity, extracted from satellite imagery.

The dependent variables measure subjective and objective resilience. The data of subjective resilience are derived from surveys of over 150,000 anonymized, geotagged resident appeals, capturing satisfaction and unmet needs post-disaster. Subjective Service Coverage is defined as the ratio of residents with resolved service requests to the total affected population per community, serving as a proxy for governmental responsiveness. Similarly, the objective resilience data are sourced from government records on infrastructure and service restoration. Objective Service Coverage quantifies the proportion of the population with restored access to critical services (e.g., power, water), calculated by aggregating operational facility service areas within community boundaries. This metric represents the physical restoration progress, measured through infrastructure service capacity recovery.

Spatial data were processed in ArcGIS Pro to align with the 779-community grid. Independent variables were extracted, clipped, and aggregated to the community level using spatial analysis tools (e.g., zonal statistics, kernel density). Dependent variables were computed by integrating survey and government data, with resident information encrypted and anonymized to ensure privacy. This dataset supports the GWRF model's spatially explicit analysis of resilience drivers and optimization strategies. The data description and processing are shown in Table 1.

Table 1. Data description

Item	Data category	Source	Data processing
1	Precipitation	Meteorological Administration (https://bj.cma.gov.cn/)	Extracted from rainfall raster data and processed using zonal statistics
2	River network	NASA (https://www.nasa.gov/)	Derived from a Digital Elevation Model and calculated using density analysis
3	Terrain slope	National Science and Technology Resource Sharing Service Platform (http://www.ircip.cn/)	Processed through slope analysis, mask extraction, and zonal statistics
4	Land cover	Wuhan University SinoLC-1 Dataset (https://doi.org/10.5281/zenodo.7707461)	Processed through coordinate transformation, cell segmentation, classified area calculation, and zonal statistics
5	Land use	Tsinghua University EULUC-China Dataset (https://data-starcloud.pcl.ac.cn/iearthdata/)	Processed through coordinate transformation, cell segmentation, classified area calculation, and zonal statistics
6	Impervious surfaces	Wuhan University CLCD Dataset(http://doi.org/10.5281/zenodo.4417809)	Extracted using masking techniques with area tables generated
7	POI	AutoNavi Map API Interface (https://lbs.amap.com/)	Processed through coordinate transformation, cell

			segmentation, kernel density analysis, and zonal statistics
8	Rail and Road network	OSM platform (https://www.openstreetmap.org/)	Processed through transformation, projection, feature splitting, and value calculation.
9	Population	LandScan (https://landscan.ornl.gov/)	Assessed through inverse distance weighting combined with zonal statistics
10	Night light	National Earth System Science Data Center (http://www.geodata.cn/)	Extracted using masking and zonal statistics
11	Perceived recovery data	Surveys of geotagged resident appeals and feedback (https://www.beijing.gov.cn/)	Calculated using LDA analysis, and performance curves
12	Physical recovery data	Government records on infrastructure and service restoration (https://www.beijing.gov.cn/)	Calculated using need-based metrics aggregation and performance curves

4.2 Spatial Heterogeneity of Subjective and Objective Resilience

Following the extreme rainstorm, both the subjective and objective resilience exhibited clear spatial differentiation across post-disaster phases, as shown in Fig.3. The smallest disparities occurred in highly urbanized areas, larger disparities in low-urbanized areas, and the largest in medium-urbanized areas. On average, highly urbanized areas showed a daily lag of -2.6% in subjective resilience compared to objective resilience, low-urbanized areas recorded -3.8% , and medium-urbanized areas reached -7.2% . At the community level, 44.2% of communities exhibited an average negative disparity exceeding -5.0% , while 13.9% experienced positive disparities.

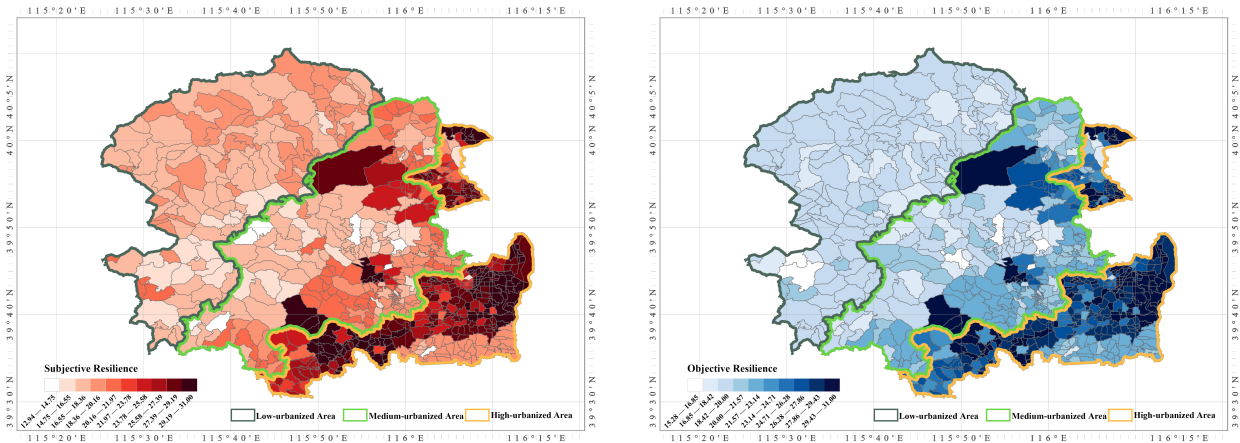


Fig. 3. Assessment of subjective and objective resilience

To further explore these disparities, spatial maps of subjective resilience (①) and objective resilience (②) were generated in Fig. 4, with disparities calculated as subjective minus objective resilience. In the maps, red indicates over-action behavior (subjective resilience lagging behind objective resilience), while blue indicates under-action behavior (subjective resilience exceeding objective resilience). The spatial pattern of disparities evolves over time. In Phase I, under-action behavior dominates in low- and medium-urbanized communities,

suggesting slower subjective recovery compared to actual functional restoration. By Phase II, most communities shift to over-action behavior, indicating that objective resilience outpaces subjective resilience, especially in low-urbanized areas where prolonged recovery needs conflict with “top-down” rapid recovery strategies. In Phase III, the pattern becomes more heterogeneous: under-action remains common in low- and medium-urbanized areas, but highly urbanized areas show no significant misalignment between subjective and objective resilience. Overall, 36% of communities displayed under-action behavior in Phase I, compared to 65% showing over-action behavior in Phase II, reflecting a temporal inversion between perceived and actual recovery conditions.

These spatial and temporal disparities reveal that post-disaster resilience trajectories are mediated not only by physical recovery capacity but also by perception – reality alignment. In highly urbanized areas, smaller gaps may stem from well-integrated infrastructure and stronger information channels, which synchronize residents’ perceptions with actual recovery progress. In medium-urbanized areas, larger mismatches suggest that functional restoration is less visible or less accessible to residents, leading to delayed subjective recovery despite objective improvements. The inversion from under-action to over-action between Phases I and II points to a psychological rebound effect, where initial caution gives way to optimism, potentially driven by visible short-term repairs. Such mismatches highlight the risk of policy misalignment if recovery assessments rely solely on either subjective surveys or infrastructure metrics.

Fig.4. Spatial heterogeneity of subjective and objective resilience across three recovery phases

4.3 Identifying influencing factors of Subjective and Objective Resilience

The selection of explanatory variables was guided by key factors influencing resilience under extreme rainstorm impacts, as summarized in Table 2 along with supporting literature. To ensure robustness, the Pearson correlation coefficient was applied to evaluate the linear association strength between each independent variable and the resilience indicators. This process evaluates potential multicollinearity, with coefficients below 0.7 indicating no significant multicollinearity among selected variables, supporting their inclusion in the GWR model.

Table 2. Independent variables

	Variable	Definition	Supporting Reference	Source	Scale
<i>Natural environment variables</i>					
1	Precipitation intensity	Average precipitation each area	(Jeong & Yoon, 2018b; Munpa et al., 2022b)	Meteorological Administration (https://bj.cma.gov.cn/)	Raster+500 m
2	River network density	River network density calculated for each area	(Chen et al., 2020; Miller, 2020)	NASA (https://www.nasa.gov/)	Raster+30m
3	Land cover index	Shannon diversity index of landscape for each area	(W. Liu et al., 2023; Y. Wang et al., 2023)	Wuhan University SinoLC-1 Dataset (https://doi.org/10.5281/zenodo.7707461)	Raster+1m
<i>Built environment variables</i>					

4	Impervious surface percentage	Percentage of impervious surfaces for each area	(F. Liu et al., 2021; X. Zhao & Huang, 2022)	Wuhan University CLCD Dataset(http://doi.org/10.5281/zenodo.4417809)	Raster+30m
5	Land use index	Shannon diversity index of land use types for each area	(Ibrahim et al., 2024; Qi et al., 2025)	Tsinghua University EULUC-China Dataset (https://data-starcloud.pcl.ac.cn/icarthdata/)	Raster+10m
6	Road density	Road density of each area	(Dong et al., 2022; Gao et al., 2024)	OSM platform (https://www.openstreetmap.org/)	Vector
<i>Socio-Economy variables</i>					
7	Population density	Average population density per area	(Yabe et al., 2020; Zahnow et al., 2019b)	LandScan (https://landscan.ornl.gov/)	Raster+1km
8	Public facility density	Kernel density of public facility per area	(Hassan & Mahmoud, 2021; Mouratidis, 2021b)	AutoNavi Map API Interface (https://lbs.amap.com/)	Raster+2km
9	Recreation facility density	Kernel density of recreation facility per area	(Akbar & Aldrich, 2025; Pan et al., 2022b)	AutoNavi Map API Interface (https://lbs.amap.com/)	Raster+2km

4.3.1 Global and local model performance

Across GWRF models for both subjective and objective resilience, the majority of variables reached their peak R^2 values at a bandwidth of 50, after which performance gradually declined with increasing bandwidth, as shown in Fig.5. This pattern indicates pronounced spatial heterogeneity, where local patterns are best captured at an intermediate neighborhood size. With $mtry=3$, most models maintained reliable R^2 fits and greater stability.

In the bandwidth optimization curve, the peak performance occurs around a bandwidth of 50, confirming it as the optimal value. Fig.5 illustrates the variation of both global and local R^2 values with bandwidth. For the global model, R^2 remains consistently high ($\sim 70\%$) regardless of bandwidth changes. For the local R^2 in Fig.6, values rise sharply from $\sim 30\%$ at bandwidth 20 to $\sim 60\%$ at bandwidth 60, then stabilize beyond 70. This convergence suggests that a bandwidth of 50 offers the optimal balance between global stability and local fitting accuracy.

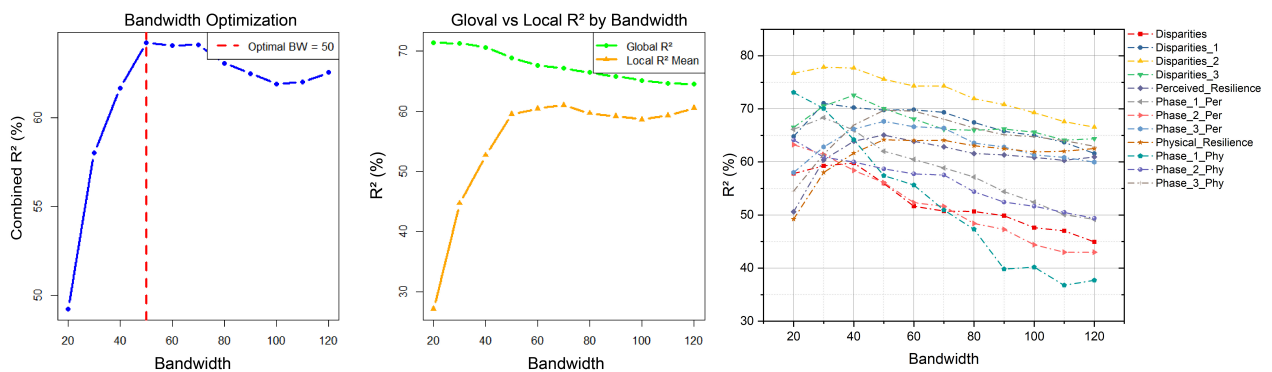


Fig. 5. Spatial pattern of the local goodness-of-fit (R^2) of the GWRF model

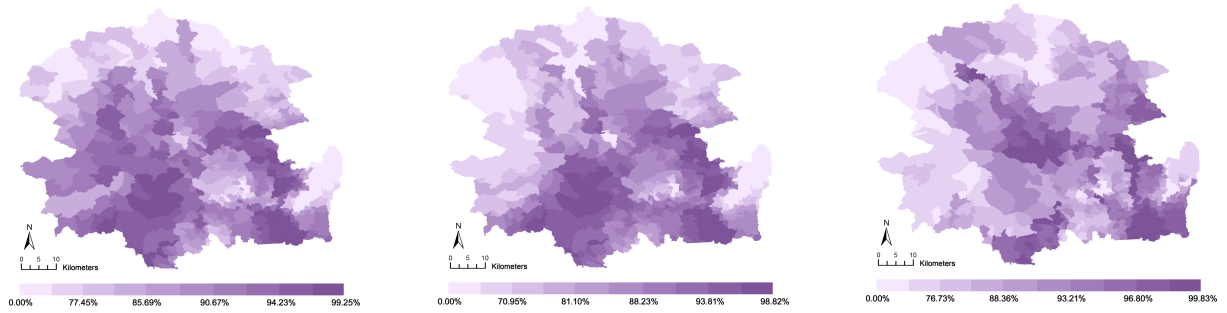


Fig. 6. Local R^2 of the GWR model of subjective, objective resilience and their disparities

4.3.2 Feature Importance and Dominant Factors

(1) Global feature importance

Fig. 7 and 8 illustrate the global %IncMSE rankings for influencing factors across the overall monitoring period and the three recovery phases—Phase I (emergency response, first 72 hours), Phase II (short-term recovery, two weeks), and Phase III (long-term recovery, one month). “Land use index,” “precipitation intensity,” and “population density” emerge as consistently high-importance variables for both subjective and objective resilience, each with wide interquartile ranges, indicating strong but variable influence.

Precipitation intensity is the dominant factor in Phase I for both resilience types, with relative importance exceeding 20%. However, its influence declines markedly to ~9% in Phases II and III. In contrast, the land use index shows minimal impact in Phase I but rises sharply in Phases II and III, surpassing 20% in relative importance, underscoring the growing role of spatial layout and land type in later recovery. Population density remains an influential factor across all phases, ranging from 13% to 17%, reflecting its persistent effect on both physical functionality and perceived conditions.

Despite these commonalities, important differences exist between the two resilience types. Impervious surface percentage and river network density have substantial impacts on objective resilience but are less influential for subjective resilience, as they affect drainage and hydrological capacity—factors not always perceived by residents. Conversely, road density exerts greater influence on subjective resilience, especially in Phase I (13%), before declining to 9% and 4% in Phases II and III. This temporal profile highlights the critical role of visible and accessible transport networks in shaping perceptions during the golden emergency window, with diminishing influence as recovery shifts to reconstruction.

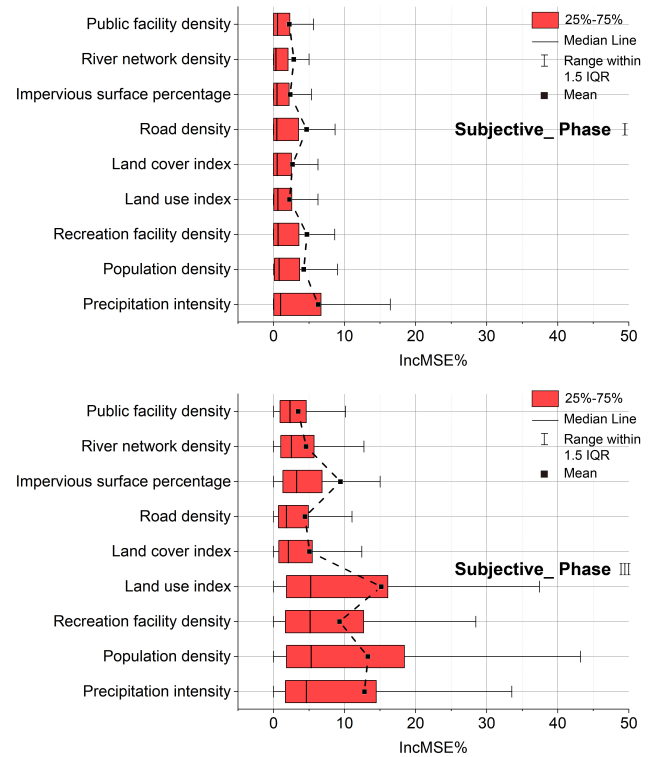
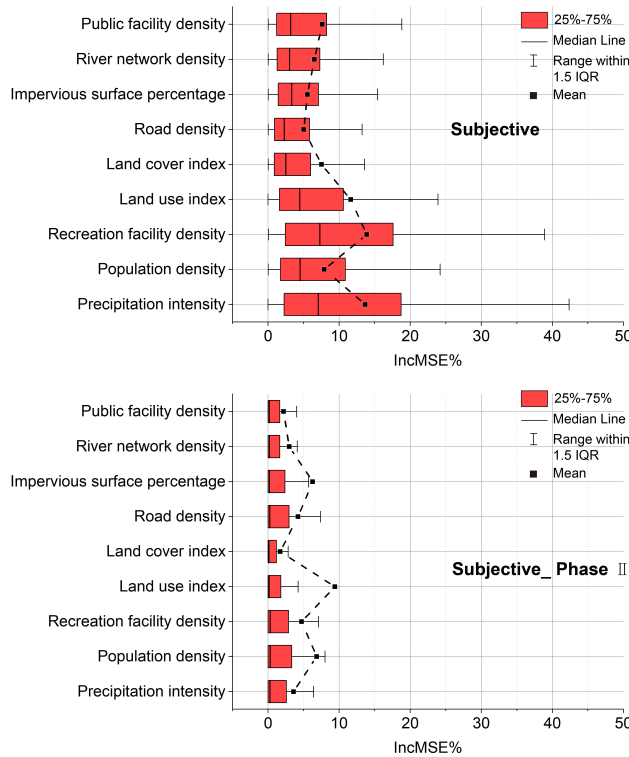


Fig. 7. The global importance of each influencing factor on subjective resilience (%IncMSE)

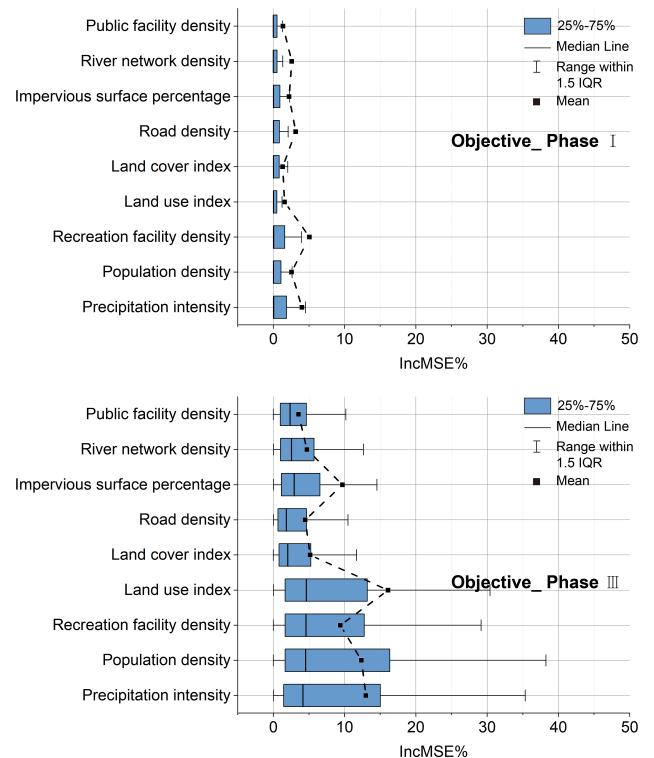
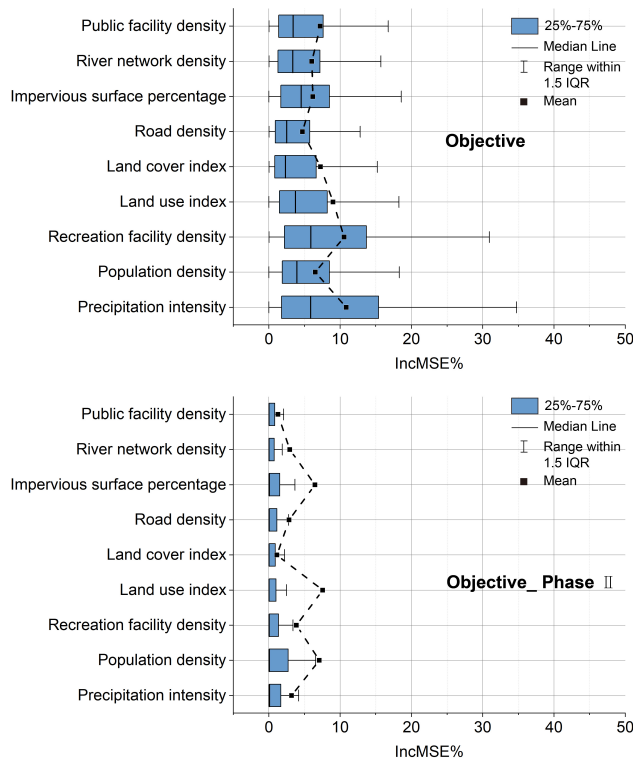


Fig. 8. The global importance of each influencing factor on objective resilience (%IncMSE)

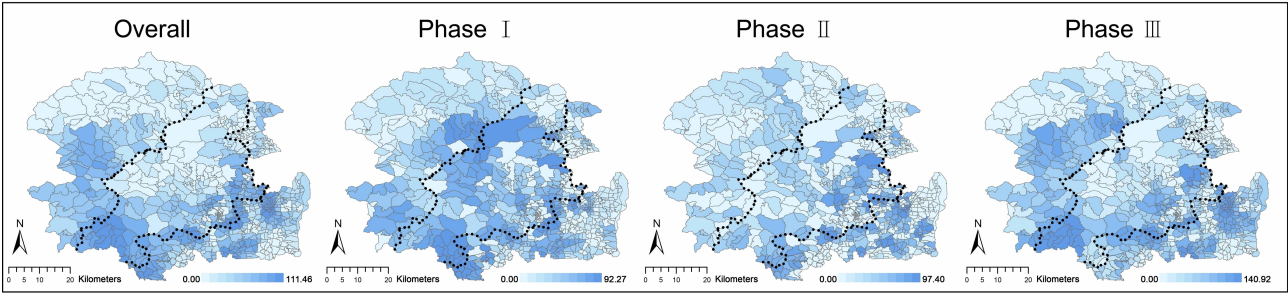
(2) Local feature importance

Fig.9 and 10 present the spatial-temporal patterns of local feature importance for subjective and objective resilience. Three notable dynamics emerge: alignment on immediate physical stressors, temporal misalignment in functional recovery drivers, and divergence in the role of psycho-social

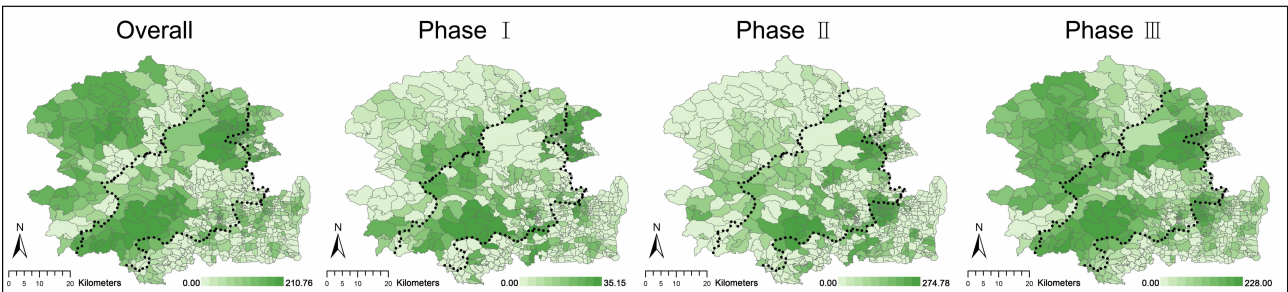
infrastructure.

First, both resilience types align in their sensitivity to direct physical hazards and persistent demographic pressures. Precipitation intensity peaks in Phase I across urbanized eastern areas, reflecting its immediate threat to infrastructure and safety. Population density likewise maintains high importance across all phases in these areas, amplifying systemic strain on both physical systems and public perception. Second, service-oriented recovery drivers reveal temporal misalignments. Objective resilience is most influenced by land use index in Phases II and III, reflecting functional rebuilding priorities. In contrast, subjective resilience weights this factor moderately throughout, as residents' perceptions remain anchored to their immediate surroundings rather than long-term planning. Finally, psycho-social infrastructure shows pronounced divergence. Recreation facility density holds significant weight for subjective resilience in Phase I, especially in dense urban centers, functioning as a “social buffer” for mental relief, information exchange, and community cohesion during acute crises. Objective resilience metrics, focused on physical recovery, register these facilities as far less critical, underscoring the limitations of purely infrastructure-driven assessments.

a. Precipitation intensity



b. Land use index



c. Population density

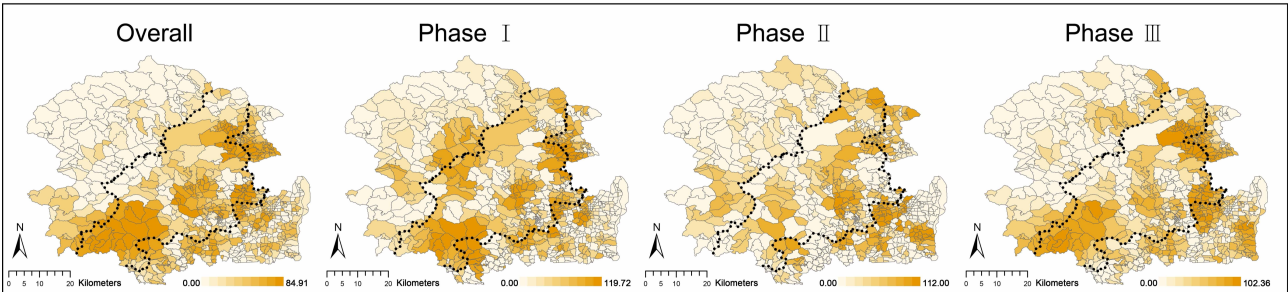
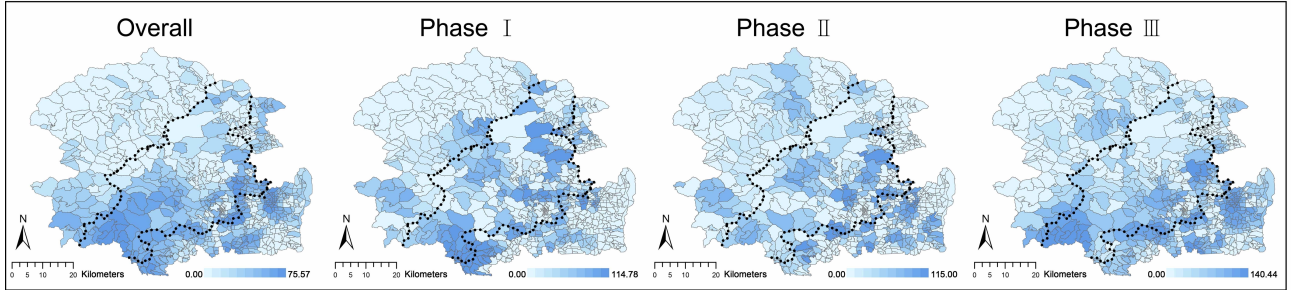
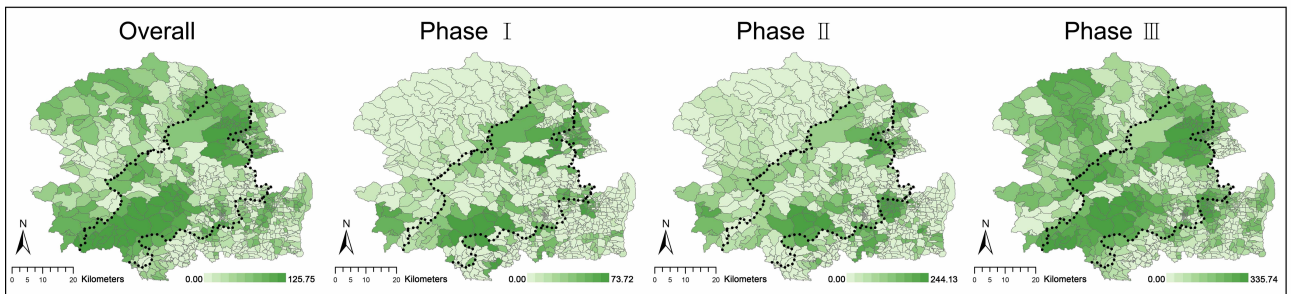


Fig. 9. The local importance of influencing factors on subjective resilience (%IncMSE)

a. Precipitation intensity



b. Land use index



c. Population density

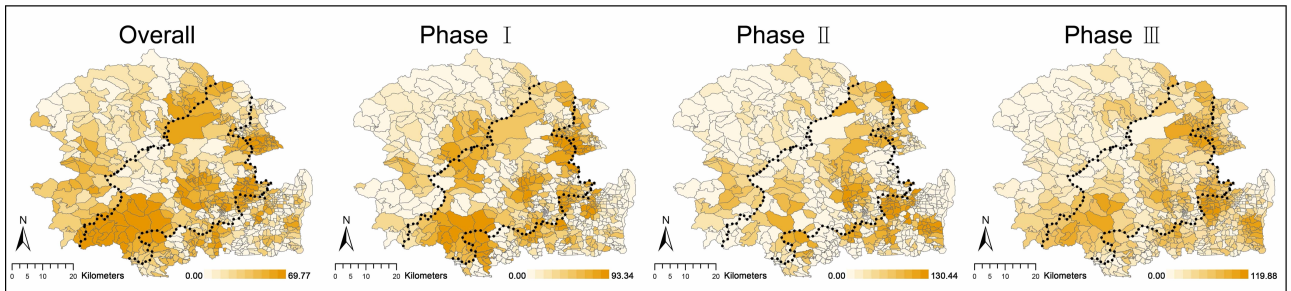


Fig. 10. The local importance of influencing factors on objective resilience (%IncMSE)

The local feature importance patterns indicate that resilience drivers are not only spatially heterogeneous but also temporally shifting in their relevance. The critical role of recreation facilities in shaping subjective resilience underlines that social cohesion and psychological well-being are integral to perceived recovery, even if they do not directly enhance functional performance. Ignoring these psycho-social dimensions in recovery planning risks overlooking cost-effective interventions that can accelerate perceived recovery and community morale, particularly in densely populated districts.

4.3.3 Nonlinear effects and adjustment guidance for factors

Fig. 11 depict the marginal effects of nine factors on subjective and objective resilience using local Partial Dependence Plots (PDPs). The results reveal predominantly non-linear relationships, with clear thresholds, saturation points, and optimal ranges. The similarity of curve shapes across resilience types suggests comparable underlying mechanisms.

Precipitation intensity and impervious surface ratio show contrasting effects. Precipitation exerts a negative influence, with resilience declining sharply up to ~360 mm before plateauing. Impervious surfaces contribute positively between 0.12 and 0.54, beyond which benefits level off, indicating diminishing returns in highly developed areas.

Land use and land cover diversity, measured by Shannon's Diversity Index (SHDI), both follow parabolic patterns—resilience peaks at moderate diversity (land use: 0.8 – 1.2; land cover: ~0.8) but

declines with excessive uniformity or fragmentation. Population density supports high resilience at low to moderate levels but drops sharply beyond $\sim 9,800$ people/km², stabilizing thereafter. River network density and road density exert positive effects up to saturation points—resilience increases with rising values (river: 0 – 0.15; roads: initial stages) but plateaus once core infrastructural needs are met. These patterns highlight the importance of targeted interventions—e.g., optimizing road connectivity in early recovery and enhancing drainage capacity in flood-prone areas—tailored to phase-specific resilience priorities.

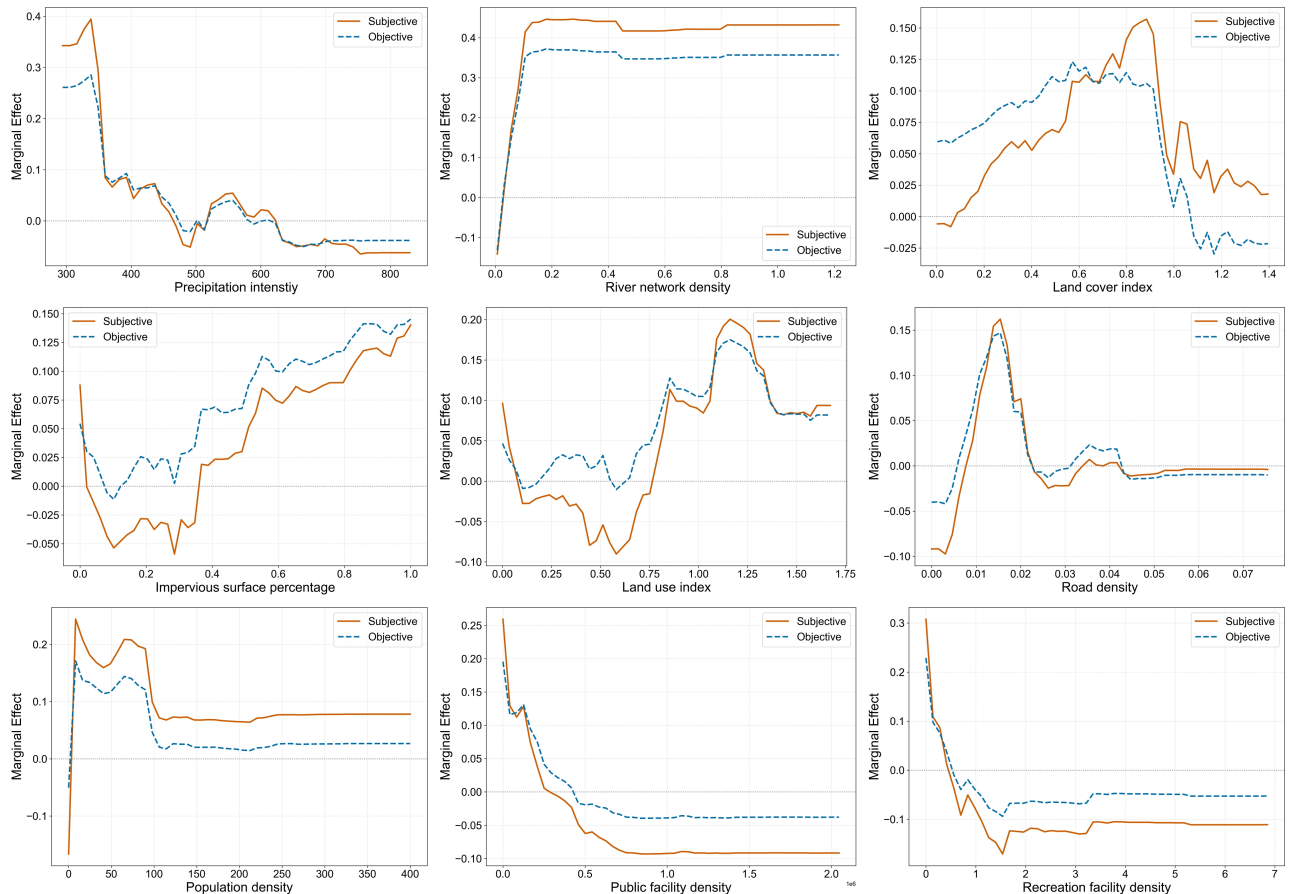


Fig. 11. The local importance of influencing factors on subjective and objective resilience

These findings confirm that while hazard exposure and demographic pressure are common resilience determinants, the salience of other drivers is strongly perception-dependent. Hydrological and land use factors dominate objective resilience because they directly influence functional capacity, yet may remain invisible to residents. In contrast, road networks and other visible infrastructure disproportionately shape subjective resilience, especially in the immediate aftermath when mobility and accessibility are top-of-mind concerns. This divergence reinforces the need for resilience assessment frameworks that integrate both tangible system performance and the community's lived experience, particularly when planning communication strategies and prioritizing early-phase interventions.

The observed non-linearities and thresholds provide actionable insights for recovery planning. They suggest that more is not always better—beyond certain points, additional investment in impervious surfaces, road networks, or land diversity yields minimal resilience gains. This calls for precision targeting: in early phases, mobility enhancement and drainage improvement offer the highest returns;

in later phases, optimizing land use mix and maintaining moderate urban density can sustain both perceived and functional recovery. These results also caution against uniform investment strategies, advocating instead for data-driven thresholds to guide phase-specific and location-specific interventions.

From a policy perspective, integrating subjective and objective metrics into routine post-disaster monitoring could enable real-time adjustment of recovery priorities. For example, where subjective resilience lags despite high functional performance, targeted communication, public engagement, and psycho-social support could bridge perception gaps. Conversely, where objective resilience is low despite high perceived recovery, structural upgrades and hazard mitigation measures should be prioritized to avoid complacency and latent vulnerabilities. Ultimately, resilient cities are those that align physical recovery trajectories with the lived experiences of their residents.

4.4 Enhancement Strategies for Resilience Improvement

4.4.1 Identification of Dominant Factors

To develop targeted and effective resilience enhancement measures, it is imperative to identify the primary factors undermining the resilience of each area. Leveraging the feature importance scores from our resilience assessment model, this study identified 306 vulnerable communities and pinpointed the most critical factor within the study area. The spatial distribution of these dominant factors is illustrated in Fig. 12, which reveals distinct patterns across different levels of urbanization. In the high and medium urbanization zones, the dominant factors are primarily socio-economic. As depicted in the Figure, impervious surface percentage, recreation facility density and public facility density are the most prevalent critical factors. This is a logical outcome of urban development, where high concentrations of buildings, roads, and other sealed surfaces increase flood risk, while the accessibility and capacity of public infrastructure (e.g., emergency services, transportation hubs) become critical for managing urban stresses. Similarly, the density of recreation facilities emerges as a significant factor in these areas, highlighting the role of accessible public open spaces in emergence and enhancing social resilience. Conversely, in the low urbanization zone, the dominant factors are more closely linked to the natural environment and land management. Precipitation intensity is the most widespread dominant factor, indicating that these less developed, often topographically complex areas are highly sensitive to extreme rainfall events, which can trigger flooding and landslides. The land use index is also a key determinant of resilience in this zone, reflecting how the composition and configuration of different land uses—such as forests, agricultural land, and low-density residential areas—mediate the impacts of environmental hazards.

In conclusion, this fine-grained identification of dominant factors provides a diagnostic foundation for policy-making. By understanding whether a community's primary vulnerability stems from its built infrastructure, land use patterns, or exposure to natural hazards, the enhancement strategies can be designed, moving beyond one-size-fits-all solutions toward a more context-sensitive approach to urban resilience.

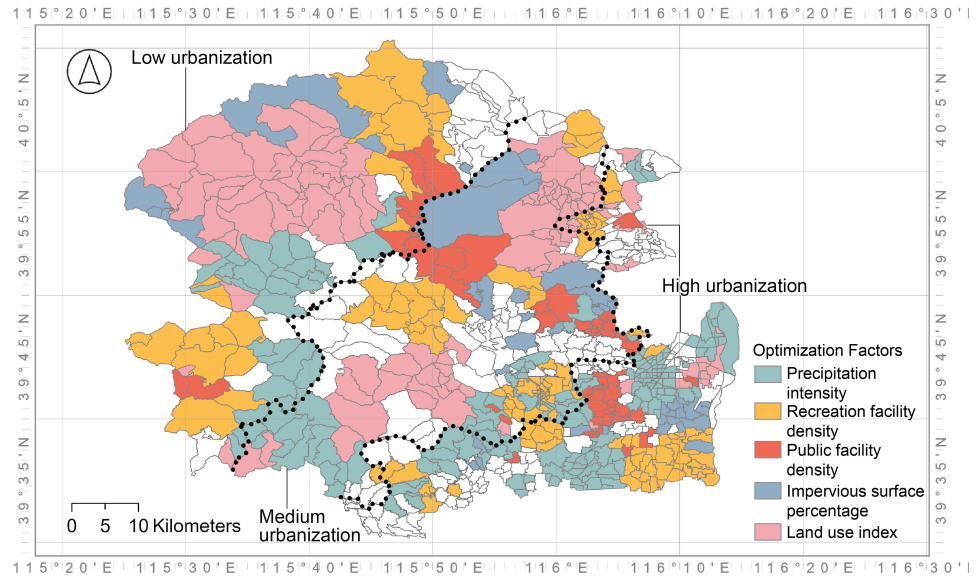


Fig. 12. Dominant Factors in each area across different urbanized communities

4.4.2 Subregion-Specific Interventions Using PDPs

After identifying the dominant vulnerability factor for each community, we use Partial Dependence Plots (PDPs) to guide the formulation of targeted intervention strategies. These relationships are generally characterized by optimal ranges, saturation points, or critical thresholds, providing a clear roadmap for effective resource allocation. The proposed interventions are tailored to the dominant factor identified for each of the 306 vulnerable communities, with specific strategies varying by the type of factor-resilience relationship.

1) Strategies for Factors with Optimal Ranges. For factors exhibiting a parabolic relationship with resilience, such as the land use index (related to land use and land cover diversity), the objective is to adjust community attributes to fall within the optimal performance window. For communities in the low urbanization zone where this is the dominant factor and diversity is below 0.8, planning policies should encourage mixed-use development and the integration of green spaces with residential or agricultural areas. Conversely, for communities where diversity is above 1.2 (indicating chaotic or fragmented land use), interventions should focus on strategic rezoning to create more cohesive functional areas and reduce fragmentation.

2) Strategies for Factors with Saturation Points. Many infrastructure-related factors show diminishing returns, where initial investments yield significant resilience gains that later plateau. For these factors, the goal is to increase values up to the saturation point. **Public and Recreation Facility Density:** These factors, prevalent in medium-to-high urbanization zones, behave similarly to the road and river network densities analyzed in the PDPs. For communities where facility density is the dominant factor and falls below the identified saturation threshold, the clear strategy is infrastructure investment. This includes expanding the road network, increasing the number of public service points (e.g., clinics, fire stations), or creating new parks and public squares. However, for communities already at or beyond the saturation point, further densification of these features would be inefficient; resources should instead be allocated to addressing other vulnerabilities. **Impervious Surface Percentage:** For those above the 0.54 threshold, where the positive effects have saturated and negative externalities (e.g., runoff) may increase, the focus should shift to mitigation. This includes

implementing green infrastructure like permeable pavements, green roofs, and bioswales to offset the negative impacts of high imperviousness without sacrificing urban density.

3) Strategies for Factors with Negative Thresholds. For factors that negatively impact resilience, especially beyond a critical threshold, interventions should focus on mitigation and enhancing adaptive capacity. Precipitation Intensity: This is the primary challenge in the low-urbanization zones. The PDP shows that resilience declines sharply as precipitation increases, with the effect stabilizing after approximately 360 mm. Since rainfall cannot be altered, the strategy is to bolster the community's coping capacity. This involves investing in nature-based solutions like restoring wetlands and riparian buffers to slow runoff, upgrading stormwater drainage infrastructure, and implementing robust early warning systems for floods and landslides. Efforts are most critical in areas sensitive to rainfall levels approaching the 360 mm threshold.

4.4.3 Prediction of Resilience Enhancement with GWRF

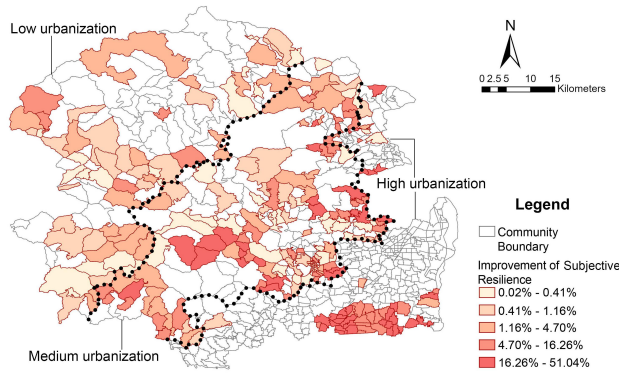
To quantify the effectiveness of the targeted interventions, we employed our predictive model to simulate the resilience enhancement for all 306 vulnerable communities. This allowed us to forecast the potential improvement in both subjective and objective resilience. The spatial distribution of these predicted enhancements is detailed in Figure 13-15, illustrating the outcomes across the study area and through the different phases of disaster management.

The simulation predicts a significant overall improvement in subjective resilience, with a mean enhancement of 7.9% across the targeted communities. The most substantial gains are spatially concentrated in the low and medium urbanization zones. This suggests that interventions targeting factors like the land use index and mitigating the effects of precipitation are highly effective at improving residents' sense of safety and confidence in their community's recovery capabilities. When disaggregated by phase, the improvements show a distinct temporal pattern: a modest initial gain of 0.8% in the emergency phase (Phase I), followed by a more substantial increase of 4.9% in the short-term recovery phase (Phase II), and culminating in the largest average improvement of 8.3% in the long-term recovery phase (Phase III). This back-loaded success indicates that while the effects on perception are not immediate, the interventions build a strong foundation for long-term confidence and social recovery.

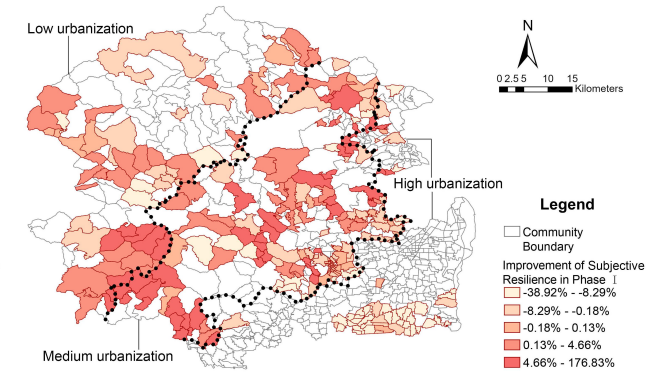
For objective resilience, the model predicts a mean enhancement of 6.2%. The temporal distribution of these gains is markedly different from that of subjective resilience. We observe a dramatic front-loading of benefits, with an average improvement of 13.2% in the emergency phase (Phase I), as depicted by the widespread, intense enhancements. This suggests that infrastructure upgrades provide an immediate and powerful boost to a community's physical capacity to withstand and respond to a crisis. The gains are more modest in the short-term recovery phase (Phase II) at 1.7%, before rising again to 10.3% in the long-term phase (Phase III), reflecting the lasting benefits of structural and systemic improvements.

In summary, physical systems benefit immediately and profoundly from infrastructural optimization, particularly in urban cores, while subjective resilience improves more gradually as communities experience enhanced long-term recovery, especially in less urbanized areas. This dual analysis underscores the necessity of a phased and context-specific approach to building holistic urban resilience.

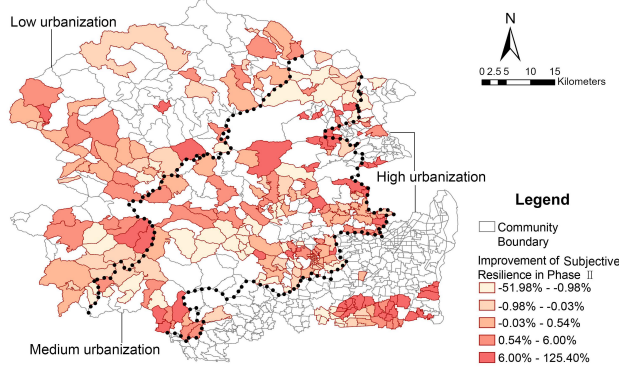
a. Improvement of Subjective Resilience



b. Improvement of Subjective Resilience in Phase I



c. Improvement of Subjective Resilience in Phase II



d. Improvement of Subjective Resilience in Phase III

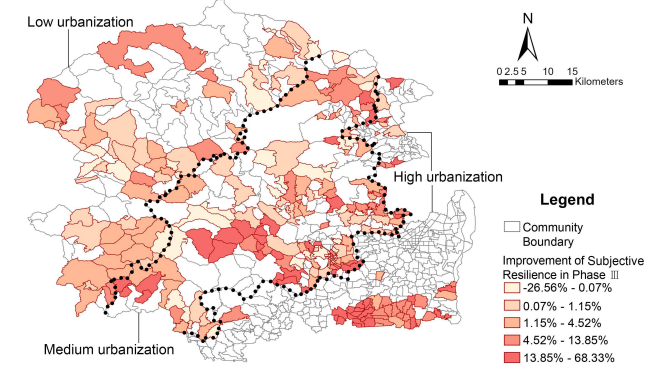
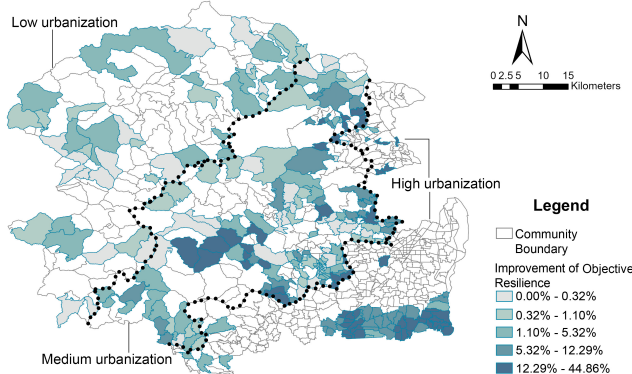
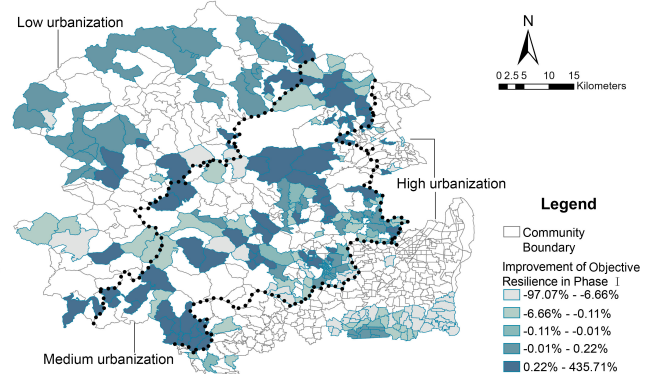


Fig. 13. Prediction of subjective resilience enhancement

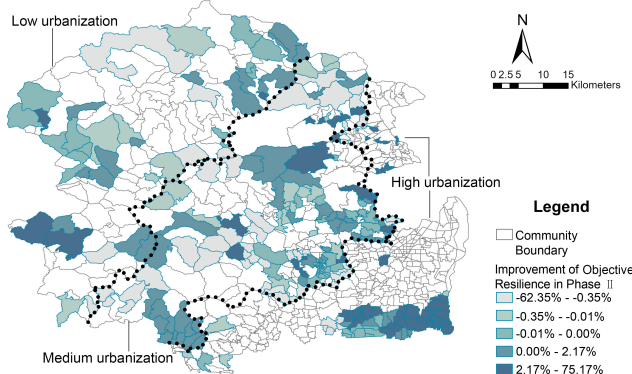
a. Improvement of Objective Resilience



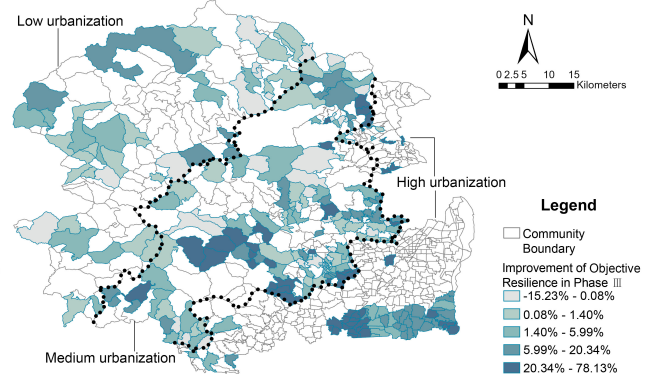
b. Improvement of Objective Resilience in Phase I



c. Improvement of Objective Resilience in Phase II

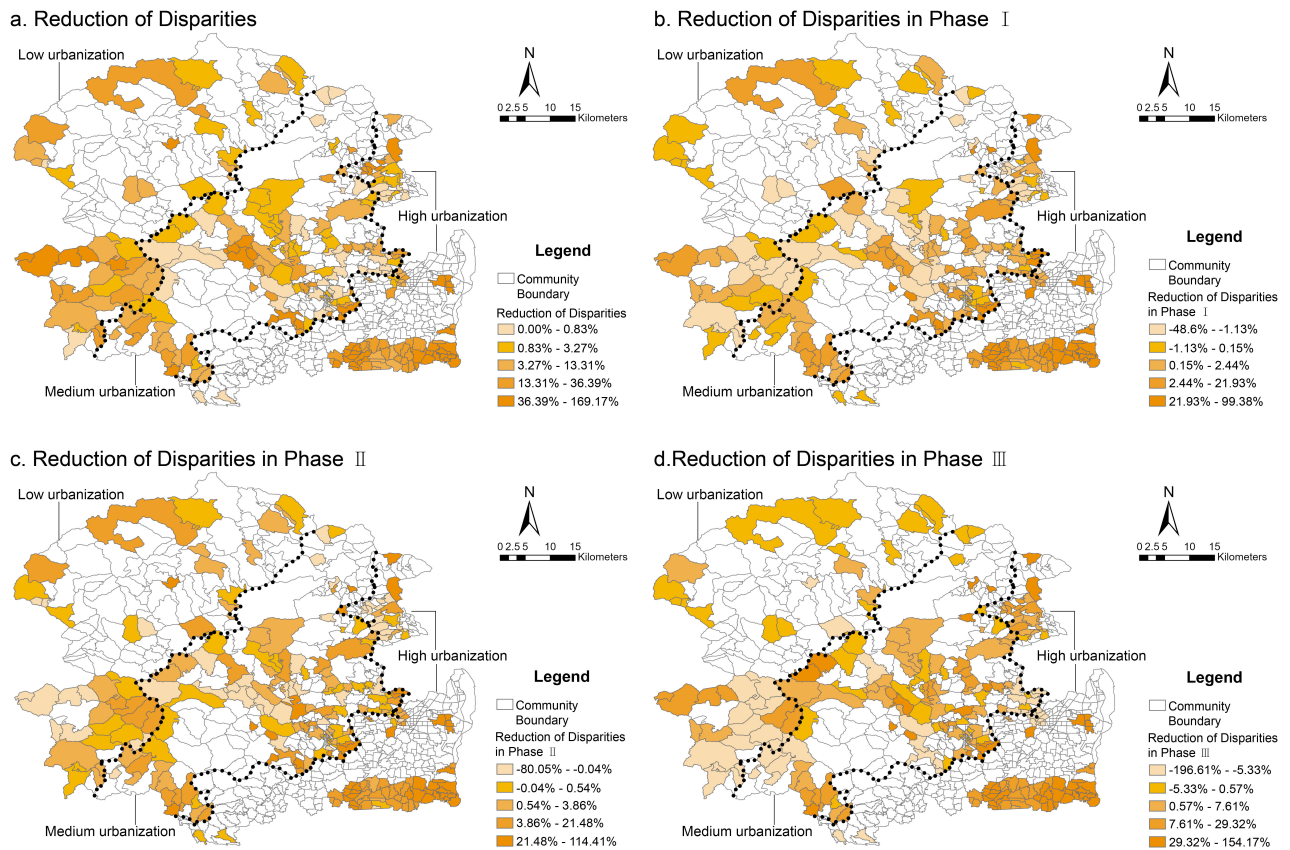


d. Improvement of Objective Resilience in Phase III



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Fig. 14. Prediction of objective resilience enhancement



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Fig. 15. Prediction of disparities between subjective and objective resilience enhancement

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5. Conclusion

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This study developed an integrated analytical framework to enhance both subjective and objective dimensions of urban resilience by diagnosing dominant vulnerability factors at the community scale and designing targeted, phase-specific interventions. Using a combination of spatially explicit machine learning, Partial Dependence Plots (PDPs), and Geographic Weighted Random Forest (GWRf) simulation, we identified 306 vulnerable communities and revealed distinct resilience patterns across urbanization gradients. In high- and medium-urbanization zones, socio-economic and infrastructural factors such as impervious surface percentage, public facility density, and recreation facility density dominated, while low-urbanization zones were primarily constrained by precipitation intensity and land use configuration. By tailoring interventions to factor-specific thresholds—whether

optimal ranges, saturation points, or negative thresholds—we demonstrated that objective resilience gains can be achieved rapidly, particularly in the emergency phase, whereas subjective resilience improves gradually over the long term. These findings highlight that effective resilience building requires context-aware, spatially localized, and temporally adaptive strategies, moving beyond one-size-fits-all policy prescriptions. The methodological framework is transferable to other hazard-prone urban regions, offering a practical decision-support tool for evidence-based resilience planning. Despite its contributions, this study has several limitations. First, the resilience assessment relied on available socio-demographic, infrastructural, and environmental datasets, which may not fully capture dynamic social processes such as informal support networks, governance capacity, or cultural coping mechanisms. Second, the identification of dominant factors was based on static pre-disaster attributes; while this provides a robust baseline for intervention, resilience is inherently dynamic, and factor importance may shift in response to evolving hazards, socio-economic changes, or climate impacts. Third, the simulation of intervention effects, while grounded in empirically observed relationships, remains a predictive approximation and does not substitute for longitudinal post-intervention monitoring. Future research should integrate time-series data, multi-hazard scenarios, and participatory approaches to better account for temporal dynamics and community agency. Expanding the framework to include real-time sensing, social media analytics, and adaptive policy feedback loops would further strengthen its applicability for proactive urban resilience management.

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