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IMPACT OF SPATIAL FACTORS ON REVENUE AND EXPENDITURE OF HOUSING MAINTENANCE FUND: A CASE STUDY IN BEIJING

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Abstract

Housing maintenance is an integral component of sustainable urban governance. However, the revenue and expenditure of housing maintenance fund often vary across regions due to socioeconomic, built-environment, and ecological settings. The study of its spatial heterogeneity can be critical for understanding regional disparities, optimizing resource allocation, and improving governance efficiency. This study proposes categorizing research samples based on functional zones, 275 subdistricts/townships within three functional zones of Beijing were examined to explore the influence mechanisms of spatial factors on maintenance fund revenue and expenditure, then compares ordinary least square (OLS), geographically weighted regression (GWR), and multiscale geographically weighted regression (MGWR) models in analyzing the impact mechanisms of spatial factors. The conclusions are as follows: (1) Functional zones coincide with sample categories, showing significant differentiation and spatial autocorrelation, which underscores the role of Beijing's master plan. (2) MGWR performs better than other models: influence factors exhibit spatial heterogeneity in maintenance fund, GDP exerts the most significant impact on fund revenue, *while population density most strongly affects fund expenditure. (3) Policy formulation should draw on ecological and socioeconomic factors to mitigate fund revenue losses, and leverage built-environment factors to improve housing maintenance.*

Keywords:
Housing Maintenance Fund, Spatial Heterogeneity, Geographically Weighted Regression, Spatial Policy Optimization

1. Introduction

1.1 Background and Literature Review

The urban expansion in China accelerated dramatically in recent decades, intensifying administrative complexity and financial pressures on municipal governments—particularly in housing management (Li, Pu, & Zhang, 2024). In the past half century, China has undergone fast urban growth, resulting in a large backlog of middle-aged and older housing stock in need of housing maintenance. However, the growing scale of real estate development and unregulated property markets have significantly complicated these maintenance efforts, creating systemic challenges for urban governance and renewal (Wang, Song, & Wang, 2021; Li, Pu, & Zhang, 2024). Housing maintenance fund constitutes a critical pillar of urban renewal. To address the challenges of "urban malaise" and optimize spatial structure and functional layout, Beijing released the Beijing City Master Plan (2016-2035) in 2017. This plan divides the entire city into three functional zones. Urban renewal serves as a key implementation strategy across these zones, aiming to optimize existing spatial resources, guide orderly growth, and promote green transformation. It further aims to establish a governance system through refined management, modernized services, and ecological priority mechanisms to support the realization of zone-specific objectives and inter-regional coordination (Beijing Municipal Commission of Planning and Natural Resources, 2017). However, significant spatial disparities exist in the revenue and expenditure of the housing maintenance fund, driven by regional variations in economic development, population density, and policy prioritization. Analyzing these spatial heterogeneities is essential for diagnosing regional inequities, enhancing fiscal efficiency, and informing evidence-based resource allocation strategies to strengthen urban resilience.

In China, housing maintenance is primarily financed through the housing maintenance fund mechanism. The specific amount of payment to the housing maintenance fund is affected by the location of the house. The mechanism collects fund and coordinates the allocation of fund to areas in need of repairs by local governments. However, the allocation and utilization dynamics of maintenance fund are governed by a complex interplay of multidimensional determinants across socioeconomic, built-environmental, and ecological domains, creating spatially heterogeneous patterns of fiscal efficiency and equity. The spatial heterogeneity of socioeconomic drivers and built-environment characteristics has exerted significant influence on both the equitability and efficiency of maintenance fund allocation, creating systemic disparities in urban resource distribution (Zhang et al., 2023; Wang, Zhao, & Zeng, 2022).

For example, regarding socioeconomic factors, Li, Sun, & Tian (2023) propose that regional disparities in economic development levels and urbanization rates significantly influence local fiscal revenues, particularly land transfer fees, thereby constraining the collection of maintenance fund as a fiscal component.

Built-environment factors impact maintenance in several ways. Li (2024) identifies that increased height elevates maintenance costs due to complex structural designs and construction challenges, necessitating frequent interventions like façade cleaning and elevator repairs. Zheng et al. (2019) confirm that aging accelerates wear and deterioration, with peak maintenance costs occurring for buildings aged 21–25 years. They further indicate that larger volumes amplify costs by expanding maintenance areas and facilities, increasing staffing and cycle demands. Population density is also one of the built-environment factors. Dong et al. (2018) reveal that high-density areas intensify building wear through intensive usage while elevating residents' expectations for maintenance quality. Methodologically, the Hedonic Price Model (HPM) established by Lancaster (1966) and Rosen (1974) estimates property values by deconstructing characteristics such as building age, area, height, and location. Wilhelmsson (2008) pioneers its reverse application to assess housing depreciation, deriving maintenance requirements from value decay.

About ecological factors, Xie & Chen (2021) demonstrate through cross-regional case analyses that eco-civilization construction—including environmental protection initiatives—imposes restrictions on urban planning and land use, ultimately reducing land conveyance revenues by limiting transferable land types and scales.

Some studies have analyzed institutional design impacts but overlooked socioeconomic, ecological, and building-specific indicators (Zilberova et al., 2024), limiting practical implementation.

Spatial-geographic extensions have been recently emphasized: Wu, Wei, & Li (2020) and Hao & Ma (2022) highlight that downtown buildings require frequent upkeep to sustain functionality in high-traffic environments, while microclimates in specific regions further shape cost patterns.

These views also corroborate the existing academic views on the factors influencing fund income and expenditure. Revenue and expenditure exhibit fundamentally different spatial mechanisms: Revenue is primarily driven by macro-scale regional capacities (Fan, Qiu, & Sun, 2020); Expenditure (e.g., building repairs, facility upkeep) responds to micro-scale localized conditions (Zheng, Wu, Kahn, & Deng, 2012).

While these studies provide insights into particular dimensions, they predominantly adopt fragmented analytical approaches that fail to capture the interactions among socioeconomic, built-environmental, and ecological determinants. Moreover, the context-specific findings lack generalizable theoretical frameworks to explain spatial heterogeneity in fund mechanisms across diverse settings.

In addition, the dynamic interplay of spatial factors not only induces spatial heterogeneity but also delivers spatial autocorrelation (Li et al., 2021; Zhao et al., 2021; Kim, 2021). Conventional correlation analyses and linear regression models often yield suboptimal results for spatial data due to ignored non-stationarity (Yu & Peng, 2019; Deilami, Kamruzzaman, & Hayes, 2016). Current fiscal management models predominantly employ ordinary least squares (OLS) methods, which assume spatial stability in unidimensional variable relationships (Zhang et al., 2025), yet rarely account for multidimensional spatial heterogeneity. Spatial models, such as Geographically Weighted Regression (GWR), address this limitation by integrating spatial autocorrelation and non-stationarity (Wu et al., 2023; Li et al., 2021c; Chen et al., 2022c; Ismaila, Muhammed, & Adamu, 2022).

Beijing is a typical example for studying the problem of housing aging. Since the founding of the PRC, Beijing has experienced rapid growth in both permanent residents and residential buildings, with population density generally decreasing radially from central urban areas outward, while building age exhibits an inverse spatial gradient. Especially in the past four decades, Beijing has experienced unprecedented urban expansion. From 1978 to the end of 2024, its permanent resident population surged from 4.790 million to 21.832 million, with the urbanization rate rising from 55.0% to 88.2% (Beijing Municipal Bureau of Statistics, 2025). This demographic expansion has exacerbated demands on municipal maintenance systems, with annual expenditure (including disbursements, utilization, and depletion) for housing maintenance fund exceeding ¥3.3 billion in 2023 (Beijing Housing Fund Management Center, 2024).

1.2 Objectives and Novel Contributions

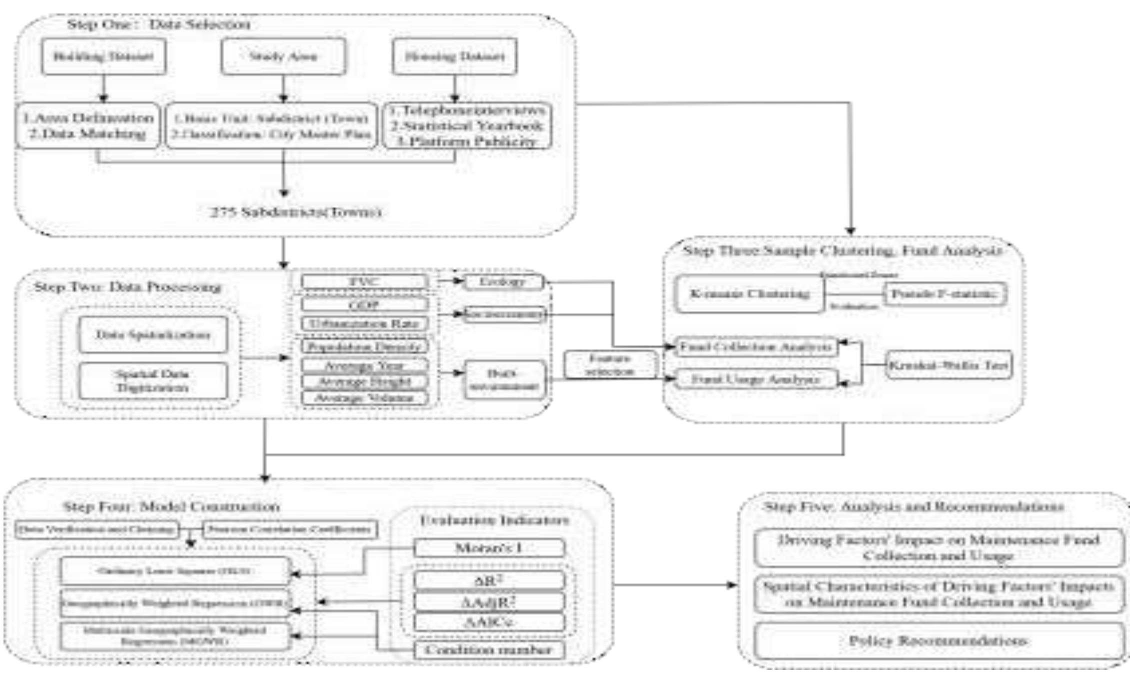
This study aims to investigate the driving mechanisms of housing maintenance fund revenue and expenditure in Beijing with consideration of spatial geography. To achieve this objective, three important questions are addressed. First, how do socioeconomic, built-environment, and ecological factors influence across space to influence fund flows? Second, how to effectively model and analyze such spatially varying mechanisms? And in what aspects can the current fund revenue and expenditure pattern be improved based on the regression results?

To address the research questions, this study integrates multisource geospatial data—including Points of Interest (POI), building footprints, and municipal records—through GIS-based processing (georeferencing, feature recognition, and spatial filtering). This synthesis constructs a unified neighborhood-level database aligning multidimensional drivers for pixel-scale regression. The classification of research units was determined based on the results of cluster analysis and functional zones. Crucially, we reconceptualize fund revenue and expenditure as distinct yet interconnected systems: Revenue (e.g., land conveyance fees) is modeled as a function of macro-scale capacities (socioeconomic/ecological factors like GDP and land constraints). Expenditure (e.g., building repairs) responds to micro-scale conditions (built-environment factors like building age and population density). This dual-system framework isolates divergent causal pathways, which has been proven through feature selection in the following text, enabling precise spatial heterogeneity modeling—transcending traditional analyses that simplistically designate a single dependent variable. Finally, spatial econometric techniques are systematically applied to quantify heterogeneous mechanisms, generating targeted policy strategies for Beijing's district-specific fund management.

2. Study Area and Methodology

The study is structured into five parts: data selection, data processing, sample classification and fund analysis, model construction, analysis and policy Recommendation.

Figure 1: *Technical Workflow*

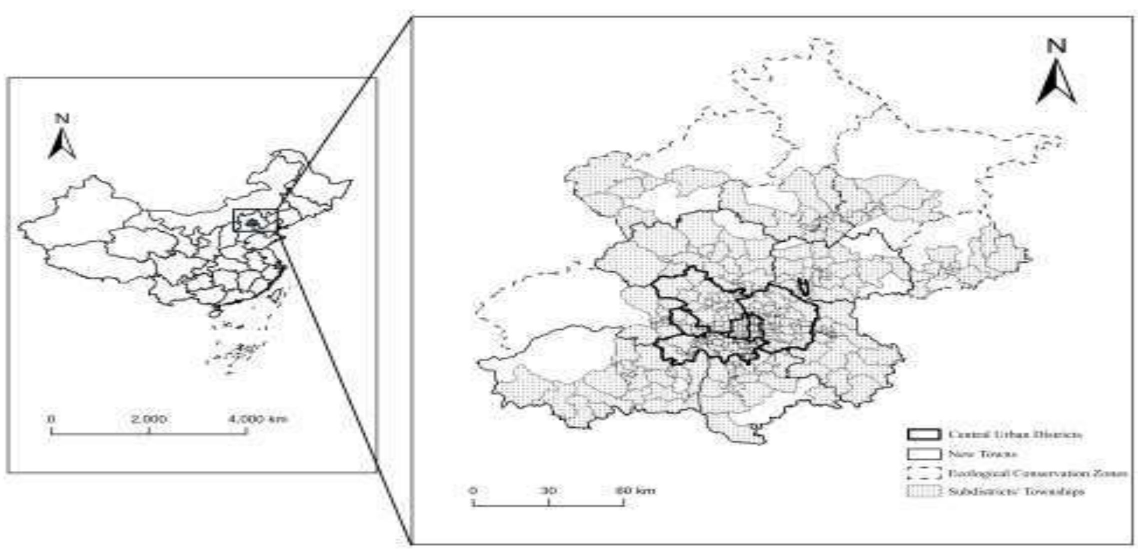


2.1 Study Area

Beijing (39°26′–41°03′ N, 115°25′–117°30′ E), the capital of the People's Republic of China, is situated in northern China along the northwest of the North China Plain. Its climate is characterized by concentrated summer rainfall with high temperatures and winter conditions dominated by the Mongolian High-Pressure System, resulting in frequent strong winds and low temperatures. This study encompasses all 16 administrative districts of Beijing. The fundamental spatial unit of analysis is the subdistrict (or township), the smallest complete administrative unit in China's urban governance system. This level is optimal as it facilitates the acquisition of housing fund data from higher district authorities and building information from grassroots community committees. Furthermore, these units exhibit a relatively high degree of internal homogeneity in their ecological, built-environment, and socioeconomic characteristics. From the total, 275 subdistricts that met all data validity criteria were selected for analysis.

The Beijing City Master Plan (2016–2035) provides a strategic framework for urban development, emphasizing sustainability and livability (Beijing Municipal Commission of Planning and Natural Resources, 2017). It classifies the study’s 275 subdistricts into three functional zones: Central Urban Districts (characterized by high-density development), New Towns, comprising Tongzhou and Plain New Towns (representing expanding suburban growth poles), and Ecological Conservation Zones (prioritizing environmental sustainability in peripheral regions). This zoning directly influences the composition, age, and value of local housing stock. Consequently, it produces distinct spatial patterns in maintenance fund revenue and expenditure, making it a relevant and policy-significant analytical framework for this study.

Figure 2: *Study Area and Functional Zoning of Beijing*



2.2 Data and Acquisition

This study integrates multisource geospatial and socioeconomic data for Beijing (2020–2024), including building footprints, residential community points, district-level demographics, FVC rasters, economic indicators, and housing maintenance fund records. All datasets were spatially aligned to Subdistrict-level units through GIS processing, with key attributes and sources detailed in Table 2.2.

Data Category	Source	Key Attributes	Spatial/Temporal Resolution	Processing Method
Building Footprint Vector	Open-access geospatial repository (Zhang et al., 2025)	Geographic locations, footprints, heights, floor areas	0.3-1 meter resolution	AI fusion (OCRNet + XGBoost) of Google Earth imagery, street-view, and POI data
Residential Community Points	Web-crawled property management databases	Geolocation, construction years, administrative districts, housing prices	Community-level point data	Multi-source validation and deduplication
District Population	Beijing Municipal Bureau of Statistics (2025)	Total population counts per district/county	District-level annual aggregates	Official census data standardization
Fractional Vegetation Cover	National Tibetan Plateau Data Center (Gao et al., 2019)	Vegetation coverage index	250m × 250m raster (annual composite)	NDVI pixel dichotomy model with land use-based calibration
Economic Indicators	Beijing Municipal Bureau of Statistics (2025)	District-level GDP, industrial output, tertiary sector share	District-level quarterly data	Official accounting system extraction
Maintenance Fund Records	Beijing Housing Fund Management Center (2024) + Supplementary interviews	Annual revenue, expenditure, transfers, interest accrual	Subdistrict-level monthly aggregates	Fiscal data integration with telephonic verification

Table 2.2: *Data Summary*

2.3 Cluster Analysis

The master plan divides Beijing into three functional areas. However, treating each zone as homogeneous could be an oversimplification, as significant differences in spatial factors can exist between subdistricts within the same area. Exist studies divide samples based on variable attributes—for instance, employing two-step clustering for mixed variables or K-means clustering for continuous variables. Since all independent variables in this study are continuous, K-means clustering is applicable.

2.4 Feature Selection

Although the influencing factors can be assigned to the income and expenditure models through literature and experience summary, in order to avoid insufficient explanatory power or cross-interpretation, feature selection should be used to select each factor. Lasso regression and Random Forest Gini index were used for feature selection. Lasso regression can shrink coefficients of non-essential variables to zero at an increasing λ, so that eliminating redundant predictors (Tibshirani, 1996). Random Forest uses Gini to measures feature importance through quantifying its capability to consistently classify nodes into pure classes. (Breiman, 2001).

2.5 Regression Analysis

Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) represent two prominent regression methodologies. OLS is characterized as a global model, generating a single set of parameter estimates assumed to be constant across the geographic area of study. In contrast, GWR is a local spatial technique that incorporates a spatial weighting matrix to produce a unique set of parameter estimates for each location. This fundamental capability to account for spatial non-stationarity allows GWR to more effectively capture localized relationships and spatial heterogeneity inherent in many geographical phenomena (Permai, Christina, & Gunawan, 2021). Consequently, while OLS may obscure local variations by imposing global estimates, GWR often yields more precise and nuanced results for data characterized by strong spatial dependence (Wu, 2020). This makes it a powerful analytical tool in disciplines such as spatial science, urban studies, and environmental modeling the mathematical formulation of GWR can be expressed as:

$$Y_i = \beta_{0i} + \beta_{1i}X_{1i} + \beta_{2i}X_{2i} + \beta_{3i}X_{3i} \ldots + \beta_{ki}X_{ki} + \quad (1)$$

where Yi indicates the observed value of the dependent variable at location i; $X1i$, $X2i$, $X3i\dots$, Xki represent the observed values of independent variables at location i; $\beta 0i$, $\beta 1i$, $\beta 2i$, $\beta 3i$ …, βki are model parameters associated with each independent variable; and εi is the error term. In GWR, each parameter β is spatially variable, determined by the spatial weights at corresponding locations. The spatial weighting matrix comprises kernel functions and bandwidths that define the weight intensity or spatial scale.

Whereas standard Geographically Weighted Regression (GWR) employs a single kernel function and bandwidth for all variables—imposing a uniform scale of spatial variation on every parameter estimate—Multiscale Geographically Weighted Regression (MGWR) relaxes this constraint.

MGWR allows different independent variables to operate at distinct spatial scales. By optimizing a unique bandwidth for each explanatory variable, MGWR more accurately captures the multiscale nature of complex spatial processes (Fotheringham, Yang, & Kang, 2017). An adaptive kernel function was utilized to adjust the bandwidth selection in response to local variations in data density and sample size.

To evaluate model performance, the adjusted R^2 (Adj. R^2) and the corrected Akaike Information Criterion (AICc) were selected as diagnostic criteria. A higher Adj. R^2 value indicates a superior model fit, denoting a greater proportion of explained variance in the dependent variable. Conversely, a lower AICc value signifies a more parsimonious model with a better-fit bandwidth and greater stability in its parameter estimates (Cavanaugh & neath, 2019). The driving factors and variable information involved in the regression analysis are shown in Table 2.2.

Factors	**Variable**	**Proxy Name**	**Source**
Building Environment	Average Height	AVEH	Li, 2024
	Average Volume	AVEV	Zheng et al., 2019
	Average Age of Building	AVEYEAR	Zheng et al., 2019;Ali et al., 2010
Socioeconomic	Population Density	POP	Dong et al., 2018
	Urbanization Rate	UR	Li, Sun & Tian, 2023；Osland, Thorsen, &

	GDP	GDP	Thorsen, 2016
Ecology	Vegetation Coverage	FVC	Xie & Chen, 2021
-	Fund Revenue	REVN	-
	Fund Expenditure	EXPN	

Table 2.2: *The driving factors and variable information*

3. Results

Spatial Distribution of Fund Revenue

Significant disparities in maintenance fund revenue were observed across the study area, with values ranging from 20897.11 to 23709867.55. The average revenue was 2918227.98 (standard deviation = 3653553.78), indicating a high degree of variability. Kruskal-Wallis test confirmed that these revenue differences were statistically significant across the three functional zones ($P < 0.05$).

Analysis of the spatial distribution (Figure 3, Table 3.1) suggests a clear hierarchy where revenue levels are highest in the central urban districts and new towns, and lowest in the peripheral ecological conservation zones. As shown in Figure 3, new towns recorded the highest mean revenue (3586251.85) followed by central urban districts (3230743.40). Ecological Conservation Zones generated significantly lower revenue, ranking third (802089.79). The central urban districts exhibited the highest standard deviation, while new towns showed the largest interquartile range (IQR), together indicating considerable instability in fund revenue within these zones.

In Figure 3, the mean expenditure was highest in central urban districts (2789746.69), followed by new towns (821462.10), and was lowest in ecological conservation zones (119385.02). Central urban districts also exhibited the largest IQR and standard deviation, indicating the greatest volatility in expenditure.

Table 3.1 *Kruskal-Wallis Test*

	Fund revenue	**Fund expenditure**
Total N	275	275
Test Statistic	43.857[a]	134.423[a]
Degree Of Freedom	2	2
Sig.(2-sided test)	0.00	0.00

a. The test statistic is adjusted for ties.

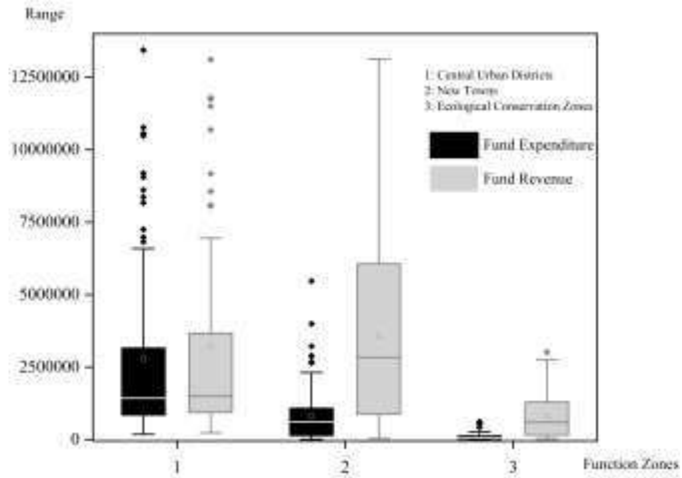
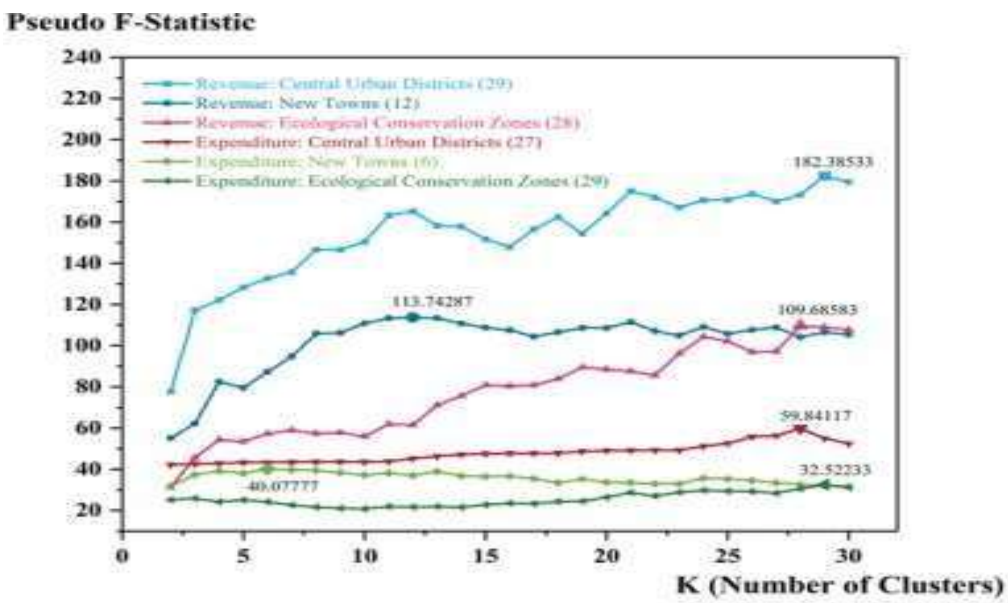


Figure 3: *Differences in Fund revenue and Expenditure across Functional Zones*

For detailed values of Figure 3, please refer to Appendix 1.

Cluster Analysis

Given that there are three functional zones and two types of fund data—revenue and expenditure—we conducted six K-means analyses. The optimal number of clusters was determined using the variance ratio criterion, which posits that a larger pseudo F-statistic indicates a more robust clustering solution (Caliński & Harabasz, 1974). The relationship between the pseudo F-statistic and the number of clusters (K) for each functional area is presented in Figure 4.



* The K that maximizes the pseudo-F statistic is the optimal number of clusters where between-cluster separation is strongest relative to within-cluster spread. Taking "Expenditure: New Towns"(the light green line) as an example, the maximum pseudo-F statistic among 30 simulated cluster analyses is 40.07777 when its research units are clustered into 6 classes, so the optimal number of clusters(K) is 6.

Figure 4: *Variation of Pseudo F-statistic with Increasing Number of Clusters (K)*

The clustering results indicate that within each functional zone, subdistricts group together due to distinct spatial factors. The lower number of clusters is 6 and 12 for the new towns and the greater numbers of clusters for the rest are from 27 to 29. This proves that spatial characteristics are significantly different. Such high spatial heterogeneity indicates the global regression model may fail. GWR may be needed to detect the local scale of variable influence in the regression as it accounts the regression relationships change with locations.

Feature Selection

Figure 5 shows that the fund revenue coefficient of POP, AVEH, AVEV and AVEYEAR is close to 0 with an increasing λ, indicating the presence of collinearity or weak predictability in the global linear model. Besides, the variable importance proves their importance is negligible in fund revenue model. Similarly, in terms of fund expenditure, although only UR strictly approaches 0 as λ increases, other two factors, FVC and GDP, are less important, so they can be ignored in fund expenditure model. Variables nullified by Lasso consistently in Figure 5 all exhibited near-zero importance scores (<0.1) in Random Forest outputs. The results of feature selection also confirm the views of the academic community in the literature.

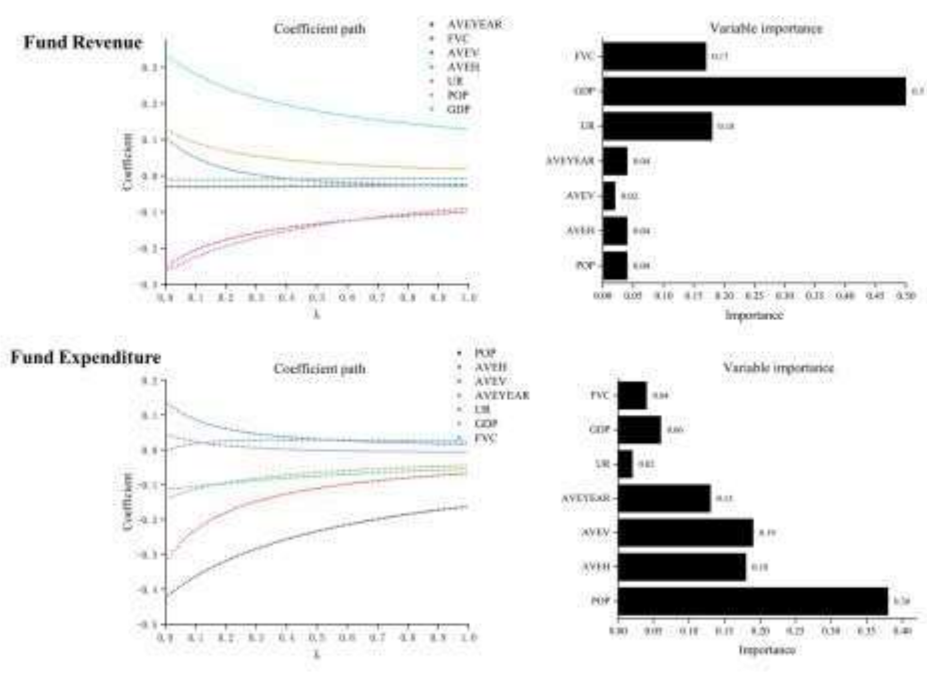


Figure 5: *Coefficient path and variable importance of maintenance fund*

Model Diagnosis and Analysis

The classical global OLS model, GWR and MGWR was employed to model the relationships between socioeconomic, ecological, and built-environment dimensions and maintenance fund revenue/expenditure respectively. The fitting results of OLS are presented in Appendix 2, where the Variance Inflation Factor (VIF) for each independent variable was below 7.5, confirming the absence of multicollinearity. However, both sets of variables yielded low AdjR^2 values less than 0.4 and 0.05, this suggests poor alignment between OLS results and overall observational patterns.

Meanwhile, the Global Moran's I test reveals that high spatial variations exist in our study area, and relevant details can be referred to in Appendix 3.

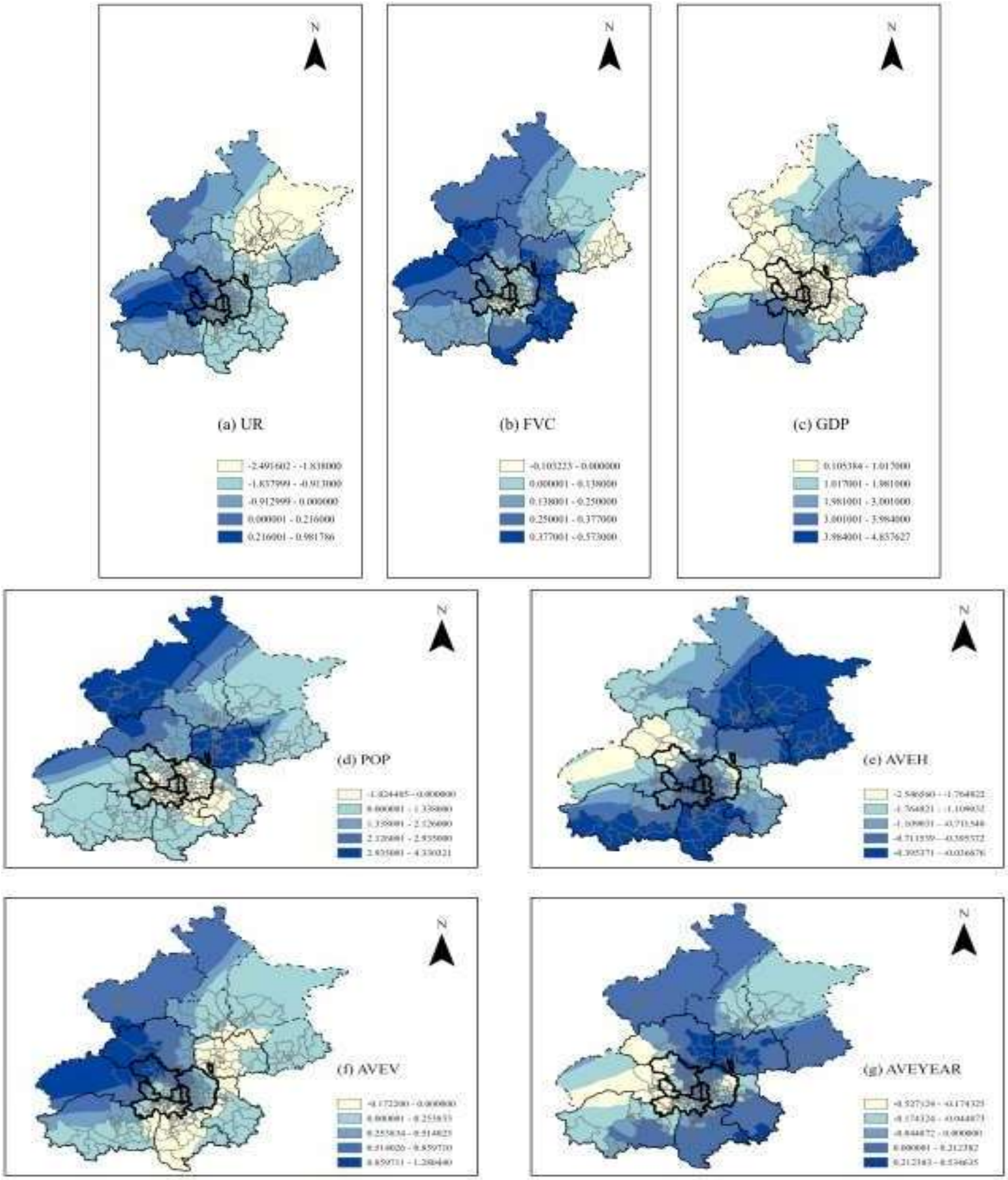
Both R^2 and AdjR^2 values are substantially improved in GWR and MGWR models compared to OLS, indicating the superior explanatory power of spatial regression models for the research objectives.

MGWR outperforms GWR in terms of R^2, AdjR^2, and AICc values. Additionally, the condition numbers for both fund revenue and expenditure models are higher in GWR than in MGWR, suggesting a potential amplified estimation variance (Sanchez-Martin, Gurria-Gascon, & Rengifo-Gallego, 2020).

Table 3.2 *Comparis on of OLS, GWR and MGWR Indicator Values*

	Revenue			Expenditure		
	OLS	**GWR**	**MGWR**	**OLS**	**GWR**	**MGWR**
R^2	0.377158	0.8916	0.9273	0.014622	0.6581	0.7172
AdjR^2	0.370263	0.8612	0.8931	0.002024	0.5031	0.6027
AICc	8970.60129	326.9177	247.0584	8934.459718	661.48	659.819
Condition number	-	754	27	-	23	13
ΔAICc$_{ols\text{-}gwr}$	-8643.683593			-8272.979718		
ΔAICc$_{ols\text{-}mgwr}$	-8723.542893			-8274.640718		
ΔAICc$_{gwr\text{-}mgwr}$	-79.8593			-1.661		

Figure 6: *Displays the estimated coefficients for each spatial factor indicator across the study area.*



*The results for areas outside the samples are obtained by inverse distance weighted interpolation

4. Discussion

4.1 Spatial heterogeneity of factors on maintenance fund revenue

At the overall study area level, urbanization rate exhibits a negative correlation with maintenance fund revenue amounts, with 225 out of 275 subdistrict/township samples showing negative coefficients. Figure 6a reveals that positively correlated coefficients are concentrated in western Beijing, primarily within ecological conservation zones and new towns, with minor occurrences in central urban districts. These areas feature relatively newer building ages and shorter urbanization histories, validating the earlier opinion that regions with higher proportions of newly constructed buildings enhance fund revenue through one-time payments. Notably, the lowest coefficient values are observed in Miyun District (northeastern Beijing), characterized by mountainous terrain and limited urban development. Despite Miyun's urbanization rate reaching approximately 70%, its extensive natural environment restricts commercial housing construction more than other ecological conservation zones, intensifying the negative correlation between urbanization rate and fund revenue.

Figure 6b indicates that Fractional Vegetation Cover (FVC) negatively impacts fund revenue in only 5% of basic spatial units, localized in easternmost Beijing and southern peripheries of central urban districts. The remaining 95% of areas show positive yet weak influences with a maximum coefficient value of 0.57, indicating limited ecological effects on fund revenue across all functional zones.

GDP exerts universally positive impacts on fund revenue throughout Beijing. Figure 6c highlights the strongest GDP effects in easternmost and southernmost regions with a maximum coefficient of 4.8. Weaker GDP impacts occur predominantly at transitional zones between new towns and other two functional areas, suggesting urban development in these regions is more constrained by Beijing's master planning regulations.

4.2 Spatial heterogeneity of factors on maintenance fund expenditure

Areas where population density negatively impacts maintenance fund expenditure are predominantly concentrated in central urban districts and new towns. Although these areas account for 42% of the total sample size, their actual spatial coverage is relatively small, as shown in Figure 6d. These regions feature high population density, particularly in central urban districts where per capita income is higher, leading residents to often opt for self-funded repairs when housing issues arise. Additionally, residential communities in new towns usually have high-rise buildings with scientifically planned layouts and more advanced property management systems. Despite potential requirements for substantial maintenance fund these areas often achieve economies of scale that enhance fund utilization efficiency (Ambrose, Highfield & Linneman, 2005), thereby diluting the positive influence of population density on fund expenditure.

The regression results in Figure 6e indicate that the average building height negatively impacts maintenance fund expenditure across all regions of Beijing, meaning more funds are allocated to lower-rise buildings. Approximately 79% of regions show positive impacts of average building volume on fund expenditure, while Figure 6f reveals that the 21% of areas with negative impacts are almost entirely located in new towns, where newly constructed residences have not yet entered the period requiring significant maintenance, which indicates the phased characteristics of housing maintenance fund expenditure

Figure 6g demonstrates mixed effects of building age on fund expenditure: 49% of samples exhibit negative impacts, and 51% show positive impacts. Areas with pronounced negative impacts are clustered in the southwestern ecological conservation zones and the peripheries of central urban districts. In contrast, most areas within central urban districts and new towns display positive correlations between building age and maintenance fund expenditure. Negative impacts can be categorized into two types: first, temporal truncation in central urban districts, where excessively aged buildings underwent multiple repairs or renovations outside the statistical timeframe of the data. Second, housing in ecological conservation zones, where stricter maintenance approval processes or voluntary abandonment of repairs may occur in addition to the first type.

4.3 The overall impacts of spatial factors

The contribution coefficients and their positive/negative ratios of each independent variable are shown in Figure 7. Except for building height (negative impact on maintenance fund expenditure) and GDP (positive impact on fund revenue), other factors exhibit both positive and negative influences on maintenance fund.

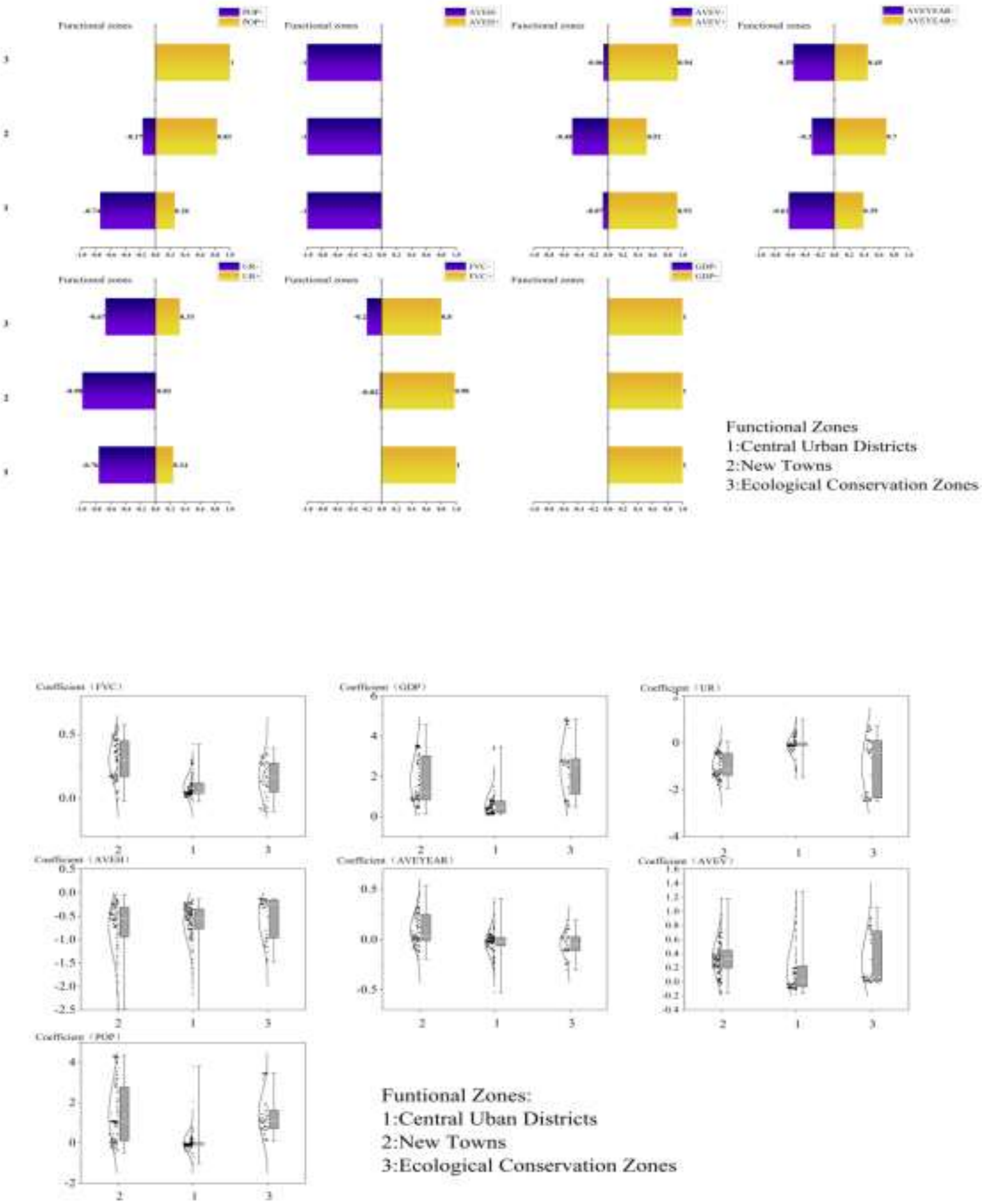


Figure 7: *Contribution Coefficients across Functional Zones*

Regarding the absolute values of average effect coefficients for urbanization rate: new towns (-0.98) > ecological conservation zones (-0.97) > central urban districts (-0.10). This indicates that urbanization rate predominantly exerts negative impacts on central urban districts (76% of subdistricts), new towns (98% of subdistricts), and ecological conservation zones (67% of subdistricts).

For FVC, the order is new towns (0.30) > ecological conservation zones (0.15) > central urban districts (0.09), suggesting FVC primarily exerts positive impacts on central urban districts (98%), new towns (98%), and ecological conservation zones (80%). GDP positively impacts all study samples across Beijing, with ecological conservation zones (2.54) > new towns (1.80) > central urban districts (0.57).

The absolute values of population density effect coefficients follow: new towns (1.42) > ecological conservation zones (1.39) > central urban districts (0.02). This implies population density mainly exerts positive impacts on central urban districts (26%), new towns (83%), and ecological conservation zones. Average building height negatively impacts all samples, with new towns (-0.72) > central urban districts (-0.63) > ecological conservation zones (-0.53).

For building volume, central urban districts (0.34) > ecological conservation zones (0.30) > new towns (0.17), indicating positive impacts on central urban districts (93%), new towns (52%), and ecological conservation zones (94%). Building age exhibits more complex effects: new towns (0.10) > ecological conservation zones (-0.05) > central urban districts (-0.03). This suggests building age negatively impacts ecological conservation zones (55%) and central urban districts (61%), while positively influencing new towns (70%).

4.4 Recommendations

Based on these results and discussions, we can develop targeted policy strategies for housing maintenance fund management in Beijing. Policy recommendations based on regression results from two perspectives: (1) leveraging ecological and socioeconomic factors to enhance fund revenue by mitigating negative impacts from variables with negative coefficients, and (2) analyzing built-environment factors to guide region-specific strategies for managing fund expenditure pressures.

Subdistricts with positive urbanization rate coefficients demonstrate strong fund revenue potential. This is primarily driven by mature urban supporting facilities, active economic activities, and concentrated population agglomeration effects. For these areas, subsequent urban renewal and residential development should be prioritized, provided they align with the city’s master plan and ecological conservation goals. No excessive policy intervention is needed here; market-oriented development can naturally amplify their revenue advantages. However, residents in these areas may face challenges such as rising living costs and increased pressure on public services amid rapid urbanization.

Subdistricts with negative urbanization rate coefficients suffer from suppressed fund revenue. The root cause lies in mismatched urbanization progress with regional functional positioning—for instance, blind redevelopment conflicting with ecological protection requirements, or inadequate economic vitality due to underdeveloped industries. For these subdistricts, cautious evaluation of redevelopment projects is essential, and targeted measures to improve FVC are recommended to mitigate the negative impacts of inappropriate urbanization. Additionally, sustained economic investment is universally effective in boosting fund revenue across all functional zones, as GDP growth directly drives tax increments and other revenue streams. This can be achieved through market-guided industrial investment rather than mandatory policy mandates. Residents here may encounter limited employment opportunities and inadequate public service supplies due to lagging economic and urban development. Subdistricts in ecological conservation zones with positive FVC coefficients also have room to enhance fund revenue by improving vegetation coverage. However, the weak effect of FVC on revenue means policymakers should temper their expectations—policy support can be moderately provided, but over-reliance on such measures should be avoided. The core challenge for residents in these areas is balancing ecological protection obligations with income growth, as strict ecological constraints may limit local industrial development opportunities.

Building volume has a positive impact on fund expenditure in central urban districts, ecological conservation zones, and approximately half of new towns—meaning excessive building density increases fiscal burdens. In contrast, sub districts in new towns with negative building volume coefficients face insufficient construction scale to meet population and economic development needs, indirectly increasing long-term expenditure risks. For the former, urban renewal should strictly regulate housing volume to control expenditure growth; for the latter, market-driven expansion of building volume is feasible without heavy policy intervention. Residents in high-building-volume subdistricts may experience overcrowded public spaces and degraded living quality, while those in low-volume new towns may face a shortage of residential and commercial facilities.

Sub districts with high positive building age coefficients have soaring fund expenditures due to aging buildings requiring frequent maintenance and renovation. Conversely, subdistricts with negative building age coefficients have relatively low current expenditures but need to prepare for future maintenance costs as buildings age. Policy interventions should include: Accelerating the redevelopment of aging buildings in high-coefficient areas (e.g., providing land use incentives for redevelopment projects); Offering maintenance subsidies for older housing in negative-coefficient zones to balance fiscal pressures and social equity. Residents in aging building areas may face safety hazards and poor living conditions, while those in newly developed areas may worry about inadequate long-term maintenance support if policy preparations are insufficient.

Sub districts with negative coefficients in population-related built-environment indicators are underutilized, while those with positive coefficients face overcrowding-driven expenditure surges. Policymakers can introduce targeted incentives to redirect population growth to negative-coefficient areas. Prioritizing high-density residential projects in these zones can simultaneously ease pressure in overcrowded regions. This approach combines policy guidance with market choices—residents in overcrowded areas will benefit from reduced public service strain, while those relocating to negative-coefficient areas may enjoy lower housing costs but need to adapt to immature supporting facilities in the short term.

5. Conclusion

5.1 Comparisons

Results indicate that the regression results of MGWR are superior to those of other regression models. This is consistent with the conclusions of Fotheringham, Yang and Kang (2017), indicating that multi-scale regression analysis is also applicable in the field of housing maintenance funds.

Spatial heterogeneity in built environment, socioeconomic, and ecological factors significantly influences fund revenue and expenditure dynamics. Our results not only confirms the existence of the effects found in previous studies, but also proves that the magnitude and positive or negative effects of these effects cannot be generalized due to regional differences.

Specifically, based on the regression results, we confirm the positive promoting effect of economic development on fund collection, as proposed by Li, Sun, & Tian (2023), while agreeing with the view of Dong et al. (2018) that excessive population density accelerates building wear and tear, leading to increased maintenance fund expenditures. We also find that although Li (2024) argues that building height increases maintenance expenditures, our results indicate that the economies of scale brought by high-rise buildings effectively alleviate the pressure on fund expenditures.

Regarding the impact of ecological factors, our new conclusions differ from the prevailing view in academia represented by Xie & Chen (2021): in most areas of Beijing, ecology and socieconomic development exhibit a synergistic trend, with areas having better ecological conditions generally having a positive impact on fund revenue, and only a few streets experiencing slight negative impacts, rather than a simple case of ecological environment restricting development.

In clustering, while Wu et al. (2020) and Wang et al. (2024) address sample heterogeneity through clustering methods, we used cluster analysis as the judgment basis, which shown that subdistricts within each functional zone are still subject to spatial influences, then we used functional zone as the criterion for classification, thereby circumventing over-fitting caused by an excessive K value, the subsequent GWR/MGWR step still captured within-zone spatial heterogeneity—yielding regression coefficients that are both policy-actionable and readily transferable across data, avoiding the disconnect between administrative boundaries and the theoretical framework.

In summary, the spatial heterogeneity of current housing maintenance funds is significantly affected by spatial factors arising from functional zones. Therefore, fund management policies can set differentiated rates at a scale between functional zones and subdistricts, and gradually refine them down to the scale of a certain subdistrict.

5.2 Contributions, limitations and prospects

This study is to prove GWR analysis is applicable to the field of housing maintenance funding and provide specific operational cases. By integrating multi-source geospatial data, we enable research and analysis at the granular level of communities and townships. Reconceptualising fund revenue and expenditure as interconnected yet independent systems allows for accurate selection of variables to model spatial heterogeneity in the fund system.

Several limitations of this study may affect the interpretation and generalization of its results. First, the limited temporal span of the sample data (covering only the five years after 2020) may have omitted historical maintenance events such as early capital investment in older urban areas, resulting in the regression model's inadequate capture of long-term trends. Second, the study lacks discussion of auxiliary funding parameters such as fund transfers, reimbursements, and interest accruals. Nevertheless, these limitations do not negate the overall value of this study, as its core contribution lies in its exploration of spatial mechanisms at the functional zone scale.

This study could be expanded into further explorations to enhance the subject's innovativeness and practical value. First, the research could be expanded to include other cities in China, enhancing the generalizability of the conclusions through comparative analysis and validating the cross-regional applicability of the functional zoning approach. Second, the new theoretical framework such as institutional economics could be introduced to broaden the analytical scope, for example, examining the impact of economic shocks or climate change on the sustainability of housing funds. Finally, the results could be validated in real-world contexts, such as by collaborating with local governments to implement pilot policies and conducting on-site follow-up evaluations. These directions are logically sound and feasible: city comparisons can draw on existing spatial databases; integrating new theories can enrich causal mechanisms; and policy validation can be achieved through collaborative research. This not only extends the value of this research but also provides forward-looking insights for subsequent work, promoting the multidisciplinary development of housing fund research.

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Appendix

Appendix 1

Differences in Fund Revenue and Expenditure across Functional Zones

Revenue	Central Urban Districts	New Towns	Ecological Conservation Zones
Q3	3767512.17	6129828.27	1309573.09
Q1	919973.73	870167.60	141345.25
IQR	2847538.44	5259660.67	1168227.84
Average value	3230743.40	3586251.85	802089.79
Median value	1494355.30	2837562.54	591276.23
Standard deviation	4267912.16	3215334.28	764322.95

Expenditure	Central Urban Districts	New Towns	Ecological Conservation Zones
Q3	3245472.25	1087249.34	137039.32
Q1	832384.50	132013.48	18588.93
IQR	2413087.75	955235.86	118450.39
Average value	2789746.69	821462.10	119385.02
Median value	1425408.60	614061.24	63444.76
Standard deviation	3458118.54	936003.88	160021.41

Appendix 2

Summary of OLS Results

Variable	**Coefficient**	**Std. Err**	**Prob>F**	**Robust_Prob**	**VIF**	**R^2**	**AdjR^2**	**AICc**
Intercept$_{REVN}$	-4800000.98	1041069.88	0.00*	0.00*	-	0.38	0.37	8970.60
UR	4204.02	18583.29	0.82	0.87	1.38			
FVC	9040429.26	1333785.38	0.00*	0.00*	1.30			
GDP	14318.80	1424.13	0.00*	0.00*	1.07			
Intercept$_{EXPN}$	2759670.67	717053.78	0.00*	0.00*	-	0.01	0.01	8934.46
POP	2.67	13.44	0.84	0.70488	1.34			
AVEH	-153584.08	82164.48	0.06	0.06	3.61			
AVEV	122.14	76.55321	0.11	0.12	3.27			
AVEYEAR	1565.35	16564.13149	0.92	0.92	1.13			

*p < 0.01

Appendix 3

Global Moran's I Results

	Fund Revenue	**Fund Expenditure**
Moran's I	0.38987	0.400442
Expected Index	-0.00365	-0.00365
Variance	0.001409	0.001385
z-score	10.482712	10.859121
Prob	0.00	0.00