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Unveiling the Spatially Heterogeneous Driving Mechanisms of Net Migration in Chinese Cities: A Geographically Weighted Random Forest Approach

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Abstract

As China transitions from rapid urbanization to high-quality development, the competition for population among cities has intensified, characterized by a shift from labor-intensive migration to multi-dimensional lifestyle choices. However, traditional migration models often assume global linearity, failing to capture the complex non-linear thresholds and spatial non-stationarity inherent in migration decisions. This study employs a novel Geographically Weighted Random Forest (GWRf) model to analyze net migration flows across 278 Chinese cities using high-granularity mobile signaling data from the 2020 Spring Festival travel rush. The results reveal that GWRf significantly outperforms traditional OLS, GWR, and global Random Forest models, effectively handling spatial heterogeneity and non-linearity. Wage levels are the dominant global driver, exhibiting a distinct “S-curve” non-linear threshold, while population scale shows a significant U-shaped effect, highlighting the transition from agglomeration economies to congestion costs. Migration drivers exhibit profound spatial heterogeneity: western inland cities are “wage-driven,” the Pearl River Delta is “employment-structure driven,” and the northeastern “Rust Belt” is increasingly sensitive to “innovation investment” (technology expenditure). These findings challenge the “one-size-fits-all” approach to population policy, offering precise, spatially targeted strategies for urban planners to mitigate population shrinkage and enhance urban vitality.

Keywords: net migration; Geographically Weighted Random Forest (GWRf); spatial heterogeneity; non-linear thresholds; urban shrinkage



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1. Introduction

Over the past four decades, China has experienced the largest and fastest urbanization process in human history, a transformation that has fundamentally reshaped the nation’s economic geography [1]. Intercity population mobility has served as the core engine for this growth, facilitating the efficient allocation of labor resources across spatial boundaries [2]. However, as China’s economy transitions into a “New Normal” and the national demographic dividend begins to wane, the nature of urban competition has shifted dramatically. Cities are no longer merely competing for labor quantity but are engaging in a fierce “War

for Talent” to secure high-quality human capital [3]. Consequently, a significant “Matthew Effect” has emerged in population flows: core urban agglomerations continue to attract high-end elements and population, while many small-to-medium cities and traditional industrial bases face the severe challenge of “population shrinkage” [4]. In this context, Net Migration Flow—the balance between inflows and outflows—has become a critical barometer of urban vitality, directly impacting local fiscal sustainability, real estate market stability, and the efficiency of public service provision. Understanding the determinants of net migration is therefore essential for formulating scientific urbanization policies and achieving coordinated regional development.

The existing literature on migration drivers is extensive, predominantly grounded in the classical “Push–Pull” theory and neoclassical economics [5]. These traditional frameworks typically posit that wage differentials and employment opportunities are the fundamental drivers of population movement [6]. However, as living standards in China have risen, the motivations for migration have evolved from survival-oriented choices to multi-dimensional pursuits of a “better life” [7]. Contemporary scholars have increasingly incorporated non-economic factors into their analytical frameworks, such as environmental comfort (e.g., PM_{2.5} concentrations), public service quality (education and healthcare), and urban scale [8]. Despite a consensus that high wages and quality services attract population, empirical findings on specific indicators remain debated. For instance, does a higher total GDP necessarily guarantee net population inflow? Is high housing cost a screening mechanism for talent or a repulsive force? These controversies suggest that the influence of drivers is not a simple linear accumulation but likely involves complex threshold effects or diminishing marginal returns that traditional linear models fail to capture.

Methodologically, early research heavily relied on Ordinary Least Squares (OLS), Gravity Models, or panel data regressions [9]. These approaches generally assume a global, linear relationship between independent and dependent variables. However, urban systems are inherently complex and non-linear. For example, the attraction of wages may exhibit a “threshold effect,” where income levels only become attractive after surpassing a subsistence baseline; similarly, urban scale may display an “U-shape” effect due to the trade-off between agglomeration economies and congestion costs. Linear models are ill-equipped to identify these critical tipping points. Recently, machine learning algorithms like Random Forest (RF) have been introduced to migration studies due to their robust ability to handle non-linearity and multicollinearity [10]. However, while global machine learning models solve the linearity issue, they often overlook another core characteristic of geographical data: spatial non-stationarity.

China’s vast territory encompasses regions with vastly different development stages, resource endowments, and policy orientations. The drivers of population inflow in the affluent coastal east likely differ fundamentally from those in the resource-dependent northeast or the less developed west [11,12]. A global model that applies a single set of parameters to all cities inevitably masks these local mechanistic differences. In addressing spatial data, traditional geostatistics (e.g., Kriging) excel at spatial interpolation for a single continuous variable, but lack the capacity to model complex, multi-variable, non-linear causal relationships. While Geographically Weighted Regression (GWR) addresses spatial heterogeneity [13], it remains bound by linear assumptions. To simultaneously address the dual challenges of non-linearity and spatial heterogeneity, the Geographically Weighted Random Forest (GWRF) model has emerged as a promising solution [14]. GWRF offers several structural advantages over alternative approaches. Compared to gradient-boosted methods (e.g., XGBoost, LightGBM), GWRF explicitly incorporates geographical weighting into the model architecture rather than treating spatial coordinates as ordinary features,

which ensures that the resulting local variable importance scores are theoretically grounded in geographical proximity rather than being artifacts of a global optimization process. Compared to standard GWR, GWRF relaxes the linearity constraint while preserving local interpretability through spatially disaggregated feature importance maps. By constructing local random forest models for specific spatial locations, GWRF thus retains the high prediction accuracy of machine learning while offering the local interpretability of GWR.

Despite its potential, the application of GWRF in migration studies remains rare, particularly in the context of Chinese cities. Furthermore, existing applications often lack rigorous justification for bandwidth selection and robust cross-validation on small sample sizes. Addressing these gaps, this study employs an improved GWRF model to analyze net population flows across 278 Chinese cities. We specifically focus on the return-to-home phase of the 2020 Spring Festival travel rush, a temporal window that has been extensively validated in the recent literature for exploring directional migration mechanisms in China. This period is of particular methodological significance as it provides a “clean” observation window that precedes the large-scale implementation of COVID-19 containment measures. By doing so, our analysis captures authentic long-term settlement intent and mobility logic while remaining entirely unaffected by the subsequent pandemic-induced travel restrictions and behavioral distortions [15].

Building upon these considerations, this study addresses three interrelated research objectives:

1. To identify the dominant global determinants of net migration and detect potential non-linear threshold effects, such as critical wage “take-off” points, that govern population redistribution;
2. To examine the spatial non-stationarity of these driving mechanisms and determine whether distinct migration regimes exist across China’s diverse geographical regions;
3. To validate the methodological advantages of the GWRF model by benchmarking its predictive performance and local interpretability against traditional OLS, GWR, and global RF approaches.

By decoding the spatially contingent and non-linear logic of migration, this research provides a scientific basis for formulating differentiated population strategies that are sensitive to local development thresholds, ultimately promoting regional balance and sustainable urbanization.

2. Literature Review and Theoretical Framework

2.1. Evolution of Migration Theories: From Flow Mechanisms to Urban Attraction

Research on population migration has transitioned from modeling micro-foundations of directional flows to analyzing the aggregate competitive capacity of cities. Early studies, such as Zipf’s (1946) Gravity Model [9], established the foundational role of population size and distance in determining mobility. While Lee’s (1966) Push–Pull theory [5] provides a robust conceptual framework for understanding the binary choice between origin and destination, its traditional application focuses on directional O–D flows.

However, for urban policy and spatial planning, the *Net Migration Flow*—the aggregate balance of all inflows and outflows—serves as a more critical indicator of urban vitality and resource-carrying capacity [4]. The existing literature increasingly treats net migration as the result of a city’s holistic attraction, where individuals “vote with their feet” based on a bundle of urban attributes. Unlike directional models that emphasize the push–pull asymmetry between two locations [16], net migration research identifies how a city’s endogenous characteristics determine its overall population trajectories [17], which fundamentally defines its future growth and development potential.

2.2. The “Linearity Bias” and the Necessity of Non-Linear Response

The relationship between urban attributes and net migration has long been modeled under the assumption of global linearity. Standard econometric approaches (e.g., OLS and spatial regressions) typically assume a constant marginal effect, implying that a unit increase in a driver (e.g., wages) yields a uniform impact across all development stages.

However, actual migration responses often exhibit complex non-linearities, such as **Threshold Effects** and **Saturation Points**. As noted by Shi et al. (2025) [16], economic and environmental factors often need to surpass specific critical masses to significantly alter migration intensity. For instance, a city’s wage level may follow an “S-curve” response where attraction only accelerates after breaching a subsistence threshold, while urban scale may exhibit a U-shape due to the trade-off between agglomeration and congestion. Traditional models that overlook these thresholds risk producing biased estimates and ineffective policy recommendations.

2.3. Spatial Non-Stationarity in Migration Mechanisms

Beyond non-linearity, migration mechanisms in China are characterized by profound spatial non-stationarity [8,18]. In a country with vast regional disparities, the drivers of population inflow in affluent coastal hubs differ fundamentally from those in shrinking industrial bases or developing inland cities. While global machine learning models excel at capturing non-linearity, they often neglect these local spatial variations. Conversely, Geographically Weighted Regression (GWR) addresses spatial heterogeneity but remains bound by linear assumptions.

2.4. Theoretical Framework: Spatially Heterogeneous Non-Linear Attraction

To address these challenges, this study proposes a **Spatially Heterogeneous Non-linear Attraction Framework**. Following recent taxonomic approaches in urban studies [16,19], we categorize urban determinants into five dimensions: Economic Drivers (E), Industry and Employment (I), Public Services and Innovation (S), Environment and Cost (V), and Population Scale (P). We conceptualize net migration as a spatially varying, non-linear function of these attributes:

$$NetFlow_i = f_{spatial}(E_i, I_i, S_i, V_i, P_i) \quad (1)$$

In this framework, the relationship between urban attributes and population redistribution is governed by two complementary mechanisms. First, the non-linear nature of migration responses is captured through the Random Forest structure, which allows for the identification of irregular thresholds, saturation points, and phase transition intervals for each attribute dimension. Second, the framework accounts for spatial heterogeneity through local geographical weighting, recognizing that the sensitivity of net population flow to specific attributes varies fundamentally across different regional regimes and urban contexts.

Operationally, this study leverages the unique behavioral signature of China’s Spring Festival (Chinese New Year) travel rush to measure $NetFlow_i$. As the most important traditional holiday in China, the Spring Festival prompts hundreds of millions of workers to return to their hometowns for family reunions, creating the world’s largest annual human migration event (commonly known as *Chunyun*). During this pre-festival homebound phase, migrant workers temporarily return from their work cities to their hometowns, producing a mass “reversal flow.” Because the individuals participating in this homeward flow are precisely those who have made prior long-term settlement decisions in their work cities, the magnitude of a city’s seasonal net outflow directly reveals its accumulated stock of permanent in-migrants. For example, cities such as Beijing and Shanghai experience

massive holiday outflows precisely because they have attracted millions of long-term settlers throughout the year; this observed seasonal outflow is therefore evidence of strong permanent attraction, not population loss. Reversing the sign of this seasonal flow therefore yields a measure of each city's permanent net migration attraction—consistent with the “revealed preference” paradigm in which migrants “vote with their feet” [20]. Accordingly, the “net migration” reported throughout this study refers to this derived permanent migration indicator, not the raw directional flow observed during the Spring Festival itself.

By focusing on the 2020 Spring Festival return-to-home phase as a “clean” observation window preceding pandemic-induced distortions, this integrated approach provides a refined and authentic understanding of the complex mechanisms driving China's contemporary population redistribution [15,18].

3. Data

3.1. Study Area and Data Source

This study focuses on 278 prefecture-level cities across China. The net migration data is derived from national mobile signaling data provided by China Unicom during the 2020 Spring Festival travel rush (Chunyun). We specifically selected the return-to-home phase, covering the 15 days before the Spring Festival (10 January to 24 January 2020). The dataset captures approximately 814 million individual movement records across 89,373 directed city pairs. The sample of 278 cities was determined by data availability: China Unicom excluded cities with extremely low volumes of paired inter-city flow records from its processed dataset due to signal reliability concerns. As a result, the excluded cities are predominantly located in sparsely populated areas of western China (e.g., parts of Tibet and Xinjiang), while the densely populated eastern and central regions are comprehensively covered.

The selection of this specific temporal window is based on several critical methodological considerations. First, while the COVID-19 pandemic significantly disrupted the subsequent return-to-work phase, the homebound phase remained largely unaffected [16]. Critically, official statistics confirm that the national railway passenger volume during the pre-festival phase (10–24 January 2020) increased by 17.2% compared to the same period in 2019, reaching approximately 168 million passenger-trips [21]. Public awareness of the novel coronavirus only crystallized after Zhong Nanshan's confirmation of human-to-human transmission on 20 January 2020, and the subsequent lockdown of Wuhan on 23 January—by which point the national homecoming flow had essentially concluded according to historical travel patterns [15]. In stark contrast, the post-festival return-to-work phase (25 January–14 February) saw railway passenger volume plummet by 83.9% to only 42.48 million passenger-trips [21]. Consequently, the pre-festival window provides a “clean” observation period to capture authentic inter-city migration intent and mobility logic before the pandemic-induced behavioral distortions occurred.

Second, following the sampling strategy of the recent literature [16], this study restricts the research population to individuals aged 19 to 59. This exclusion is theoretically grounded in the “new economics of migration,” which posits that the decision-making unit often shifts from the individual to the family [22]. Consequently, the migration of minors and the elderly is frequently “passive” or “tied,” driven by family dependencies rather than independent responses to urban attributes [23]. Accurately identifying these sociodemographic heterogeneities is crucial for capturing the authentic labor-led mobility mechanisms and reducing model noise [24].

As discussed in the theoretical framework (Section 2.4), we exploit the reversal pattern of this seasonal flow—reversing the sign of each city's holiday net outflow—to construct a measure of permanent net migration attraction [16]. Compared to traditional household registration (*hukou*) statistics, this mobile signaling-based indicator offers supe-

rior spatial granularity and more sensitively captures the actual direction of population flows where individuals “vote with their feet,” a behavioral manifestation of the local expenditure theory [20].

3.2. Variable Selection and Preprocessing

Based on the classical Push–Pull Theory and the characteristics of China’s urban development, this study constructed a driving factor system comprising 11 core indicators:

1. **Economic Drivers:** Per capita GDP and Average Wage. Wages are the direct incentive for population movement, while per capita GDP reflects macro-economic strength.
2. **Industry and Employment:** Tertiary Industry Share and Registered Urban Unemployment Rate. The share of the tertiary industry represents industrial upgrading and employment absorption capacity, while the unemployment rate acts as a primary push factor.
3. **Public Services and Innovation:** Per capita Fiscal Expenditure, per capita Education Expenditure, and per capita Science and Technology Expenditure. These measure the quality of soft infrastructure and future development potential.
4. **Environment and Cost:** Annual average PM_{2.5} Concentration and Minimum Monthly Wage. The latter serves as a proxy for the local cost of living, as minimum wage standards in China are administratively set by provincial and municipal governments based on local economic conditions, consumer price indices, and housing cost levels. While granular city-level housing price data would be an ideal complement, its limited availability across all 278 cities necessitates this proxy approach.
5. **Demographics and Scale:** Gender Ratio and Urban Population Scale (log-transformed) to control for the non-linear impacts of agglomeration and congestion effects.

Detailed variable definitions and descriptive statistics are presented in Table 1.

Table 1. Variable definitions and descriptive statistics of the GWRF model for net population flow.

Variable Name	Description	Min	Max	Mean	Std. Dev.
Net Migration	Pre-Spring Festival net outflow (attraction proxy)	−1,451,142	3,192,970	10,074.20	630,415.70
Population Scale	Permanent population in 2019 (10k)	31.40	3208.90	461.25	389.71
GDP Scale	Gross Domestic Product in 2019 (100m RMB)	231.20	38,156.00	3319.40	4710.50
Fiscal Expenditure	General public budget expenditure (100m RMB)	31.80	8179.20	575.80	815.50
Education Expenditure	Expenditure on education (100m RMB)	4.50	1136.00	93.90	119.10
Tech Expenditure	Expenditure on science and tech (100m RMB)	0.20	548.40	18.40	54.05
Average Wage	Annual average wage of employees (RMB)	44,953	173,204	77,291.21	16,385.50
PM _{2.5}	Annual average PM _{2.5} concentration (µg/m ³)	11.33	69.16	38.35	12.18
Industrial Structure	Share of tertiary industry (%)	28.33	83.52	49.15	8.24

Table 1. Cont.

Variable Name	Description	Min	Max	Mean	Std. Dev.
Minimum Wage	Minimum monthly wage standard (RMB)	1180	2480	1517.62	200.46
Unemployment Rate	Registered urban unemployment rate (%)	0.04	3.14	0.60	0.41
Gender Ratio	Ratio of males to females (%)	96.37	130.05	104.53	4.52

After screening for data completeness and availability, the final analysis includes a sample of 278 cities. Due to significant differences in population scale among cities, using raw indicators directly may result in a significant “large city effect.” Regions with larger scales typically hold absolute advantages in inflow volume and economic totals, which can mask the true mechanisms of other variables in small and medium-sized cities, leading to biased estimation [25]. This phenomenon is often linked to the sub-linear or super-linear scaling laws of urban indicators [26].

To control for this, indicators closely related to population scale (GDP, Fiscal, Education, and Tech Expenditures) were processed by dividing the raw value by the permanent population (in millions) and multiplying by 100 to obtain the value per 10,000 people. The dependent variable “Urban Net Population Flow” was processed in the same manner. Finally, multi-collinearity diagnostics showed that the Variance Inflation Factor (VIF) for all variables was below 10, a widely accepted threshold for mitigating the adverse effects of multicollinearity in regression analysis [27].

4. Methodology

To unravel the complex mechanisms driving net migration, this study constructs a methodology centered on the Geographically Weighted Random Forest (GWRF) model. Figure 1 illustrates the overall analytical framework, comprising data preparation, global baseline modeling, explicit local spatial modeling, and mechanism analysis. All calculations and machine learning models in this study were implemented using Python 3.12.9.

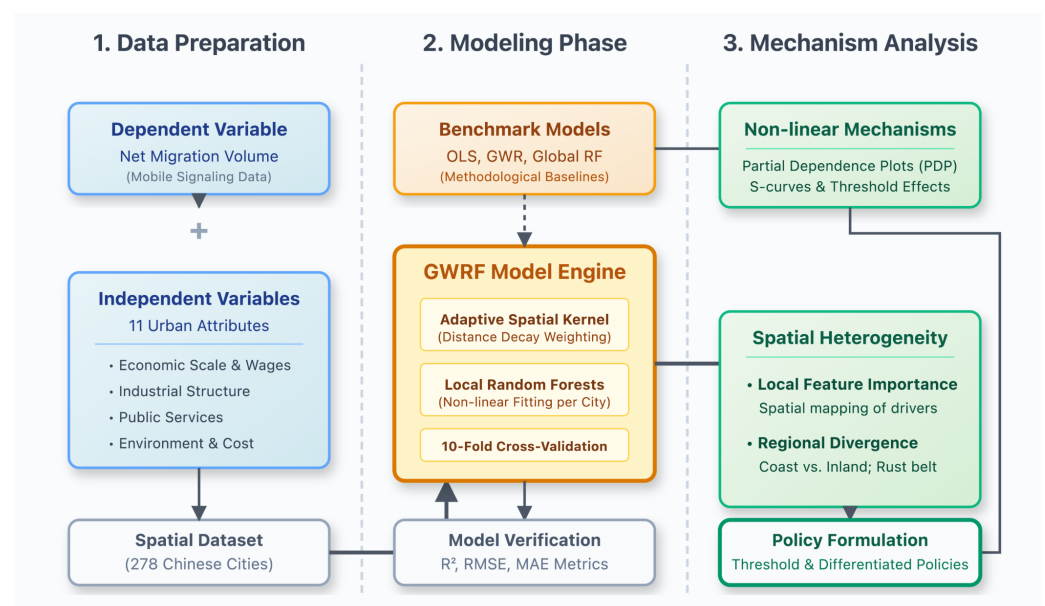


Figure 1. Methodological flowchart of the analytical framework.

This study adopts a comprehensive analytical framework that integrates spatial statistics and machine learning. First, a global Random Forest (RF) is utilized to identify key driving factors and analyze their non-linear responses. Second, the Geographically Weighted Random Forest (GWRF) model is introduced to reveal the spatial non-stationarity of the driving mechanisms through local modeling. Finally, the superiority of the proposed method is validated by comparing it with traditional models, including Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and global Random Forest.

4.1. Random Forest and Partial Dependence

Random Forest (RF) is a machine learning algorithm based on an ensemble of decision trees. Compared to linear regression, RF can automatically capture high-order interactions and non-linear relationships among variables while maintaining strong robustness against multicollinearity [28]. This study first constructs a global RF model to calculate the *Global Feature Importance* of each variable based on the Out-of-Bag (OOB) permutation accuracy decrease method.

Furthermore, Partial Dependence Plots (PDP) are employed to visualize the marginal effect curves of key variables, such as wage levels and science and technology investment, on net migration flows [29]. This approach allows for the identification of potential *Threshold Effects* or U-shaped patterns within the migration drivers.

4.2. Geographically Weighted Random Forest

While global RF addresses non-linearity, it ignores the inherent spatial heterogeneity of geographical data. Therefore, this study adopts the Geographically Weighted Random Forest (GWRF) model, which represents an extension of Geographically Weighted Regression (GWR) logic into the machine learning field [14]. The core concept is to construct an independent local random forest model for each research unit (city). For a target city i , the construction of the local model follows the principle of distance decay:

1. **Local Weighting:** Sample points closer to city i are assigned higher weights during model training, while the weights of sample points beyond a specific bandwidth (b) are set to zero. This study utilizes an *Adaptive Bisquare Kernel* function to determine the spatial weights, following the established geographical weighting principles [30]:

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

where d_{ij} represents the distance between city i and observation j .

2. **Bandwidth Optimization:** The choice of bandwidth directly determines the model's fit and spatial smoothness. This study employs the *Incremental Spatial Autocorrelation* (ISA) algorithm to search for the optimal bandwidth. The algorithm identifies the bandwidth value that minimizes the spatial autocorrelation (Moran's I) of the model residuals, ensuring that the errors are randomly distributed and the local models are statistically valid [14].
3. **Prediction Synthesis:** The final prediction results are based on a spatially weighted average of the predicted values from all local models within the optimal bandwidth, balanced with the global model's predicted values to ensure robust generalization.

4.3. Model Evaluation and Validation

To mitigate the risk of overfitting potentially caused by small sample sizes, this study implements a rigorous 10-fold cross-validation (10-Fold CV) procedure [31]. In each round of validation, the dataset is randomly partitioned into a training set (90%) and a testing

set (10%). Data standardization parameters are calculated solely within the training set to prevent data leakage. The average coefficient of determination (R^2) and Root Mean Square Error (RMSE) across the ten rounds are calculated as robust indicators of the model's generalization capability. Additionally, the performance of GWRF is benchmarked against OLS, GWR, and global RF models to confirm the applicability and superiority of the chosen methodology. We note that the fold partitioning follows a standard random scheme rather than a spatial blocking strategy [32]. While spatial block cross-validation can reduce optimistic bias from spatial autocorrelation leakage, at the prefecture-level granularity of this study ($n = 278$), the relatively coarse spatial resolution and the adaptive bandwidth of the GWRF model itself substantially mitigate this concern. We acknowledge this as a methodological caveat and recommend that future studies with finer-grained spatial units adopt spatially explicit validation frameworks.

5. Results

5.1. Spatial Distribution Pattern of Net Migration

Figure 2 illustrates the spatial distribution characteristics of urban net migration flow across China during the 2020 Spring Festival. It is observed that the spatial pattern of population mobility exhibits significant regional disparities. Economically developed regions along the eastern coast and a few inland provincial capitals show large-scale net population inflows, with first-tier cities such as Beijing, Shanghai, Guangzhou, and Shenzhen particularly prominent. In contrast, the vast majority of cities in Central and Western China, primarily in provinces like Henan, Anhui, Sichuan, Hunan, and Hubei, exhibit a state of net population outflow. This spatial polarization reflects a clear “Matthew Effect” in China's urban system, where core regions increasingly siphon resources from the periphery [33].

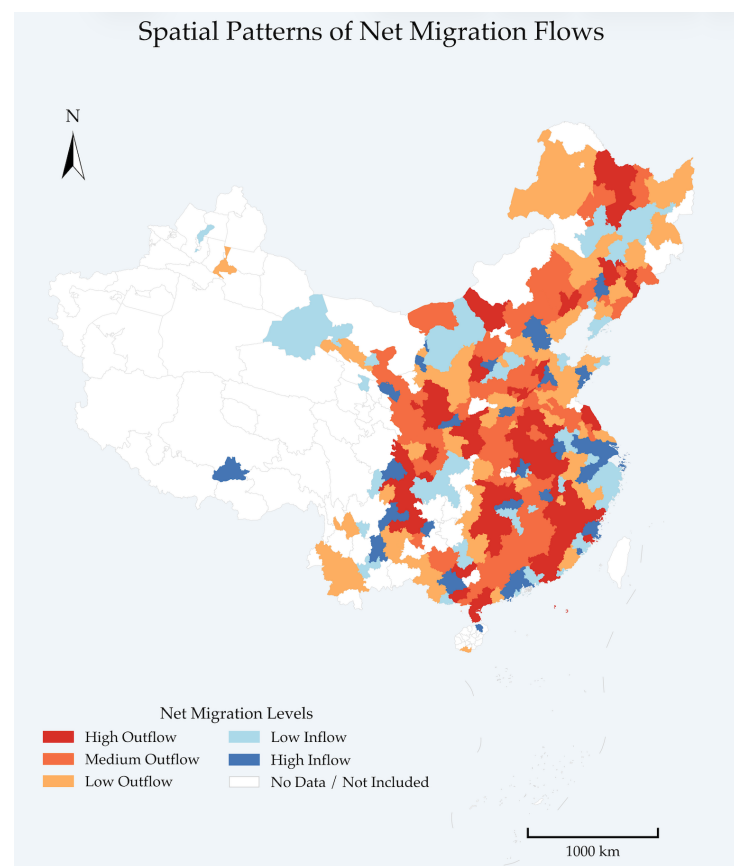


Figure 2. Spatial distribution of net urban migration flows across 278 Chinese cities.

Figure 3 depicts the distribution histogram and Kernel Density Estimation (KDE) curve of urban net migration flow. The distribution is highly skewed, with most cities clustered near zero, indicating a dynamic equilibrium between migration and return. However, a few core cities far exceed others in net inflow, creating a gap in urban mobility. Both ends of the curve exhibit long tails: the right tail indicates the extreme attraction effect of core cities, while the left tail reflects significant population outflow in others.

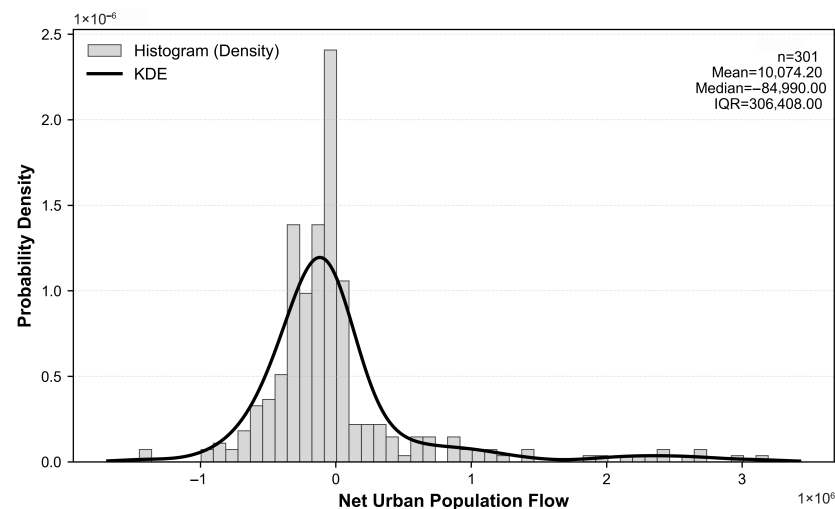


Figure 3. Distribution histogram and Kernel Density Estimation curve of net population flow.

These statistics suggest that China’s urban population migration is not uniform but follows a pattern of “small-scale movement in most cities and extreme concentration in a few.” To understand the driving mechanisms behind these disparities and their spatial heterogeneity, this study utilizes the GWRP model for further analysis.

5.2. Random Forest Model: Global Feature Importance

Feature Importance (FI) quantifies the contribution of each explanatory variable to reducing prediction impurity in the Random Forest model [28]. Based on the global RF model results in Figure 4, the relative importance of driving factors reveals a distinct hierarchy of influence.

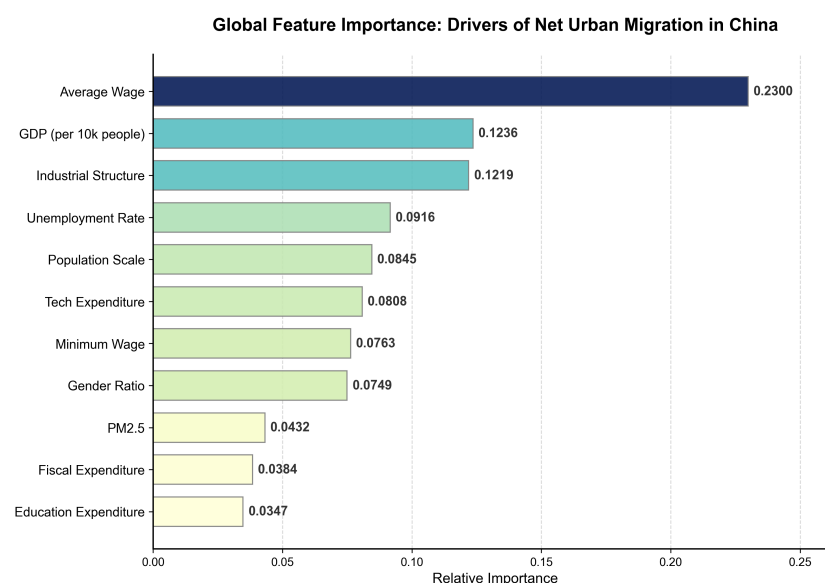


Figure 4. Global feature importance of driving factors for urban net migration.

1. **Core Economic Incentives (Wage and Wealth).** “Average Wage” (Importance = 0.230) stands out as the most decisive variable, nearly doubling the importance of the second-ranked factor. This reinforces the “income maximization” hypothesis [34], indicating that actual labor compensation remains the fundamental magnet for population redistribution. This is followed by “Per Capita GDP” (0.124), representing a city’s macro-economic strength. The substantial gap between wage and GDP importance suggests that migrants are driven more by individual disposable income than by a city’s aggregate wealth.
2. **Industrial Structure and Labor Market.** The “Tertiary Industry Share” (0.122) ranks third, acting as a critical employment reservoir due to its capacity to absorb labor. Meanwhile, the “Unemployment Rate” (0.092), serving as a primary push factor, also shows high significance, implying that job security is a baseline requirement for migration stability.
3. **Agglomeration and Innovation Potential.** “Population Scale” (0.084) and “Per Capita Science and Technology Expenditure” (0.081) represent the attraction of urban agglomeration and future development prospects, respectively. High technology investment signals industrial vitality and the potential for professional career growth.
4. **Environmental Quality and Public Services.** Factors such as “PM_{2.5}” (0.043) and per capita fiscal or education expenditures rank lower in the global model. This indicates that while quality-of-life amenities are increasingly valued, economic opportunity and job security still constitute the dominant decision-making logic for the majority of intercity migrants in China.

5.3. Non-Linear Threshold Effects: Partial Dependence Plots (PDP)

Partial Dependence Plots (PDPs) further characterize the marginal impact trajectories of key drivers on net migration, revealing significant non-linear features and threshold effects [29].

1. **The “S-shaped” Growth and Saturation of Economic Drivers:** The PDP curve for average wage shows a classic “S-shaped” pattern. Below 80,000 RMB, growth is flat (the “low-level equilibrium trap”). Once the 80,000 RMB threshold is breached, the slope rises sharply, showing strong increasing marginal returns. Beyond 90,000 RMB, the curve flattens again, suggesting that for ultra-high-income cities, salary becomes less of a decisive factor compared to other non-economic elements. Figure 5 illustrates the response curves for income-related factors.

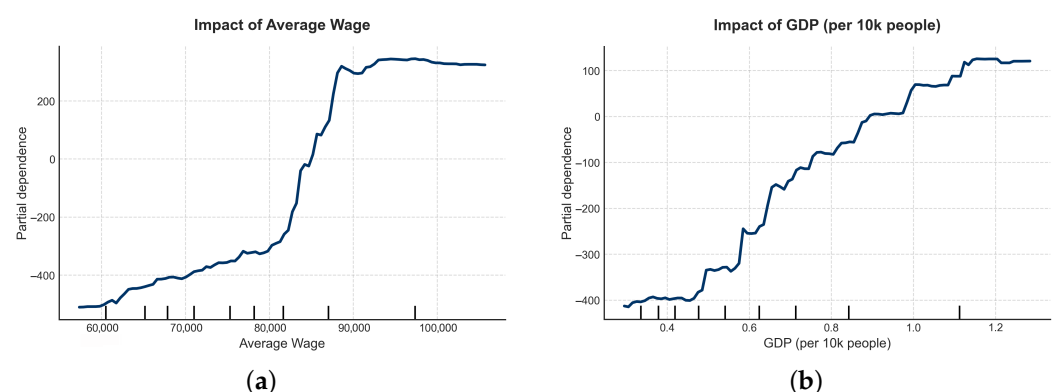


Figure 5. PDP results for economic drivers: (a) average wage; (b) per capita GDP.

2. **The “Threshold Effect” of Industry and Innovation:** For Tertiary Industry Share, the impact is minimal below 50%. However, once it exceeds 55% (the mark of a post-industrial city), net flow increases explosively. This indicates that only when the service industry forms a scale effect can it effectively transform into an employment

reservoir. Similarly, per capita tech expenditure shows a long stagnant period below 0.004 million RMB, followed by a vertical surge after crossing this “critical mass” threshold (Figure 6).

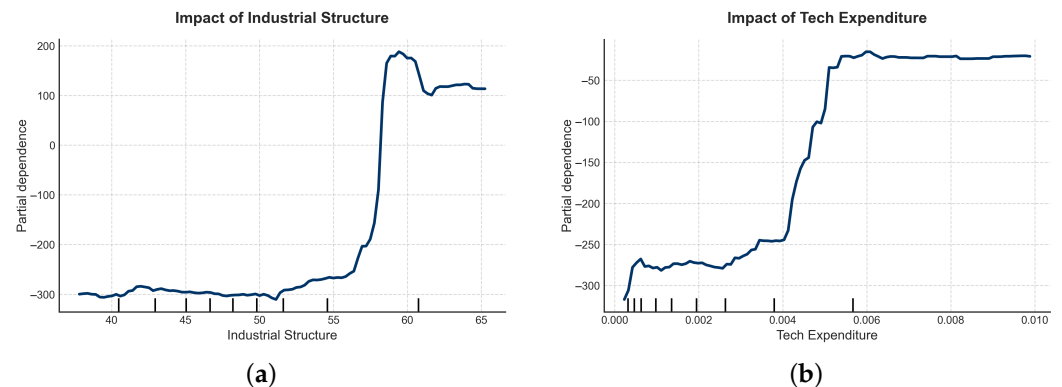


Figure 6. PDP results for industry and innovation: (a) tertiary industry share; (b) per capita science and technology expenditure.

3. **The “U-shaped” Scale Point and Asymmetric Unemployment Shock:** Population scale shows an U-curve. Between $\log(\text{population})$ values of 9 and 10, the agglomeration effect is dominant. However, above 10.5 (super-cities), the curve slope plateaus or slightly declines, indicating that “congestion effects” (high housing prices, traffic) begin to offset the benefits of agglomeration. For unemployment, once it exceeds 0.7%, the curve drops sharply, indicating a psychological “red line” for migrants (Figure 7).

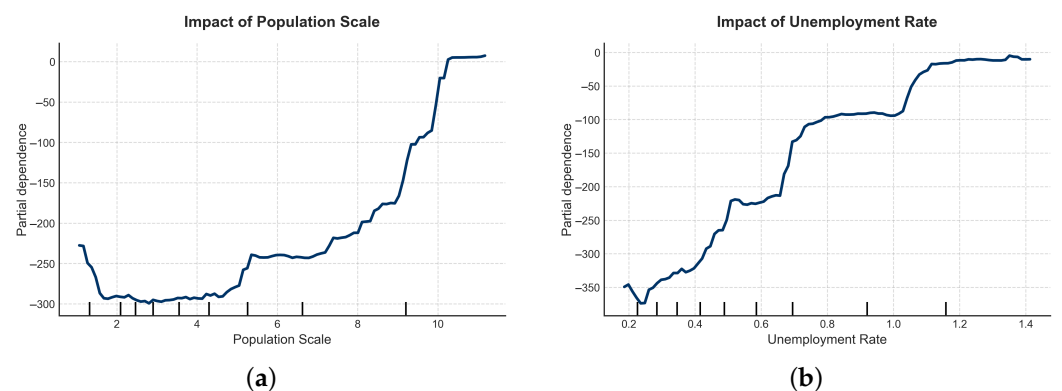


Figure 7. PDP results for scale and employment: (a) population scale; (b) registered urban unemployment rate.

Based on the PDP analysis, it is evident that China’s urban migration mechanism is not a simple linear push–pull process but is characterized by “take-off thresholds” (e.g., tech and tertiary industry) and “saturation inflection points” (e.g., wage and scale). This requires policymakers to focus on breaching critical thresholds to maximize the benefits of population attraction.

5.4. Spatial Heterogeneity: Mapping GWR Local Mechanisms

The primary advantage of the GWR model lies in its ability to reveal the spatial non-stationarity of driving factors. By mapping the Local Feature Importance (LFI) output by the model, we find that the driving mechanisms of China’s inter-city net migration exhibit a striking “North–South divergence” and a “Gradient shift” (Figures 8–10). This aligns with recent empirical findings that identify macro-scale spatial heterogeneities in migrants’ long-term settlement and hukou transfer intentions [18].

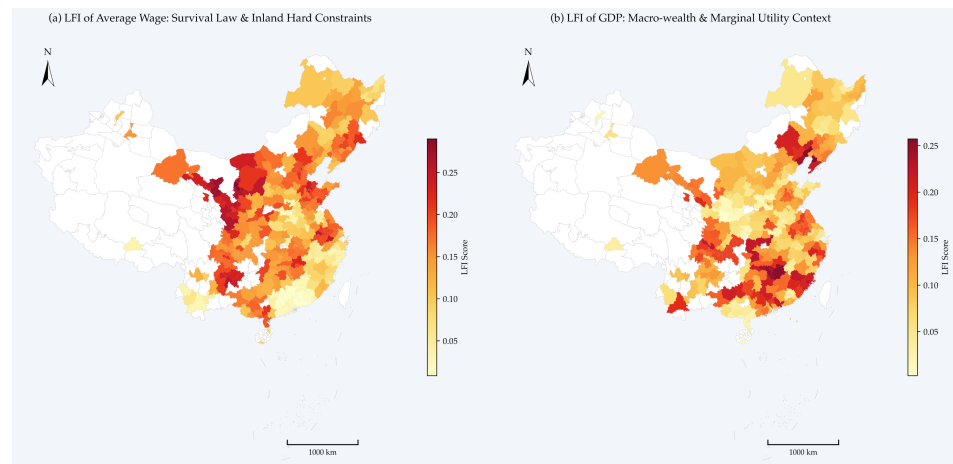


Figure 8. Spatial heterogeneity of economic drivers: (a) average wage as a survival constraint in inland regions, and (b) GDP representing the macro-wealth context and the law of diminishing marginal utility.

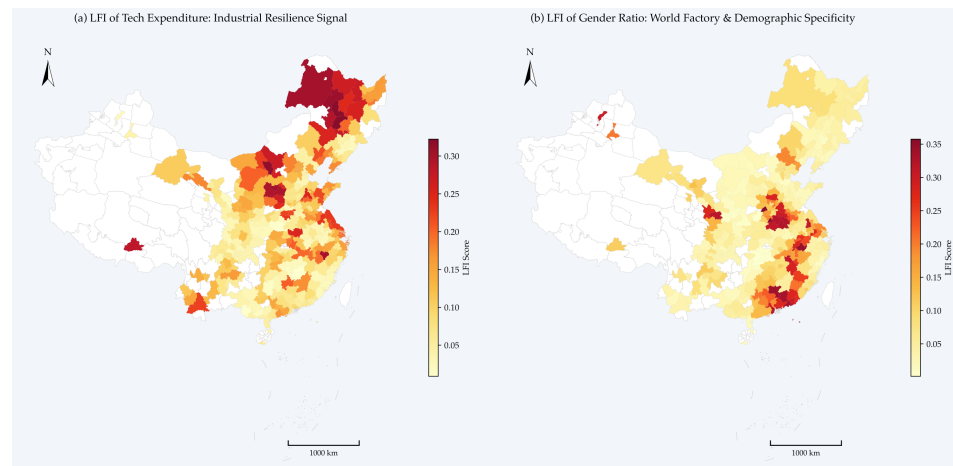


Figure 9. Spatial heterogeneity of industrial drivers: (a) tech expenditure as a signal of resilience in the Rust Belt, and (b) gender ratio locked into the PRD's "World Factory" demographic preferences.

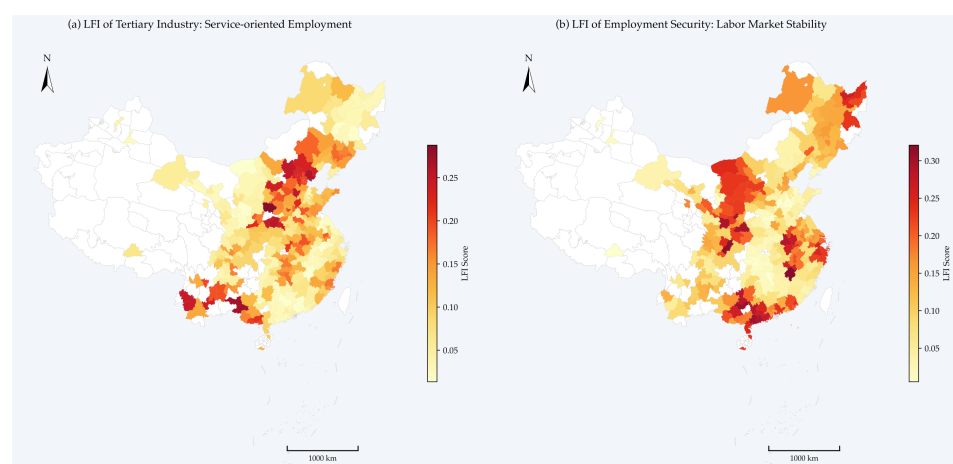


Figure 10. Spatial heterogeneity of mature-stage drivers: (a) tertiary industry facilitating service-oriented employment, and (b) employment security as the cornerstone for labor market stability.

5.4.1. Spatial Variation of Economic Drivers: Wage and GDP

While "Average Wage" is the most important factor globally, its local importance (LFI) shows a distinct "West-high, East-low" gradient (Figure 8a). High-importance clusters

are primarily concentrated in underdeveloped inland areas such as the Northwest (e.g., Yinchuan, Xining) and Southwest (e.g., Guiyang, Liupanshui), where LFIs often exceed 0.25. In these regions, wage income constitutes the absolute hard constraint for individual survival, thus exerting the strongest marginal driving force on mobility.

Conversely, in the developed Pearl River Delta (PRD) (e.g., Shenzhen, Guangzhou, Dongguan), the importance of wages drops to extremely low levels (<0.05), as illustrated in the marginal utility context of Figure 8b. This validates the law of diminishing marginal utility: when income reaches a high threshold, marginal growth in wages is no longer the core magnet. Instead, demands for environmental quality, public services, and social inclusiveness begin to dominate the migration logic in these mature urban systems [35].

5.4.2. The Role of Technology Investment in Shrinking Industrial Cities

High-importance areas for “Per Capita Science and Technology Expenditure” are primarily clustered in Northeast China (the “Rust Belt”) and resource-dependent cities in North China (Figure 9a), with FI values generally above 0.25.

These regions face severe industrial decay and population shrinkage [19]. High-intensity tech investment is often viewed as a signal of urban industrial upgrading and the potential for future high-quality employment. Therefore, in these areas, tech expenditure serves as a crucial signal of industrial resilience, helping to stabilize and attract human capital.

5.4.3. Industrial Specialization and Demographic Flows in Manufacturing Hubs

The importance of the “Gender Ratio” exhibits extreme regional specificity, locked into the Pearl River Delta (Figure 9b), with LFIs reaching approximately 0.30.

This phenomenon is a reflection of China’s unique “World Factory” model. The PRD’s vast electronics and textile manufacturing sectors have a strong preference for specific demographic groups [36]. Consequently, gender structure becomes a key valve regulating large-scale migration flows in this region, a feature not observed in areas dominated by heavy industry or services.

5.4.4. Service Industry Development and Labor Market Stability

“Tertiary Industry Share” (Figure 10a) and “Unemployment Rate” (proxied by Employment Security in Figure 10b) show higher importance in East China and some central provincial capitals. This indicates that in these mature urbanization stages, a service-oriented employment structure and a stable job market are the cornerstones for maintaining net population inflow.

5.5. Dominant Driving Factors: A Typological Perspective

To identify each city’s “core magnet” or “push force,” we extracted the factor with the highest local feature importance for each city, defining it as the Dominant Factor. This provides a new typological perspective on the micro-mechanisms of migration (Figure 11).

1. **“Wage-oriented” Cities (Survival Law):** Clustered in the Northwest (Lanzhou, Yinchuan) and Southwest (Guiyang, Yibin). Improving income levels is the most direct means of stemming outflow and attracting return migration in these regions where survival needs still carry overwhelming marginal utility.
2. **“Technology-aspiring” Cities (Rust Belt Transformation):** Dominant in the Northeast (Harbin, Changchun, Qiqihar) and North China (Taiyuan, Baotou). The key to retaining talent here lies in the “incremental expectations” created through technological innovation rather than current stock wealth.

3. **“Gender-structure-driven” Cities (World Factory Effect):** Highly concentrated in the PRD (Shenzhen, Dongguan, Foshan) and manufacturing bases in the Yangtze River Delta (Suzhou, Wuxi). The gender-based preferences of the light industry directly shape local migration patterns.
4. **“Employment-security-driven” Cities (Stability Seekers):** In core cities like Shanghai, Hefei, and Ningbo, the unemployment rate (*Unemployment Rate*) replaces wage as the dominant factor. Middle-class and skilled workers attracted to these hubs prioritize long-term career stability over short-term wage premiums.
5. **“Scale-dependent” Cities (Agglomeration vs. Congestion):** Clustered in traditional industrial zones in Liaoning and Hubei (e.g., Anshan, Jingzhou). These cities rely on existing urban-scale inertia to maintain attraction or face outflow due to congestion effects.

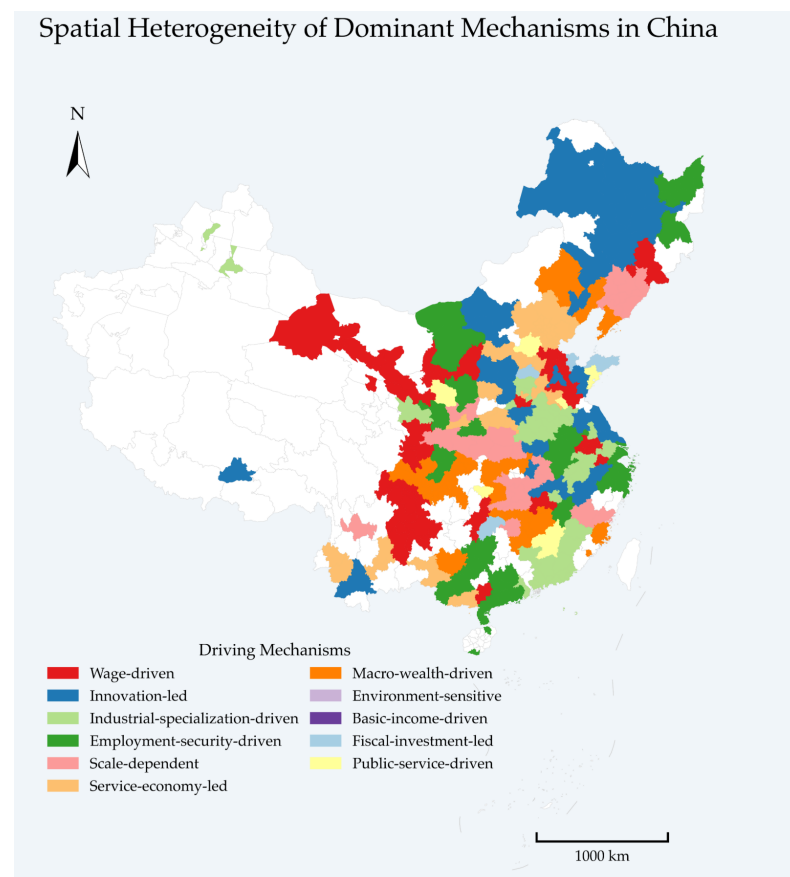


Figure 11. Spatial distribution of the dominant driving factors for urban net migration in China. The map illustrates the geographic mosaic of five major migration typologies and additional socio-economic drivers across 278 cities.

5.6. Regional Heterogeneity: The “Mosaic” of Migration Mechanisms

To reveal spatial non-stationarity at a macro scale, we divided the 278 cities into seven geographical regions and calculated the average LFI. The resulting heatmap (Figure 12) depicts a clear “Mosaic Puzzle” of China’s migration mechanisms.

1. **Northwest and Southwest:** Average wage exhibits the highest regional importance (0.206 in NW, 0.155 in SW). In inland regions, material rewards are the decisive factor. Policies focusing on “soft environments” (e.g., education, PM_{2.5}) without competitive salaries may see limited results.
2. **South China:** This region is extremely sensitive to the “Unemployment Rate” (0.206, the region’s top factor), even surpassing wages (0.075). Migration here is highly

“employment-following,” reacting rapidly to job market fluctuations. The “Gender Ratio” importance (0.165) is also the highest in the country.

3. **North and Northeast:** These regions show the highest sensitivity to “Per Capita Technology Expenditure” (0.174 and 0.157, respectively). Facing the transition from old to new kinetic energy, increasing innovation input is crucial for curbing population loss.
4. **Central China:** “Population Scale” (*City_Scale_Log*) is more significant here (0.151) than elsewhere. With the “Strong Provincial Capital” strategy in cities like Wuhan and Zhengzhou, large cities are exerting a powerful siphon effect on surrounding smaller cities.

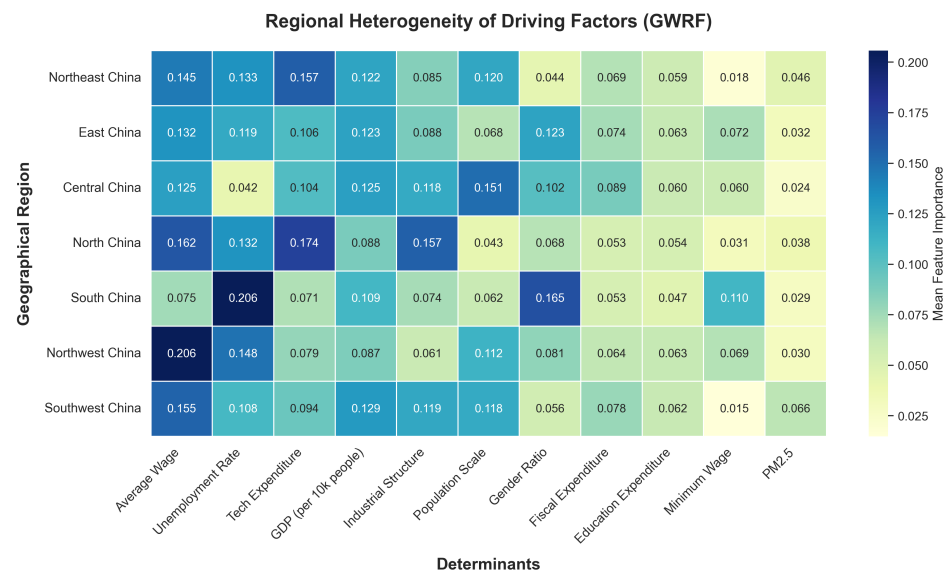


Figure 12. Heatmap of the average local feature importance (LFI) for net migration drivers across seven geographical regions in China.

5.7. Comparative Analysis of Model Performance

To systematically evaluate the superiority of the Geographically Weighted Random Forest (GWRF) model in explaining the mechanisms of China’s urban net migration, this study constructed a benchmark consisting of three traditional models: Ordinary Least Squares (OLS), Geographically Weighted Regression (GWR), and global Random Forest (RF). Based on a consistent 10-fold cross-validation (10-Fold CV) framework, a horizontal performance comparison was conducted. Table 2 presents the main performance indicators (R^2 , RMSE, and MAE) for the four models.

Table 2. Comparison of model performance indicators.

Model	R^2	RMSE	MAE
OLS	0.502786	598.930617	445.287326
GWR	0.573326	554.821538	413.068687
RF (CV)	0.572496	555.360448	414.014966
GWRF (CV)	0.584774	547.327639	412.216709

5.7.1. Advantages of Non-Linear Models

Comparing linear models (OLS, GWR) with non-linear machine learning models (RF, GWRF) reveals that the latter generally exhibit superior performance. The R^2 of the OLS model is only 0.503, indicating that a simple global linear assumption can only explain approximately half of the variation in population mobility. In contrast, the global RF model improves the R^2 to 0.572, and the RMSE decreases from 598.93 to 555.36. This significant improvement (an increase in explanatory power of approximately 14%) strongly validates

the conclusions of the previous PDP analysis—that there are substantial threshold and saturation effects in the driving mechanisms of population migration (such as the S-curve of wages) that cannot be captured by linear models.

5.7.2. Advantages of Spatial Models

A comparison between global models (OLS, RF) and spatial local models (GWR, GWRF) shows that the introduction of geographical weighting mechanisms yields significant performance gains. When spatial location information is introduced via the GWR model, the R^2 jumps from 0.503 (OLS) to 0.573, and the MAE drops to 413.07. This indicates that even within a linear framework, accounting for spatial non-stationarity can substantially reduce estimation error, confirming that the population mobility mechanisms in different regions of China (e.g., Northwest vs. Southeast) are fundamentally different. However, despite capturing spatial heterogeneity, the purely linear GWR model's performance remains inferior to the spatial-nonlinear hybrid GWRF.

5.7.3. The Integrated Superiority of GWRF

The GWRF model, which combines the non-linear fitting capability of machine learning with the spatial heterogeneity capture of GWR, achieved the best performance across all evaluation metrics. The 10-fold cross-validated R^2 of the GWRF model reached 0.585, the highest among all models, while its RMSE (547.33) and MAE (412.22) were the lowest. Compared to the poorest-performing OLS, GWRF's explanatory power improved by nearly 16.3%. Even compared to the second-best GWR model, GWRF further reduced prediction error by effectively characterizing complex non-linear relationships.

Crucially, the stability of this superior performance is underscored by the results of the rigorous 10-fold cross-validation framework. This validation approach ensures that the model's accuracy does not stem from overfitting to local data, but rather from its genuine capacity to capture the complex “spatial + non-linear” coupling mechanisms inherent in migration processes. Nevertheless, we acknowledge that the absolute R^2 of 0.585 indicates that approximately 42% of the variance in net migration remains unexplained. This residual is likely attributable to omitted variables—most notably granular housing price data and climate comfort indices—as well as unobserved individual-level heterogeneity in migration preferences. Despite this limitation, the GWRF model's consistent superiority over all benchmark models confirms its value as an analytical framework for this complex geographical process.

In summary, the model comparison results indicate that inter-city net migration in China is a complex geographical process characterized by both high non-linearity (e.g., economic thresholds) and spatial non-stationarity (e.g., regional differentiation). Traditional single-framework models—whether purely linear or purely global—fail to fully capture this complexity. The GWRF model, with its flexible local non-linear modeling architecture, provides an optimal methodological toolkit for parsing such complex urban geographical issues.

6. Discussion

This study employs the GWRF model to unveil the complex determinants of net migration in China. By moving beyond global and linear assumptions, our findings offer a nuanced understanding of the “black box” of migration decision-making in a transitional economy.

6.1. Re-Theorizing Migration: Thresholds and Asymmetry

Our findings challenge the traditional “linear” assumption prevalent in neoclassical migration models. Instead of a constant marginal effect, we demonstrate that economic

drivers exhibit distinct non-linear thresholds. This corroborates recent evidence that human mobility is governed by complex spatial interactions that transcend simple distance-decay or linear income functions [37]. Specifically, the “S-curve” response to wages reveals a *low-income trap*. For cities with average annual wages below approximately 80,000 RMB, marginal wage increases fail to trigger significant population inflow. Migration sensitivity peaks only within the critical “take-off” interval (80,000–90,000 RMB). This non-linearity suggests that migrants’ utility functions are step-wise rather than continuous; they require a minimum threshold of economic security before considering migration, and beyond a certain saturation point, their focus shifts to non-monetary amenities.

Furthermore, we identify a distinct asymmetry between push and pull forces. Economic factors (e.g., GDP, wages) act as significantly stronger pull forces at destinations than as push forces at origins. This implies that while the promise of prosperity is a potent magnet, local economic stagnation does not automatically expel populations, likely due to “mooring” forces such as social capital and place attachment [38]. Conversely, environmental degradation (PM_{2.5}) exhibits a “threshold expulsion” effect, acting more strongly as a push factor once pollution exceeds tolerance limits.

6.2. The Spatial Mosaic of Migration Regimes

A critical contribution of this study is the delineation of a “spatial mosaic” of migration regimes, reflecting China’s uneven development and diverse urban functions:

1. **The “Survival-Oriented” West:** In the Northwest and Southwest, wages remain the absolute dominant driver. This aligns with Maslow’s hierarchy of needs: where basic economic sufficiency is the primary concern, direct income maximization outweighs “soft” amenities, reflecting the pragmatic economic rationality of migrants in less-developed regions [34].
2. **The “Structural-Screening” South:** In the Pearl River Delta, migration is driven by structural factors like gender ratios and unemployment. This reflects a labor market shaped by light manufacturing that generated specific demographic demands.
3. **The “Transformation-Hope” North:** In the Northeast “Rust Belt,” technology expenditure plays a pivotal role. In these shrinking cities, innovation investment serves as a signal of industrial upgrading and future opportunity.
4. **The “Stability-Quality” East:** In the affluent Yangtze River Delta, drivers shift towards stability (*Unemployment Rate*) and quality of life, suggesting a transition to a mature migration stage where high-human-capital workers become increasingly sensitive to urban consumption and quality of life [39].

6.3. Institutional Underpinnings of Spatial Heterogeneity

The spatial mosaic of migration regimes identified above is not merely a product of economic geography but is deeply rooted in China’s institutional landscape. First, the household registration (*hukou*) system remains the most fundamental institutional constraint on permanent settlement. Although progressive reforms have relaxed hukou acquisition in small and medium-sized cities, the stringent requirements in first-tier cities (Beijing, Shanghai, Guangzhou, Shenzhen) continue to channel highly skilled migrants toward these destinations while constraining low-skilled workers to circular migration patterns [11]. This institutional filter helps explain why wage sensitivity peaks in western cities—where hukou barriers are lower and economic calculus dominates—while it diminishes in eastern megacities where non-economic institutional factors complicate settlement decisions. Second, differentiated regional development strategies—the Western Development Program (*Xibu Da Kaifa*), the Northeast Revitalization Plan, and the Yangtze River Delta integration initiative—have created region-specific policy environments that shape

the relative importance of migration drivers. Our finding that technology expenditure is disproportionately important in northeastern “Rust Belt” cities can be partially attributed to the central government’s targeted industrial upgrading investments in these regions [19]. Third, emerging empirical evidence on intraprovincial migration in China confirms that short-distance moves are increasingly governed by local institutional conditions rather than by aggregate economic differentials [12], a finding consistent with our observation that GWRF captures fundamentally different driver profiles at the local level.

6.4. Policy Implications: From Expansion to Precision

The identification of non-linear thresholds and spatial regimes necessitates a paradigm shift from extensive expansion “to precision intervention” [4]. First, resource allocation should be threshold-based. For cities trapped below the economic “take-off” line, resources should be concentrated to breach the critical thresholds identified in this study to trigger the acceleration phase of the S-curve. Second, strategies must be spatially differentiated. Inland cities should prioritize industrial transfer and income elevation, while shrinking industrial cities should pivot toward investing in innovation ecosystems to project “future hope” and mitigate the negative feedback loops of urban decay [19]. Meanwhile, coastal megacities must focus on mitigating congestion costs through housing affordability and public service equalization.

6.5. Limitations and Future Directions

Several limitations of this study warrant acknowledgment. First, while the Spring Festival homebound data provides a high-resolution snapshot of permanent migration stocks, it remains a cross-sectional proxy rather than a direct measure of long-term settlement decisions. The circular nature of this seasonal migration means that repeat visitors and temporary movers cannot be fully distinguished from permanent settlers. Future research incorporating longitudinal panel data would help track the temporal evolution of migration patterns. Second, the omission of city-level housing price data, due to limited availability across all 278 cities, may lead to some upward bias in the estimated importance of wage-related variables. The Minimum Wage variable partially captures local cost-of-living differentials, but incorporating granular housing cost data remains an important direction for future work [40]. Third, although the pre-festival phase of the 2020 Spring Festival travel rush was largely unaffected by COVID-19, the broader post-pandemic context may have shifted migration preferences in ways not captured by our data.

7. Conclusions

This study addresses the critical challenge of modeling intercity net migration during China’s transition toward high-quality urbanization [41]. By integrating a Geographically Weighted Random Forest (GWRF) model with high-granularity mobile signaling data from the 2020 Spring Festival, we have moved beyond the traditional constraints of global linearity and spatial stationarity. Our investigation reveals that urban attraction mechanisms are characterized by complex non-linear thresholds and profound spatial heterogeneity. Specifically, we demonstrate that the dominant drivers of migration shift fundamentally across regional contexts—ranging from survival-based wage incentives in the West to structural demographic screening in the South, and from industrial transformation expectations in the North to stability-seeking behaviors in the East.

Theoretically, this study moves away from the conventional directional flow paradigms by proposing a Spatially Heterogeneous Non-linear Attraction Framework. This framework provides a more realistic depiction of how urban attributes collectively determine a city’s capacity to retain and attract population under varying local constraints. Methodologically,

the GWRF approach demonstrates clear superiority over traditional OLS and GWR models. By achieving a high predictive accuracy ($R^2 = 0.585$) while enhancing model transparency through local interpretability, GWRF proves to be a robust and insightful toolkit for complex urban analytics [14].

These distinct spatial regimes suggest that China's urbanization policy must undergo a paradigm shift toward "precision management." Policymakers should abandon "one-size-fits-all" strategies in favor of spatially tailored interventions that account for local economic and industrial thresholds [42]. Future research should bridge the gap between static analysis and dynamic prediction by integrating longitudinal panel data to track the evolution of these non-linear thresholds in the post-pandemic era. Additionally, incorporating multidimensional cost factors, such as granular housing price data, will be essential for further decoding the complex screening effects in China's expanding megacities [40].

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