

Research on Urban Resilience and Sustainable Development of Changchun and Hohhot Based on Multi-Dimensional Analysis

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Abstract: In the context of population aging and increasing global extreme climate events, this study focuses on evaluating the urban resilience and sustainable development capacity of two cities (Changchun and Hohhot). By integrating data from multiple sources and applying techniques such as big data statistical analysis, random forest, and decision tree, the research addresses several key aspects. Firstly, housing prices in different areas of the two cities are predicted, and the total existing housing stock is estimated. Secondly, the service levels of various departments in the two cities are quantitatively analyzed to identify commonalities and differences. Thirdly, the resilience of the two cities in coping with extreme weather and emergencies is evaluated, along with their sustainable development capacity. Based on these analyses, future development plans are formulated for each city, including investment areas, amounts, and expected improvements in smart city development. The results show differences in housing prices, service levels, and resilience between the two cities, with Changchun generally showing more balanced development and higher resilience in some aspects. The study also acknowledges limitations in data and models and suggests future research directions for further optimization.

Keywords: Urban resilience; Resilience evaluation; Sustainable development; Big data statistical analysis; Random forest; Decision tree.

1. Introduction

Research on urban resilience and sustainable development is both necessary and urgent. With frequent extreme weather events and economic downturns globally, cities, as core regions, must be resilient to these shocks to ensure sustainable development. China's aging population is accelerating, with negative growth expected for the first time in 2022 and projected to decline over the long term. This impacts urban development, necessitating strategic adjustments and responses tailored to demographic changes. Research on diverse aspects of cities can inform planning, such as providing accurate housing price forecasts and quantitative analysis services to identify weaknesses and enhance competitiveness. When fiscal resources are limited, research can help formulate rational investment plans and achieve efficient resource utilization. Furthermore, research can drive improvements in urban facilities and services, enhancing residents' well-being and sense of belonging.

With the increasing severity of population aging and extreme climate events, urban resilience and sustainable development have become research hotspots. Xu Dandan [1] conducted a comparative study on housing price prediction, using multiple linear regression and BP neural network models to demonstrate the application of predictive modeling in housing price trend analysis. Cui Huiying [2] improved the prediction accuracy of second-hand housing prices by improving the extreme random forest algorithm, demonstrating the advantages of machine learning methods in complex problems. At the same time, urban resilience assessment has also received widespread attention, especially when responding to external pressures such as extreme weather. Zhou Liangjin and Zhao Mingyang [3] analyzed

Shenzhen's second-hand housing prices using the random forest algorithm, showing that machine learning can not only predict economic variables, but also provide guidance for resilience planning. In addition, Li Jing [4] explored the application of big data technology in urban planning, emphasizing the importance of big data technology for urban dynamic analysis and decision support. The urban resilience assessment system proposed by Hu Zhichao et al. [5] integrates social and economic factors to assess the ability of cities to respond to extreme events, providing an important resilience analysis framework for cities such as Changchun and Hohhot. The above research provides valuable experience for cities on how to predict housing prices, assess resilience, and develop sustainable development strategies. However, further improvement is still needed in data integration and model optimization.

2. Study Design

2.1. Benchmark Regression

It is assumed that the data and POI data obtained from 58.com are highly reliable and contain sufficient information for a comprehensive analysis. Population and GDP data collected from the Internet are considered to have a direct, stable, and significant impact on house prices and housing stock, while other unconsidered factors are assumed to have only negligible effects. It is assumed that the real estate market in each region is in a state of relative equilibrium, i.e. supply and demand factors remain relatively stable, and short-term fluctuations do not disrupt the long-term trends and relationships used in the model. In addition, during the analysis period, the impact of external factors not included in the data provided, such as unexpected policy changes, sudden

natural disasters or major social events, is assumed to be minimal. Finally, the relationship between housing characteristics (e.g., area, age), surrounding amenities, and economic factors is assumed to be consistent within different regions of each city, enabling the promotion of the model across regions and facilitating a meaningful and accurate assessment of the real estate market and urban development.

To provide a specific forecast of future housing prices in cities 1 and 2, and to estimate the total existing housing stock, this study employed a variety of machine learning regression models for housing price forecasting. The specific steps involved data preprocessing, feature selection, model building and training, model prediction, and result evaluation and analysis.

First, we perform data preprocessing. From the basic information on real estate sales in 58 cities on a given day, we see a high number of missing values. The characteristic variables for visualizing missing values are shown in Figures 1 and 2. The bar chart in Figure 1 shows the statistics for missing variables in City 1, while the pie chart in Figure 2 shows the statistics for missing variables in City 2. If all null values in City 1 were deleted, the original 4,600+ data points would be reduced to just over 900. This approach to handling missing values is inefficient. Therefore, this paper employs the methods of replacing and filling missing values. For numerical variables, random forests are used for prediction and filling, while for numeric variables, modal sequences are used for filling.

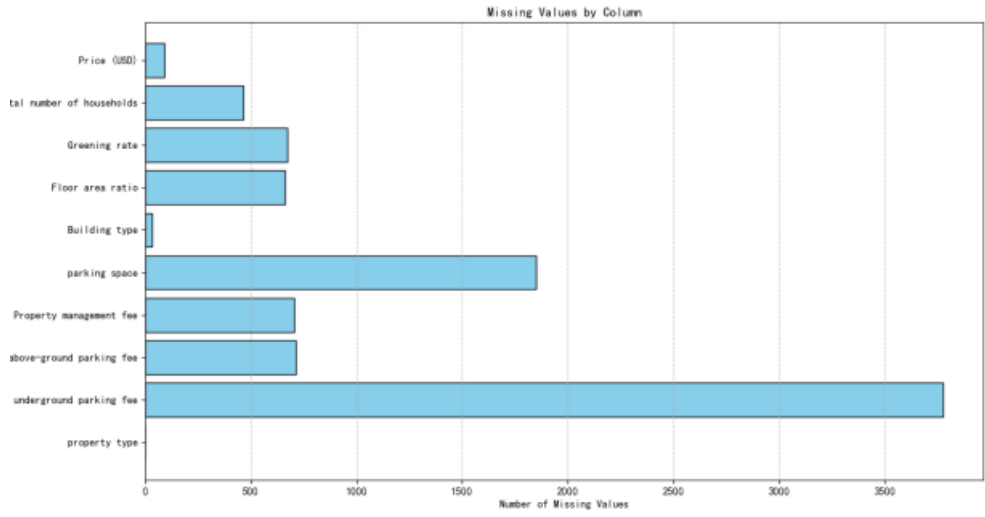


Figure 1. Missing Values by Column

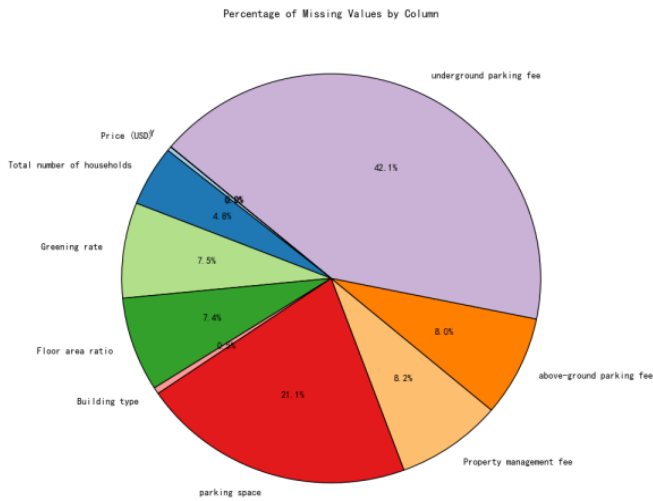


Figure 2. Percentage of Missing Values by Column

Next, perform data encoding and standardization. Label encoding: For categorical variables, such as building type, use LabelEncoder to convert them to numeric values. Min-max normalization: Normalize the feature and target variables, scaling all values to the range [0, 1]. This makes the model more stable during training and prevents large variations in feature values from affecting the results.

In order to ensure the reliability and accuracy of the prediction results, this study selected the following four models:

(1) Linear regression: used to capture the linear relationship between characteristics and housing prices. Linear regression is the most basic regression analysis method used to study the linear relationship between dependent variables and

independent variables. It assumes that there is a linear relationship between the target variable (housing price) and multiple characteristics (such as the total number of households, greening rate, floor area ratio, etc.). The mathematical formula assumes that the model is:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (1)$$

Where: y is the target variable (house price). X_1, X_2, \dots, X_n are a characteristic variable. β_0 is the intercept, $\beta_1, \beta_2, \dots, \beta_n$ is the regression coefficient of the feature. ε is the error term, which represents the deviation of the predicted value from the actual value.

(2) Decision tree regression: It can deal with nonlinear relationships and model the nonlinear effects of features.

(3) Random forest regression: By integrating multiple decision trees, random forest can improve the generalization ability of the model and reduce overfitting.

1) Residual fitting: Each new tree is fitted based on the residuals of the previous step. 2) Gradient descent optimization: The model is improved stepwise by minimizing residuals, and each step updates the model along the negative gradient direction of the loss function.

$$y_i = f(x_i) + \eta \cdot h(x_i) \quad (2)$$

Where: $f(x_i)$ is the predicted value of the previous step model. $h(x_i)$ is the weak learner (tree) generated by the current step. η is the learning rate, which is used to control the update step size.

Overall, the advantages and disadvantages of the four models are summarized as follows: After the model is

constructed, housing prices are predicted for each region by citycode and adcode, and the results are obtained. A common approximate method for estimating the total existing housing stock is to multiply the total number of households (representing the total number of residential units in the city, which can be obtained through censuses or statistics) by the average per-household area to obtain the total housing area in the city. When specific housing area data is unavailable, relevant indicators such as floor area ratio can be used to approximate the average per-household area. While not absolutely accurate, it can serve as a useful approximation in the absence of data.

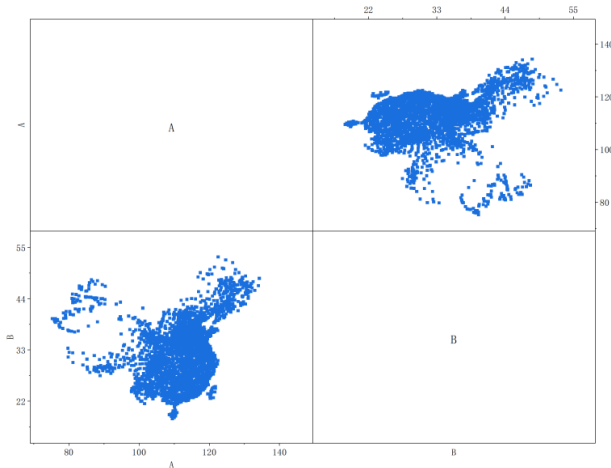


Figure 3. Matrix scatter plot



Figure 4. Comparison of Predicted Average Prices by Region for Different Models

Figures 3 and 4 present comparative housing price forecasts from four different models for City 1 (Changchun, Jilin Province) and City 2 (Hohhot, Inner Mongolia). As a major industrial city in Northeast China, Changchun boasts a strong manufacturing base in industries such as automobiles and railways. It enjoys a relatively stable economy, excelling in sectors like industry, manufacturing, and education. Its diversified economic structure strongly supports the stability of local housing prices. Hohhot, the capital of Inner Mongolia, has seen strong economic growth in recent years, particularly in resource-based industries and the service sector. However, its economic foundation and industrial structure are relatively homogenous compared to Changchun, making it more

susceptible to economic fluctuations, which could lead to significant fluctuations in housing prices.

From the model results, it can be seen that the decision tree model performs well in the prediction of both cities. The decision tree can effectively capture the nonlinear relationships between housing prices in different regions, especially in cities with large regional differences like Hohhot. Therefore, the predictive effect of the decision tree in Hohhot is particularly significant. For Changchun, the random forest and gradient boosting models also perform well, indicating that the housing prices in Changchun have a relatively stable linear and nonlinear relationship with various features, making it suitable for prediction using ensemble models.

Generally speaking, through the results of house price forecast model, we can see the significant differences between Changchun and Hohhot in house price distribution and regional economic structure. Changchun's housing prices are relatively stable, indicating that its regional balanced development is good; However, the housing prices in Hohhot are quite different, which reflects the characteristics of high economic concentration. Decision tree model can better capture this regional difference and provide an effective reference for house price forecasting. This provides valuable policy suggestions for Changchun and Hohhot in the future urban development, housing security and regional balanced development.

2.2. Benchmark Regression

Indicator Quantification and Standardization (1) Define Key Indicators: For each service category, define key indicators to quantify the level of service. Accommodation services: the number of hotels and inns, the proportion of high-end hotels, etc. Commercial residential: the number of residential areas, the area of commercial zones, etc. Medical and health: the number of hospitals and clinics, the number of doctors per thousand people, etc. Public facilities: the number of parks, libraries, community centers, etc. (2) Standardization: Standardize each service indicator (for example, through Z-score or Min-Max standardization) to ensure that different service indicators are compared on the same scale.

Quantitative Analysis Method (1) Calculate Regional Averages: Calculate the average level of each service category in different regions for each city, representing the city's service level in that service category. (2) Visual Comparison: Use graphics to display the service levels of the two cities in each service category to intuitively show their strengths and weaknesses.

Analysis of Commonalities and Uniqueness Identify similarities between the two cities in each service category. For example, if both cities have a certain coverage rate of basic public services (such as medical care and education), they can be summarized as commonalities. Plot the difference coefficients of each service category as bar charts or bar graphs to intuitively show the degree of difference between the two cities in each service category.

Accommodation Service Data For the accommodation service data of the two cities, first, visualize the data to observe the distribution of the number of different types of accommodation facilities. Figures 5 and 6 show the 4-16 types of accommodation facilities in City 1, while Figures 6 and 8 show the statistical data of 19 accommodation services in City 2. Due to the large number of categories, which are difficult to quantify, the data is re-classified into larger

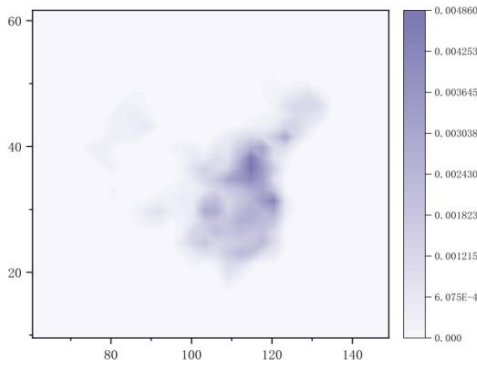


Figure 9. 2D Density plot

(1) Medical and health data (medical and health facilities) are very important in responding to public health emergencies (such as epidemics), and the distribution and quality of medical resources are important components of urban resilience

(2) Public facilities data (public facilities), such as shelters and emergency centers, help to deal with extreme weather or other disaster events.

(3) The accessibility and resilience of Transportation facilities data determine the evacuation and material transportation capabilities in the event of emergencies.

(4) The distribution and capabilities of Government and social organizations data (government and social organizations) directly affect the response speed and efficiency in emergencies.

1) Determine the distribution weight

First, it is necessary to assign weights to four selected indicators (medical and health facilities, public facilities, transportation facilities, government and social organizations). The weights can be determined based on expert opinions or data analysis. The following is an example weight allocation: Medical and health facilities (Medical and health data): 30%; Public facilities (Public facilities data): 25%; Transportation facilities (Transportation facilities data): 25%; Government and social organizations (Government and social organizations data) 20%.

2) Quantification of indicators

(1) Weight allocation, the weight allocation operation is performed according to the situation of each subcategory

(2) Normalized count, to better compare the number of transportation facilities in different categories, we can normalize (normalize) each class count to a range of 0 to 1, usually using Min-Max normalization:

$$\text{Normalized} \cdot \text{count} = \frac{\text{Actual} \cdot \text{Count} - \text{Minimum} \cdot \text{Count}}{\text{Max} \cdot \text{Count} - \text{Min} \cdot \text{Count}} \quad (3)$$

This can eliminate the impact of quantity differences.

(3) Calculate the weighted score

For each category of facilities, the weighted score is calculated using the following formula:

$$\text{Weighted} \cdot \text{score} = \text{normalized} \cdot \text{count} \times \text{category} \cdot \text{weight} \quad (4)$$

The weighted scores of all categories were then added to get the total score of the transportation facilities.

Based on the aforementioned scoring predictions, further weighted calculations were applied to obtain the quantitative scores of City 1 and City 2 for four different indicators. The weight distribution for the four selected indicators (medical and health facilities, public facilities, transportation facilities, government and social organizations) is as follows:

In the assessment of urban service levels, different types of

facilities are assigned varying weights: medical and health facilities (based on medical and health data) account for 30%, public facilities (from public facilities data) make up 25%, transportation facilities (derived from transportation facilities data) also represent 25%, and government and social organizations (using government and social organizations data) contribute 20%. Based on these weights, the final scores are calculated as follows: for City 1, the score is $1.13 = 0.7365$ (it seems there might be some missing context for this calculation result presentation, but presented as given); and for City 2, the score information is yet to be fully provided.

Based on the quantified scores for sustainable development capabilities of City 1 (Changchun, Jilin) and City 2 (Hohhot), we can see that Changchun's score (0.7365) is slightly higher than Hohhot's (0.6735), indicating that Changchun has relatively stronger resilience in emergency management and sustainable development.

The reason for City 1 (Changchun, Jilin) having a higher score: Changchun has a relatively balanced distribution in various government agencies, social organizations, and emergency management resources, especially performing well in the quantity and importance of core emergency management institutions (such as public security and fire departments). This balanced distribution allows Changchun to respond and provide support more quickly in the face of emergency events such as extreme weather and public health incidents.

Challenges for City 2 (Hohhot): Hohhot's relatively lower score may indicate that it has certain shortcomings in key areas, such as the distribution and accessibility of emergency management institutions or social support facilities. Especially at the grassroots level, emergency resources (such as community-level emergency centers, traffic management, etc.) may be relatively weak, limiting overall emergency resilience. In addition, Hohhot may have an insufficient distribution or quantity of some social organizations and public welfare facilities (such as the Red Cross, charitable organizations, consumer associations, etc.), which affects the support strength in responding to emergencies.

2.4. Benchmark Regression

The main investment areas, investment amounts, and expected levels of smart city development improvements are listed for the two cities respectively, aiming to continuously leverage their strengths and address their shortcomings.

1) Plan Background and Objectives

Based on the previous analysis, Changchun City and Hohhot City each have different shortcomings and development potentials in the development process of smart cities, including transportation facilities, public services, medical health, and social organizations. In order to enhance the resilience of both cities in response to extreme weather and emergencies, strengthen the level of public services, and promote sustainable urban development, the following future development plan is formulated. The main objectives of this plan include:

(1) Enhance the city's emergency resilience in extreme events.

(2) Optimize the layout of urban infrastructure and improve the efficiency of resource utilization.

(3) Promote the construction of smart city platforms to achieve intelligent allocation of government, business, and social resources.

(4) Achieve sustainable development and improve the

quality of life for residents.

2) Main Investment Areas

(1) Medical and Health Facilities

Investment Content: Enhance the city's response capacity to public health emergencies by increasing the number of comprehensive hospitals, emergency centers, and community medical service points within the city. Introduce smart medical systems, including telemedicine and intelligent diagnostics, to alleviate the uneven distribution of medical resources.

Investment Amount: about 30%-40% of the total budget.

Expected Outcomes: Changchun City can alleviate the concentration of medical resources in central areas and improve medical accessibility in peripheral areas. Hohhot City can increase basic medical service points in areas lacking medical facilities, enhancing the capacity to respond to public health events.

(2) Public Facilities and Services

Investment Content: Add public toilets, shelters, emergency facilities, etc., especially in densely populated or under-equipped areas. Increase smart management functions to achieve real-time monitoring and maintenance of facilities, ensuring their availability.

Investment Amount: about 20%-25% of the total budget.

Expected Outcomes: Improve the city's emergency response capabilities in extreme weather or natural disasters. Changchun City will enhance facility management and information transmission, further improving existing public service facilities. Hohhot City will increase emergency shelters and public service facilities, enhancing overall emergency capabilities.

(3) Transportation Infrastructure

Investment Content: Optimize the layout of existing bus stations, parking facilities, and entrances/exits to increase the coverage of public transportation and parking facilities. Build an intelligent transportation management platform, including real-time traffic monitoring, traffic flow prediction, and emergency evacuation functions, to ensure smooth traffic during emergencies.

Investment Amount: about 20%-25% of the total budget.

Expected Outcomes: Changchun City will introduce an intelligent transportation dispatch system in areas with dense traffic nodes, optimizing daily and emergency traffic flow. Hohhot City will increase the density of bus stations and parking facilities, enhancing residents' travel convenience and emergency evacuation capabilities.

(4) Emergency Response Capabilities of Government and Social Organizations

Investment Content: Construct emergency management centers equipped with intelligent dispatching platforms to enhance the coordination capabilities of governments and social organizations, improving rapid response and information dissemination during emergencies.

Investment Amount: about 15%-20% of the total budget.

Expected Outcomes: Improve the response speed of both cities' governments and strengthen the government's rapid response capabilities to emergencies. Changchun City will enhance the efficiency of government emergency command, optimizing the event response process. Hohhot City will expand social organizations and community-level emergency sites, enhancing grassroots emergency handling capabilities.

3) Investment and Implementation Phases

Short-term Plan (1-3 years)

Objective: Address the insufficiency of existing

infrastructure and increase the number of medical service points, public facilities, and transportation infrastructure.

Funding Sources: Local financial allocations, smart city special funds.

Key Projects: Construction of shelters, addition of community clinics, initial construction of intelligent traffic dispatch systems.

Medium-term Plan (3-5 years)

Objective: Improve the smart city management platform by introducing real-time monitoring, forecasting, and emergency dispatch functions.

Funding Sources: Public-Private Partnership (PPP) model, government and enterprise cooperative investments.

Key Projects: Improvement of smart medical platforms, completion of intelligent traffic dispatch systems, construction of government emergency centers.

Long-term Plan (5-10 years)

Objective: Comprehensively enhance the city's smart management level and achieve digital and intelligent management of infrastructure.

Funding Sources: Rolling investment, ensuring long-term stable funding support through phased allocations.

Key Projects: Construction and data integration of intelligent emergency platforms, achieving comprehensive smart management of transportation, medical care, and public services.

4) Expected Outcomes and Smart City Development Improvement

Specific expectations for improving the level of smart city development:

Healthcare: By building medical facilities and intelligent medical platforms, medical accessibility is expected to increase by more than 25%, and rescue response times in emergencies are expected to be reduced by 30%.

Public Services: The coverage and efficiency of public service facilities are expected to improve, with a 20% increase in resident satisfaction with public facilities.

Traffic Management: The traffic congestion rate is expected to decrease by 15%, evacuation efficiency in emergencies is expected to improve, and the intelligent traffic dispatch system is expected to cover all main areas of the city.

Emergency Management: The emergency response capabilities of governments and social organizations are expected to increase by 50%, forming an efficient emergency management system.

5) Plan Implementation Monitoring and Feedback

Monitoring Mechanism: Conduct annual project progress evaluations, record the completion of Key Performance Indicators (KPI), and adjust investment ratios in a timely manner.

Resident Feedback: Regularly conduct resident satisfaction surveys to collect evaluations and suggestions on smart city services to improve project implementation.

3. Conclusion

Through in-depth research on housing price forecasting, service level analysis, urban resilience assessment, and future development plan formulation for City 1 (Changchun) and City 2 (Hohhot), this study comprehensively analyzes the current situation and development needs of the two cities. Provide reference for real estate market regulation and housing planning in terms of housing prices; Service level analysis helps cities to learn from each other and optimize

services; Urban resilience assessment identifies the strengths and weaknesses of the city and formulates investment plans; The future development plan provides direction for sustainable urban development. However, there are issues with data quality and model limitations during the research process. Future research needs to further optimize data collection and processing methods, improve model construction, enhance understanding and response capabilities to complex urban development systems, in order to better promote the development of cities towards high-quality and sustainable directions. While improving residents' quality of life, it also enhances the resilience and adaptability of cities to various challenges. In terms of emergency management, increasing the response capacity of the government and social organizations by 50% will greatly improve the efficiency and effectiveness of urban emergency rescue, enhance urban cohesion and disaster resistance, ensure urban stability and sustainable development, and continuously strengthen the construction of emergency management system to adapt to risk changes.

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