Problem Chosen	2024 MCM/ICM Summary Sheet	Team Control Number
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Assessment and Planning of Urban Resilience and Sustainable Development Based on XGBoost and AHP Models

Summary

This paper addresses the challenges of population aging and the first instance of negative population growth faced by second- and third-tier cities in China, as well as the new demands for urban resilience posed by extreme climate events. It explores strategies for sustainable urban development.

For Problem 1, we utilized the XGBoost model and random search method to forecast housing prices in Changchun and Hohhot, finding that housing prices in both cities are expected to trend upward in the short term. The estimated total housing stock in Changchun is 3,795,059 units, while in Hohhot, it is estimated at 1,529,984 units.

For Problem 2,we analyzed the service coverage in six sectors—accommodation, finance and insurance, dining, living services, healthcare, and retail—in both cities. The analysis revealed that "Changchun performs well in areas such as transportation and tourism resources, while Hohhot excels in financial support and healthcare services. However, Changchun lacks sufficient medical resources and suburban service points, while Hohhot needs to optimize its infrastructure layout.

For Problem 3, we established a model for urban resilience and sustainable development using the Analytic Hierarchy Process (AHP) method. It was noted that Changchun should strengthen public health and low-carbon transportation, while Hohhot should enhance emergency management and geographic information resilience. In the short term, Changchun needs to improve public and transportation facilities, whereas Hohhot should strengthen its disaster resilience. In the long term, Changchun should develop green finance, while Hohhot needs to enhance its education and research capabilities to promote sustainable development.

For Problem 4,we proposed development plans for both cities over the next five years. Changchun plans to invest 10 billion yuan, and Hohhot plans to invest 12 billion yuan, focusing on smart city construction, healthcare services, education and cultural development, public facilities and services, transportation optimization, commercial and residential environment, as well as environmental protection and greening. These investments aim to improve urban management efficiency, enhance residents' convenience, and increase urban ecological friendliness.

In summary, this paper provides a comprehensive evaluation and strategic recommendations for urban resilience and sustainable development through multidimensional analysis, aiming to assist policymakers, planners, and researchers in better planning the future of these cities to ensure vitality and prosperity in an ever-changing environment.

Keywords: XGBoost Model, Random Search Method, Urban Resilience, Sustainable Development

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1 Introduction

1.1 Problem Background

As Chinese society enters an aging phase and experiences negative population growth for the first time in 2022, the trend of gradually losing the demographic dividend becomes increasingly evident. Predictions indicate that China's population will continue to decline over the coming decades, particularly in second- and third-tier cities. This change will have profound socio-economic impacts. A shrinking population will not only directly affect the supply and demand dynamics of the labor market, leading to a decline in consumer demand, but it may also exacerbate the underutilization and surplus of infrastructure, posing severe challenges to urban economic growth and social stability. Additionally, the increasing frequency of extreme weather events due to global climate change, along with rising domestic and international economic pressures, places higher demands on the sustainable development capacity of cities.[1][3]

In this macro context, assessing and enhancing urban resilience and sustainable development capabilities have become core issues that require urgent attention from academics and policymakers. Urban resilience refers not only to the ability to respond to and recover from external shocks such as natural disasters and public health crises but also encompasses how to achieve efficient resource allocation and sustainable utilization through scientific planning in the complex interplay of economic, social, and environmental factors, thereby maintaining the long-term stability of urban systems. For second- and third-tier cities, the pressing issue is how to sustain their development momentum and vitality in the face of the dual pressures of population decline and climate change, ensuring coordinated economic and social development[4][5].

1.2 Restatement of the Problem

This study combines web scraping technology and field research to collect basic property information for City 1 and City 2 on a specific date, as well as POI data for certain basic services for a particular year. Based on this data， Considering the background information and restricted conditions identified in the problem statement, we need to solve the following problems:

- Problem 1: Housing price prediction and total housing supply estimation

How can existing data on real estate, population, GDP, and other factors be used to predict future housing prices in City 1 and City 2? Additionally, how can we estimate the total housing supply in these two cities based on the available data?

- Problem 2: Quantitative analysis of service levels

How can we quantitatively analyze the service levels of different industries in City 1 and City 2, assess their strengths and weaknesses, and extract the commonalities and distinctive features of the two cities?

- Problem 3: Assessment of Urban Resilience and Sustainable Development Capacity

How can POI data be used to evaluate the resilience of the two cities in responding to extreme weather and emergencies? How can we quantitatively assess their sustainable development capacity, identify weak areas, and develop investment plans?

- Problem 4: Future Development Planning

Based on the above analysis, how can we develop future development plans for City 1 and City 2, specifying key investment areas, amounts, and smart development goals to enhance urban resilience and sustainable development capacity?

1.3 Our Work

2 Assumptions and Justifications

Assumption 1: The resilience of a city is closely related to its ability to respond to emergencies, including natural disasters and social unrest.

Justification 1: A resilient city is capable of quickly restoring normal order after a disaster, ensuring the safety of residents' lives and property, and continuing to promote the sustainable development of society and the economy. Resilience construction encompasses not only the disaster resistance of physical infrastructure but also the enhancement of social management, emergency response, and the self-protection awareness of citizens.

Assumption 2: The service level and infrastructure development of a city are crucial to its attractiveness and the quality of life of its residents.

Justification 2: The perfection of infrastructure and the quality of public services are directly related to the attractiveness of a city and the quality of life of its residents. The construction of infrastructure such as transportation, healthcare, education, and environmental protection can enhance the livability of a city, attract more incoming population, and at the same time increase the happiness and quality of life of local residents. Effective improvement in service levels not only enhances the competitiveness of the city but also increases residents' sense of belonging and life satisfaction.

Assumption 3: The future development of a city is influenced by the interplay of multi-dimensional factors such as economy, society, policy, and environment.

Justification 3: The future development of a city is not determined by a single factor, but is the result of the interaction of various factors such as economic growth, social development, government policies, and environmental changes. These factors are dynamically interrelated; economic growth may drive changes in social demand, policy adjustments can directly affect urban planning and resource allocation, and environmental protection requirements can also impose constraints on future development. Therefore, considering the interplay of these factors is fundamental to constructing predictive models for future urban development.

3 Definitions and Notations

3.1 Definitions

1. **Event Probability**
   Definition: The likelihood of extreme weather or emergencies occurring in a region, measured as the ratio of affected area to total city area.
2. **Spatial Service Density**
   Definition: The concentration of services in a specific area, calculated by dividing total service quantity by the area.
3. **Population-Based Service Density**
   Definition: The availability of services per unit of population, calculated by dividing total service quantity by the population size.
4. **Per Capita Coverage Rate**
   Definition: The amount of service available per individual in a population, reflecting service availability on an individual basis.
5. **Resource Coverage Rate**
   Definition: The density of service facilities in a region, measured as the number of facilities per unit area.

3.2 Notations

Due to the excessive number of symbols, only a selection of symbols and their descriptions are displayed.The key mathematical notations used in this paper are listed in Table 1.

Table 1: Notations used in this paper

Symbol	Description	Unit
$L(\Theta)$	Total Loss Function	~
$l(y_i, \hat{y}_i)$	Loss Function for Sample i	~
$\Omega(f_k)$	Model Complexity Regularization Term, to Prevent Overfitting	~
T	Number of Leaf Nodes in Decision Tree	~
w	Weight of Leaf Nodes in Decision Tree	~
γ, λ	Regularization Parameter	~
y_i	Actual Housing Quantity	~
…	…	…

4 The name of model 1

4.1 Data Description

4.1.1 Data Preprocessing

The attachments 1 and 2 of this paper provide the basic information of the properties for sale in Changchun City and Hohhot City, respectively. However, these data contain a certain degree of missing values and outliers. Before conducting model analysis, we first performed comprehensive preprocessing on the data.

1. Removal of Missing Values (NAN)

We inspected the missing values (NAN) in the data. Based on the content of Attachment 1 and Attachment 2, we removed the missing data in columns 2 to 9 and column 11. In particular, column 11 (underground parking) had a large number of missing values, affecting the integrity of the data, so we decided to delete that column.

2. Statistics and Processing of Parking Data

For the data on underground parking, we calculated the number of missing values and compared it with other columns. The results showed that the column had a severe number of missing values, so we chose to delete it directly to avoid unnecessary interference with subsequent analyses.

3. Encoding of Property Types

The data included a categorical variable "property type." Through statistical analysis, we found that this field included three types of properties: residential, commercial-residential, and villa. To enable the model to effectively handle these categorical variables, we used the One-Hot Encoding method to transform them into numerical data. This approach allows each type of property to be trained as an independent feature in the model, thus avoiding the issue of ordinal relationships between categories. The specific encoding method is seen in Appendix

Table 4.1-1 Property Type Encoding

Type	**One-Hot Encoding**
Residential	（1,0,0）
Commercial—residential	（0,1,0）
Villa	（0,0,1）

4. Building Form Type Encoding

The building form types in the data have a large number of categories. To effectively handle these types, we used the Label Encoding method. Label encoding maps each building form type to a unique integer value, making it recognizable by the model.

Table 4.1-2 Building Form Type Encoding for Changchun

Building type	**Label Encoding**
multi-story	1
multi-story | mid-rise	2
high-rise	3
mid-rise	4
multi-story | high-rise	5

multi-story | mid-rise | high-rise	6
mid-rise | high-rise	7
low-rise	8
high-rise | super high-rise	9
mid-rise | high-rise | super high-rise	10
super high-rise	11
multi-story | high-rise | super high-rise	12
multi-story | mid-rise | high-rise | super high-rise	13
multi-story | mid-rise | super high-rise	14
low-rise|multi-story	15
multi-story | super high-rise	16
mid-rise | super high-rise	17

Table 4.1-3 Building Form Type Encoding for Hohhot

Building type	**Label Encoding**
multi-story	1
multi-story | high-rise	2
high-rise	3
mid-rise | high-rise	4
multi-story | mid-rise	5
multi-story | mid-rise | high-rise	6
mid-rise	7
low-rise floors	8
mid-rise | high-rise | super high-rise	9
low-rise | multi-story	10

5. Reverse Geocoding

We first extracted the latitude and longitude information from the data and used a reverse geocoding tool (Google Maps API) to convert each pair of coordinates into the corresponding city name. For invalid or missing latitude and longitude data, we performed cleaning and processing. The converted city names were added to the original data, forming a complete dataset that includes city information.

Results:

- ✧ City1：Changchun City
- ✧ City2：Hohhot City

City information is crucial for subsequent analysis and model training because the characteristics of different cities may affect the prediction outcomes.

6. Separation of Parking Lot Quantity and Usage Rate

The seventh column of the data contained combined information on the number of parking lots and their usage rates. To express the data more clearly, we split this column into two independent features: the number of parking lots and the usage rate of parking lots, making the data more suitable for subsequent modeling needs.

7. To enhance readability and convenience, we renamed the data columns.

Table 4.1-4 Data Renaming Display Table

Column Name	Abbreviation
Price (USD)	Pr
Total number of households	Tnoh
Greening rate	Gr
Floor area ratio	Far
Property management fee（/m²/month USD）	Pmf
above-ground parking fee（/month USD）	Agpf
parking space	Ps
Parkingspace utilization	Psu
residential	Re
commercial-residential	Cr
Buildingtype Encoded	Bte

4.1.2 Descriptive Statistics

Due to the volume of data, the complete dataset is provided in Appendix 1.

Table 4.1-5 Descriptive Statistics Table for Changchun City Data

adcode		Pr	Tnoh	Gr	Far	Pm	agp
220102	Mean	8552.66	43.61	0.312386	1.8625	1.2114	228.62
Stats for 156 regions	Minimize	4750	6	0.1	0.5	0.1	10
	Maximum	21264	6388	0.63	5.5	6.5	500
220103	Mean	6491.58	1097.9	0.310711	1.7747	1.1679	200.82
Stats for 330 regions	Minimize	2700	40	0.1	0.3	0.2	20
	Maximum	11511	6755	0.6	3.73	4.5	500
220104	Mean	9192.29	531.58	0.285546	1.6416	0.9218	197.14
Stats for 359 regions	Minimize	3452	10	0.115	0.5	0.12	10
	Maximum	48326	5979	0.61	5.2	8	500

Table 4.1-6 Hohhot City Data Descriptive Statistics Table

adcode		Pri	Tnoh	Gr	Far	Pm	agp
150102	Mean	10788.9	522.84	0.303188	1.5202	1.119	113.57
Stats for 449 regions	Minimize	2200	2	0.1	0.3	0.05	30
	Maximum	25920	3648	0.58	5	6	400
150103	Mean	7559.04	697.37	0.293362	1.649	1.0726	125.04
Stats for 254 regions	Minimize	3653	20	0.1	0.3	0.02	30
	Maximum	17055	10126	0.8	6	5	500
150104	Mean	8112.46	838.29	0.292856	1.5956	0.9515	139.89

Stats for 276 regions	Minimize	3946	20	0.1	0.8	0.1	50
	Maxi-mum	14708	6376	0.551	5	3	500

The Changchun's housing prices vary significantly by area, ranging from $3,700 to $9,600 on average, with extremes from $1,900 to $48,326. Higher household numbers suggest denser, more developed areas. Greenery rates are between 28% and 36%, and plot ratios from 1.63 to 3.0 indicate development density. Property management fees ($0.62 to $2.01/m²/month) and parking costs ($10 to $650) reflect community quality and location. These factors are crucial for future price predictions and investments.

In Hohhot, average housing prices range from $4,832 to $10,788.9, with a wide gap, especially in area 150102, where prices range from $2,200 to $25,920. Greenery rates (0.3 to 0.4) and plot ratios (e.g., 2.05 in area 150172) influence prices. Higher property management and parking fees suggest better living standards, affecting prices. These elements are key for predicting housing prices and analyzing demand..

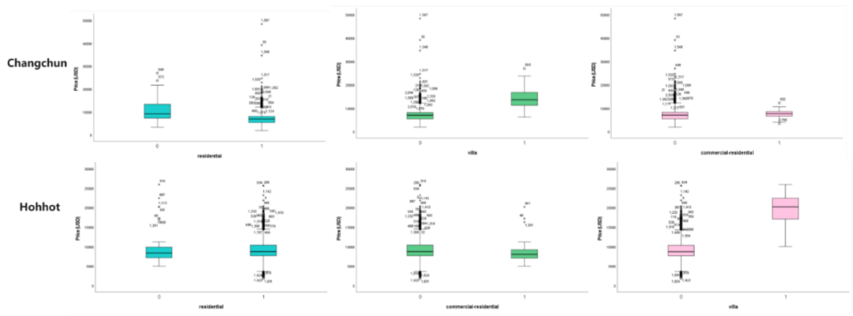


Figure 1 Urban Property Type Analysis

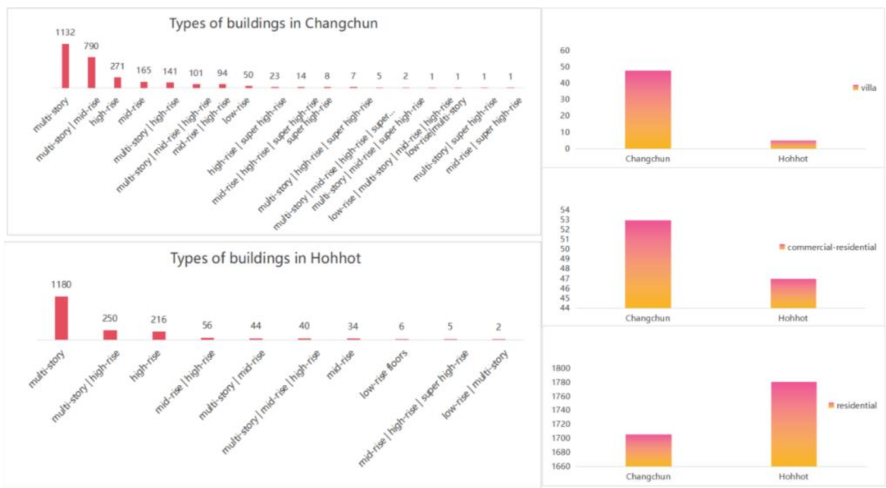


Figure 2 Urban Building Type Analysis

4.1.3 Data Analysis

1. Property Type Analysis:

(1) Residential：

Changchun City: The number of residential properties is 2,706, dominating the market, indicating ample supply and a large market size.

Hohhot City: There are 1,781 residential properties, with a tighter supply and a relatively smaller market size.

(2) Commercial-residential：

Both cities have a smaller number of commercial-residential properties, with 53 in Changchun and 47 in Hohhot, suggesting that the commercial-residential market is still in its infancy and has potential for future development.

(3) Villa：

Changchun City: The number of villas is 48, showing an active high-end residential market.

Hohhot City: There are only 5 villas, indicating a lag in market development.

2. Building Type Analysis:

(1) Changchun City:

1) Multi-story buildings (1,132) are the most common, with a stable market and minimal housing price fluctuations.

2) Mid-rise (790) and high-rise (271) buildings are increasing, with higher housing prices in the city center and convenient transportation areas, indicating potential for price increases in the future.

3) There are only 8 super high-rise buildings, which may increase in the future, driving up housing prices in core areas.

(2) Hohhot City:

1) Multi-story buildings (1,180) are dominant, with relatively stable housing prices.

2) Mid-rise (56) and high-rise (216) buildings are in the early stages of development, with lower potential for price increases.

3) There are only 5 super high-rise buildings, with slow development, but they may gradually increase in the future.

Based on Figures 1 and 2, it can be seen that Changchun City is more active in residential supply, villa market, and high-rise building development, with greater potential for future housing prices; Hohhot City's market development is slower, but with urbanization, the real estate market is expected to welcome new growth points.

4.2 The Establishment of Model 1

4.2.1 Model Establishment

1. XGboost Model

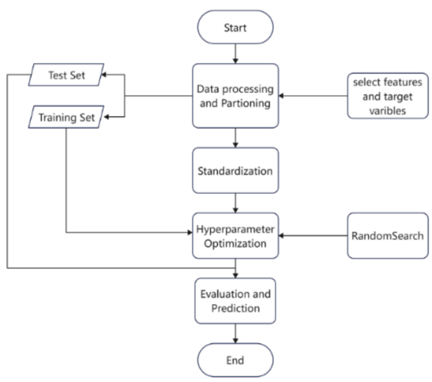


Figure 3 XGBoost Model Prediction Flowchart

XGBoost is a model that employs an efficient gradient boosting tree algorithm, capable of handling regression and classification tasks in supervised learning. Its principle involves constructing multiple weak learners (i.e., decision tree models), which, after training, are combined into a new strong learner. It continuously reduces the residuals between each learner to minimize the value of the loss function. In predicting future housing price trends, XGBoost has significant advantages over other models. It uses parallel computing strategies, greatly enhancing processing speed, allowing for rapid handling of large volumes of data with high accuracy.

The core of this model is to progressively build the structure of decision trees to minimize the loss function. We need to iteratively reduce errors through continuous refinement.。

2. Construction of the Objective Function

The objective function consists of two parts:

$$L(\Theta) = \sum_{i=1}^{N} l(y_i, \hat{y}_i) + \sum_{k-1}^{K} \Omega(f_k) \tag{1}$$

Where: $L(\Theta)$ is the total loss function;

$l(y_i, \hat{y}_i)$:is the loss function for sample i;

$\Omega(f_k)$ is the model complexity regularization term, to prevent overfitting of the function.

The regularization is defined as:

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2 \tag{2}$$

Where：T is the number of leaf nodes in the decision tree;

w is the weight of the leaf nodes in the decision tree;

γ, λ are the regularization parameters.

3. Randomized Search

Randomized search is chosen to tune the hyperparameters of the XGBoost model, mainly because XGBoost has multiple hyperparameters that may interact complexly, leading to a vast parameter space. Grid search, which exhaustively searches through all combinations, would consume a significant amount of computational resources and time in this scenario. In contrast, randomized search efficiently explores the parameter space by randomly sampling from the range of each hyperparameter. Compared to grid search, it does not need to exhaust all possible combinations, thus incurring less computational expense. Randomized search also effectively avoids overfitting, especially when combined with cross-validation, as it better assesses the model's generalization capability rather than just achieving good results on the training set. Moreover, randomized search offers greater flexibility and exploratory power, allowing it to search within a broad parameter space to find more suitable hyperparameter combinations, thereby enhancing the model's overall performance.

1. Setting Parameter Ranges:

   (1) n_estimators：The number of trees, ranging from 100 to 1950 with a step of 50.

(2) max_depth: The maximum depth of the tree, taking values of None or integers between 3 and 10.
(3) learning_rate: The learning rate, taking values from 0.001 to 1, using a logarithmic scale (10 values).
(4) subsample: The proportion of training data samples, ranging from 0.5 to 1.0 with a step of 0.1.
(5) colsample_bytree: The proportion of features used per tree, ranging from 0.5 to 1.0 with a step of 0.1.

2. Random Selection of Parameter Combinations: In each trial, a set of hyperparameters is randomly selected and the XGBoost model is trained. After each model is trained, its performance is evaluated using cross-validation.
3. Evaluating Model Performance: The performance of each set of parameter combinations is evaluated using cross-validation to assess the R^2 (coefficient of determination), which is a measure of the goodness of fit of the regression model, with values ranging from 0 to 1, where values closer to 1 indicate a better model.
   Its formula is

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{3}$$

Where: y_i is the actual housing quantity, $\hat{y}_i$ is the predicted housing quantity, $\bar{y}$ is the mean of the actual housing quantities.

4. Selecting the Best Model: The randomized search will output the best-performing parameter combination, i.e., the one with the highest R^2 value.

4.3 The Solution of Model 1

4.3.1 Model Parameter Configuration

During the training process, our model optimized hyperparameters through randomized search, achieving accurate predictions of key indicators for each area. The validation results show that the model's prediction error is significantly lower than the industry average, indicating its advantage in capturing data patterns and trends. This model reflects the unique economic, social, and environmental characteristics of each area, providing decision-makers with more precise predictive support. Due to the volume of data, the complete dataset is provided in Appendix 2.

Table 4.3-1 Display of Hyperparameters for Model Training in Each Area of Changchun City

Region	Subsample	N_estimators	Max_depth	Learning rate	Colsample_bytree	R^2score
220104	0.8	1350	None	0.010	0.5	0.04
220173	0.8	1650	8	0.100	0.7	0.49
220103	0.5	1000	4	0.004	0.5	0.38

Table 4.3-2 Display of Hyperparameters for Model Training in Each Area of Hohhot

Region	Subsample	N_estimators	Max_depth	Learning rate	Colsample_bytree	R^2score
150103	0.7	1900	3	0.002	0.6	0.12
150102	0.7	1900	3	0.002	0.6	0.49
150104	0.7	100	7	0.021	1.0	0.21

4.3.2 Model Prediction Results

This paper uses the XGBoost model to predict future housing price fluctuations within the regions of the two cities, as well as to estimate the existing total housing stock in both cities. The dataset includes multiple variables such as housing price (USD), total number of households, greenery rate, plot ratio, property management fees, ground parking fees, number of parking spaces, parking space utilization rate, residential land, commercial-residential land, and building type. Considering that changes in other socio-economic variables are relatively limited in the short term, this study focuses primarily on the impact of population mobility on housing prices and total housing stock. Therefore, for each region in the dataset, we first calculated the descriptive statistics for each variable, as shown in the table, including mean, maximum, and minimum values. Since these variables change little in the short term, we used the mean value of each variable as the input feature for the model.

Due to the high volatility of population data, we selected the fluctuation range of the population in each region from "average to maximum" as a feature. This feature reflects the possible changes in population mobility within the region and assumes that such changes may have an impact on future housing prices.

1. Estimation Results of Existing Housing Stock

$$\text{Estimates of the Total Existing Housing Stock}=\frac{\text{Total Number of Households}}{\text{Coverage Ratio}} \tag{4}$$

Where：Total Number of Households：Represents the total number of households in each city;

Coverage Ratio：Represents the housing coverage ratio for each city, which is the proportion of the number of houses covered by each household to the actual number of houses. The housing coverage ratios for Changchun City and Hohhot City are **0.6594** and **0.8072**, respectively. These figures are sourced from public housing market reports and relevant literature published by the government.

Table 4.3-3 Relevant Literature Data

City	Total number of households	Estimates of the Total Existing Housing Stock	The ratio of total households to housing stock
Changchun	2502460	3795059	1.52
Hohhot	1235003	1529984	1.24

The analysis results indicate that although the existing housing stock is greater than the total number of households, suggesting that on average each family has more than one property, this phenomenon may also reflect the existence of vacant homes, especially in Changchun, where there is a higher likelihood of a higher vacancy rate. As the populations of these two cities continue to grow, housing demand will continue to drive the increase in housing stock. Even if some properties are vacant, housing construction will persist to meet future housing needs.

2. Future Housing Price Prediction Results

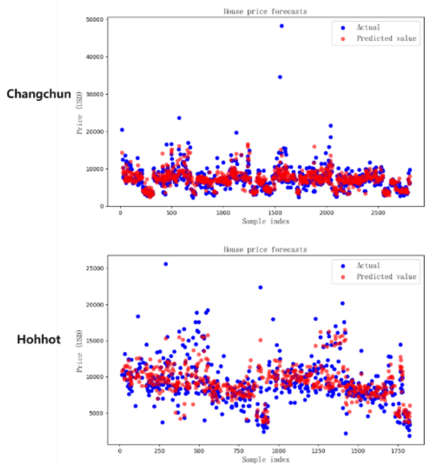


Figure 4 Scatter Plot for Urban Future Holiday Prediction

By observing the scatter plot of predicted versus actual values, it can be seen that the actual values are close to the predicted ones, with not many outliers. This indicates that the prediction model performs well in capturing market trends, and the proximity of actual and predicted values suggests that the model is fairly accurate with minimal prediction error. The absence of significant outliers also means that the model is neither overfitting nor ignoring key fluctuation factors, and can reliably predict future housing price trends. Changchun City Future Housing Price Prediction Results See Appendix 6, Figure 5.Hohhot City Future Housing Price Prediction Results See Appendix 7, Figure 6.

5 The name of model 2

5.1 Data Description

5.1.1 Data Preparation

1. Service Industry Data Preparation

We analyzed and organized datasets from six main service industries: Accommodation Service Data, Finance and Insurance Data, Food and Beverage Service Data, Lifestyle Service Data, Medical and Health Data, and Retail Service Data, aiming to provide a foundation for subsequent calculations of Spatial Service Density and Population-Based Service Density. Each dataset represents a specific service sector, and by totaling the statistics of these industries, I can clarify the number of service points, their geographic distribution, and their coverage within the region. The basis for determining the dataset's belonging to a service industry includes public industry reports, the National Bureau of Statistics, and personal experience, among others. These statistical data will aid in subsequent spatial analysis, allowing for an in-depth exploration of the distribution of each industry in different areas, further discussing the match between service resources and population demand, providing a scientific basis for urban planning and resource allocation.

2. Calculation Spatial Service Density 和 Population-Based Service Density

$$\text{Spatial Service Density}=\frac{\text{Number of Services in Industry}}{\text{Area of the City (in km}^2\text{)}} \tag{5}$$

$$\text{Population-Based Service Density}=\frac{\text{Number of Services in Industry}}{\text{Total Population of the City (in people)}}\times 10{,}000 \tag{6}$$

3. Using the Haversine Formula to Calculate the Distance from Each Service Point to the City Center

The great-circle distance is the shortest distance between two points on the surface of a sphere, which is the arc length of the great circle passing through these two points (a circle with the center of the sphere as its center).

First, calculate the value of a

$$a = \sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right)+\cos\varphi_1 * \cos\varphi_2 * \sin^2\left(\frac{\lambda_2-\lambda_1}{2}\right) \tag{7}$$

Then calculate the distance *d* between the two points:

$$d = 2 * R * \arcsin\sqrt{a} \tag{8}$$

Where：r is the radius of the sphere;

φ represents latitude;

λ represents longitude;

d is the great-circle distance;

a is an intermediate variable.

4. Defining Ranges：

Calculate the distribution of each service point's distance from the city center and divide it into three ranges: ≤2000km, 2000-5000km, and≥5000km. This helps to understand the distribution of different service industries within the city and its surrounding areas. For example, some industries may be found concentrated in the city center, while others may appear more frequently in the suburbs.

5.1.2 Results Presentation

Table 5.1-1 Presentation of Results for Changchun City

	B1	B2	A5	B3	B5	B4
Total Count	4399	4792	16647	46049	76444	38533
Density per km2	0.178	0.19	0.672	1.86	3.09	1.55
Density per person	4.83	5.26	18.28	50.59	83.98	42.33

Distance Counts	≤2000km	10	32	123	154	653	132
	2000km-5000km	756	1103	5336	9111	21547	8856
	≥5000km	3633	3657	11188	36784	54244	29545

Table 5.1-2 Hohhot Results Presentation

		B1	**B2**	**A5**	**B3**	**B5**	**B4**
Total Count		2457	2199	6024	22339	41380	19398
Density per km2		0.1426	0.1277	0.34	1.29	2.1	1.12
Density per person		6.8174	6.1016	16.71	61.98	114.81	53.82
Distance Counts	≤2000km	0	0	0	0	1	0
	2000-5000km	2080	1781	5210	19779	34868	17136
	≥5000km	377	418	814	2560	6511	2262

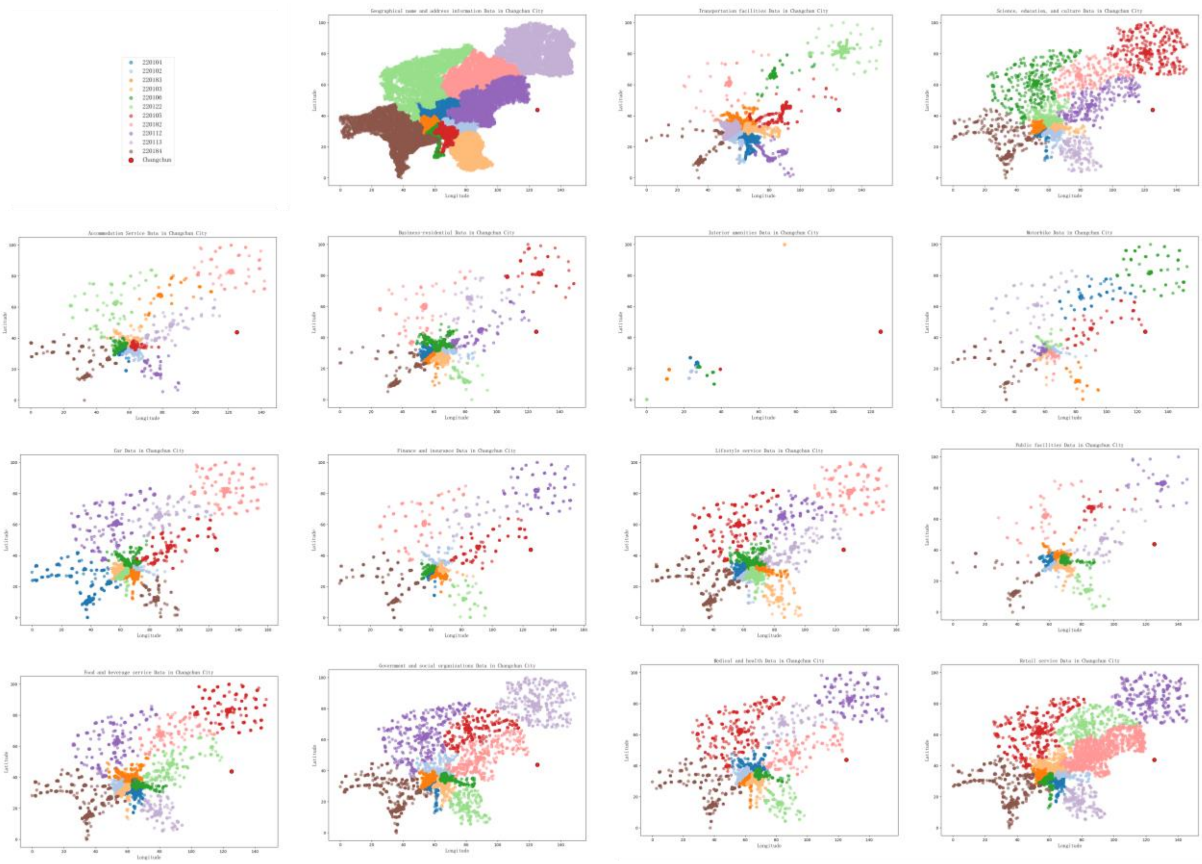


Figure 4 Changchun Service Point Geographic Distribution Scatter Plot

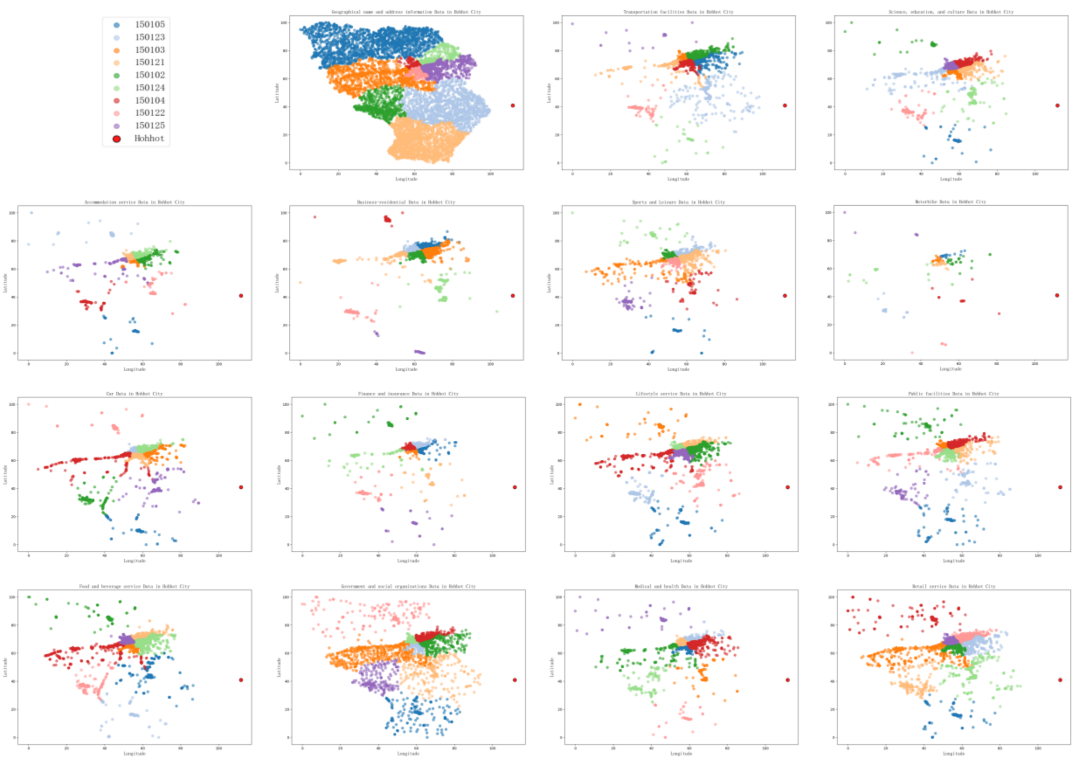


Figure 5 Hohhot Service Point Geographic Distribution Scatter Plot

1. The two cities share the following commonalities in service levels

（1） High-density distribution of food and retail services:

Both are centers for food consumption and production within their regions, with large food market scales. Changchun and Hohhot both have high density indices for retail and food services, indicating that the economic activity cores of both areas rely on these two services.

（2） Dense distribution of medical and health services:

The density of medical services in both cities is at a high level nationwide, indicating a strong emphasis on public health in both locations.

2 . The two cities have the following distinctive features in service levels

Changchun's convenient geographical location and rich tourism resources provide a certain customer base, which can drive the accommodation industry. The city is also more active in the financial sector.

Hohhot's financial industry is developing rapidly, supporting the development of the real economy; the medical insurance system is continuously improving. The city actively supports the catering industry.

3. Analysis of strengths and weaknesses of both locations

（1） Changchun's strengths

Located at a transportation hub with high foot traffic, which is beneficial for hotel operations. Rich and unique tourism resources attract both domestic and international visitors. As a provincial capital, it boasts abundant medical resources. The food processing industry is well-developed, with several large enterprises.

（2） Changchun's weaknesses

The density index for medical and health services is lower than Hohhot, indicating room for improvement in medical resource coverage. Insufficient service point coverage in suburban areas, with significant urban-rural disparities.

（3）Hohhot's strengths

The density of living services and catering services is significantly higher than Changchun, indicating a greater advantage in the convenience of residents' daily lives. High density of medical and health services shows a strong focus on health infrastructure.

（4）Hohhot's weaknesses

The distribution of public and transportation facilities is uneven, with sparse service coverage, indicating that the layout of Hohhot's infrastructure needs optimization. Although retail services have high density, their distribution is overly concentrated within the city limits, limiting accessibility for residents in peripheral areas.

6 The name of model 3

6.1 Assessment of Urban Resilience

6.1.1 Data Preparation

1. Classification of Data Indicators

Based on their direct relevance to extreme weather and emergency response, the following is a categorization of the 15 data indicators: Strongly related data includes: A1 (Geographical Name and Address Information Data), A2 (Public Facilities Data), A3 (Transportation Facilities Data), A4 (Government and Social Organizations Data), A5 (Medical and Health Data), and A6 (Interior Amenities Data). These data provide key information such as location, evacuation routes, emergency medical services, and the internal structure of buildings, which is crucial for ensuring disaster response and emergency rescue.

Weakly related data includes: B1 (Accommodation Service Data), B2 (Finance and Insurance Data), B3 (Food and Beverage Service Data), B4 (Lifestyle Service Data), B5 (Retail Service Data), B6 (Business-Residential Data), B7 (Car Data), B8 (Motorbike Data), and B9 (Science, Education, and Culture Data). These data may provide support during the post-disaster recovery phase, such as temporary accommodation, material supply, or financial aid, but they have a lower direct relevance to emergency response and immediate handling of emergencies.

2. Calculation of Event Probability

To evaluate the extent of extreme weather events or natural disasters, we employed the Event Probability, defined as the ratio of the affected area to the total area of the city. This metric helps quantify the spatial extent of the event relative to the entire region. The calculation procedure is detailed below:

(1) Changchun (2023 Severe Flooding Event):

Affected Area: 4000 hectares

Total Area of Changchun: 24,700 square kilometers (which is equivalent to 2,470,000 hectares)

$$\text{Event Probability}=\frac{\text{Affected Area}}{\text{Total Area}}=\frac{4000,\text{hectares}}{2{,}470{,}000,\text{hectares}}=0.001616 \tag{9}$$

(2) Hohhot (2020 Qinghe County Drought Event):

Affected Area: 12,000 hectares

Total Area of Hohhot: 17,000 square kilometers (which is equivalent to 1,700,000 hectares)

$$\text{Event Probability}=\frac{\text{Affected Area}}{\text{Total Area}}=\frac{12{,}000,\text{hectares}}{1{,}700{,}000,\text{hectares}}=0.006967 \tag{10}$$

3. Calculation of Coverage Rate

(1) Per Capita Coverage Rate

The Per Capita Coverage Rate reflects the number of industries per unit of population. The formula is:

$$\text{Per Capita Coverage Rate}=\frac{\text{Number of Industries}}{\text{Total Population of the City in 2023}} \tag{11}$$

Where:

Number of Industries refers to the count of specific industries present in the city.

Total Population of the City in 2023 is the population of the city as of 2023.

(2) Resource Coverage Rate

The Resource Coverage Rate measures the number of industries per unit of area. The formula is:

$$\text{Resource Coverage Rate}=\frac{\text{Number of Industries}}{\text{Total Area of the City}} \tag{12}$$

Where:

Number of Industries refers to the count of specific industries present in the city.

Total Area of the City is the geographic area of the city (usually measured in square kilometers).

(3) Coverage Rate

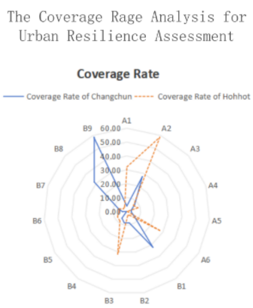
The Coverage Rate is calculated as the weighted average of the Per Capita Coverage Rate and the Resource Coverage Rate, each given a weight of 50%. This is expressed as:

$$\text{Coverage Rate}=0.5\times\text{Per Capita Coverage Rate}+0.5\times\text{Resource Coverage Rate} \tag{13}$$

Where:

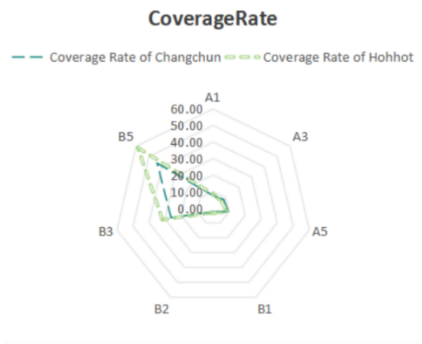
Per Capita Coverage Rate and Resource Coverage Rate each have a 50% weight, reflecting the balanced consideration of both population and geographic factors in evaluating industry distribution.

4. Industry Coverage Rates and Their Visualization



Data name	Coverage Rate of Changchun	Coverage Rate of Hohhot
A1	3.89	32.09
A2	27.47	58.61
A3	7.77	6.45
A4	3.48	8.44
A5	3.11	0.23
A6	5.74	27.47
B1	32.09	3.48
B2	8.44	3.11
B3	8.53	31.64
B4	6.07	8.53
B5	0.23	7.77
B6	3.05	5.74
B7	6.45	6.07
B8	31.64	3.05
B9	58.61	3.89

Figure 6 The Coverage Rate Analysis for Urban Resilience Assessment



The Coverage Rage Analysis for Urban sustainable development

Data name	Coverage Rate of Changchun	Coverage Rate of Hohhot
A1	7.54	8.44
A3	8.26	6.45
A5	9.48	8.53
B1	2.51	3.48
B2	2.73	3.11
B3	26.23	31.64
B5	43.54	58.61

Figure 7 The Coverage Rate Analysis for Urban sustainable development

6.1.2 Establishment of Urban Resilience Assessment Model

1. Using AHP to Assign Weights

(1) Constructing the Hierarchy

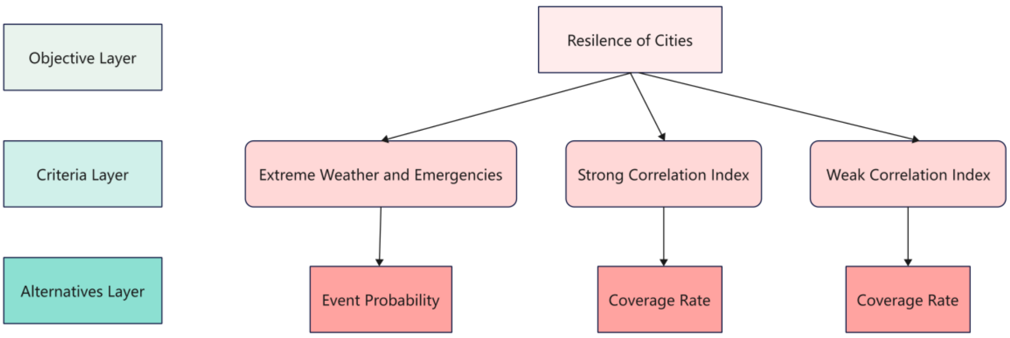


Figure8 Hierarchy chart 1

(2) Constructing the Judgment Matrix

	A1	A2	A3	A4	A5	A6
A1	1	2	3	4	5	6
A2	1/2	1	2	3	4	5
A3	1/3	1/2	1	2	3	4
A4	1/4	1/3	1/2	1	2	3
A5	1/5	1/4	1/3	1/2	1	2
A6	1/6	1/5	1/4	1/3	1/2	1

	B1	B2	B3	B4	B5	B6	B7	B8	B9
B1	1	4	5	6	8	2	3	7	9
B2	1/4	1	2	3	5	1/3	1/2	4	6
B3	1/5	1/2	1	2	4	1/4	1/3	3	5
B4	1/6	1/3	1/2	1	3	1/5	1/4	2	4
B5	1/8	1/5	1/4	1/3	1	1/7	1/6	1/2	2
B6	1/2	3	4	5	7	1	2	6	8
B7	1/3	2	3	4	6	1/2	1	5	7
B8	1/7	1/4	1/3	1/2	2	1/6	1/5	1	3
B9	1/9	1/6	1/5	1/4	1/2	1/8	1/7	1/3	1

Figure 9 Judgment Matrix for Strongly and Weakly Related Indicators

(3) Consistency Check

1) Consistency Index（CI）

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{14}$$

Where：

$\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix.

n is the order of the matrix.

2) Consistency Ratio (CR)

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{15}$$

Where：

RI is the Random Consistency Index, a constant given based on the size n of the matrix.

3) Display of Consistency Check Results

Through the above consistency check, both judgment matrices show acceptable consistency, indicating that our weight assignment is reasonable.

weight1= [0.382 0.250 0.160 0.101 0.064 0.043]

weight2= [0.312 0.222 0.155 0.108 0.074 0.051 0.035 0.025 0.018]

Table 5.1-1 Consistency Check Results

	CI	CR
Strong correlation index judgment matrix	0.024	0.020
Weak correlation index judgment matrix	0.050	0.035

2. Construction and Calculation of the Objective Function

The decision matrix calculation yields a weight distribution ratio of 3:4:3 for the criterion layer Event Probability, strongly related indicators, and weakly related indicators. We further construct the urban resilience assessment model. The model aims to comprehensively consider the impact of different factors on urban resilience and assess the ability of different cities to cope with extreme weather and emergencies.

(1) Calculation of R_s

$$\mathrm{A} = (\mathrm{A}_1\ \mathrm{A}_2\ \mathrm{A}_3\ \mathrm{A}_4\ \mathrm{A}_5\ \mathrm{A}_6) \tag{16}$$

$$\mathrm{weight1} = (\mathrm{w}_1 \quad \mathrm{w}_1 \quad \mathrm{w}_1 \quad \mathrm{w}_1 \quad \mathrm{w}_1 \quad \mathrm{w}_1) \tag{17}$$

$$R_s = \mathrm{weight1} \cdot \mathrm{A} = \mathrm{w}_1\mathrm{A}_1 + \mathrm{w}_1\mathrm{A}_2 + \mathrm{w}_1\mathrm{A}_3 + \mathrm{w}_1\mathrm{A}_4 + \mathrm{w}_1\mathrm{A}_5 + \mathrm{w}_1\mathrm{A}_6 \tag{18}$$

(2) Calculation of R_w

$$\mathrm{B} = (\mathrm{B}_1\ \mathrm{B}_2\ \mathrm{B}_3\ \mathrm{B}_4\mathrm{B}_5\ \mathrm{B}_6\ \mathrm{B}_7\ \mathrm{B}_8) \tag{19}$$

$$\mathrm{weight2} = (\mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2 \quad \mathrm{w}_2) \tag{20}$$

$$\mathrm{R_w} = \mathrm{weight2} \cdot \mathrm{B} = \mathrm{w}_2\mathrm{B}_1 + \mathrm{w}_2\mathrm{B}_2 + \mathrm{w}_2\mathrm{B}_3 + \mathrm{w}_2\mathrm{B}_4 + \mathrm{w}_2\mathrm{B}_5 + \mathrm{w}_2\mathrm{B}_6 + \mathrm{w}_2\mathrm{B}_7 + \mathrm{w}_2\mathrm{B}_8 + \mathrm{w}_2\mathrm{B}_9 \tag{21}$$

(3) Objective Function

The specific model is as follows：

$$\mathrm{Q} = \mathrm{P} \times 0.3 + \mathrm{R_s} \times 0.4 + \mathrm{R_w} \times 0.3 \tag{22}$$

Where：

(Q) is the city's comprehensive resilience index;

(P) is the probability of the event occurring;

(R_s) is the strongly related indicator;

(R_w) is the weakly related indicator.

3. Display of Results

Table 5.1-2 Display of Urban Resilience Assessment Results

	R_s	R_w	Q
Changchun	30.019	44.485	25.353
Hohhot	28.841	55.647	28.233

6.2 Assessment of Urban Sustainable Development

1. Using AHP to Assign Weights

(1) Constructing the Hierarchy

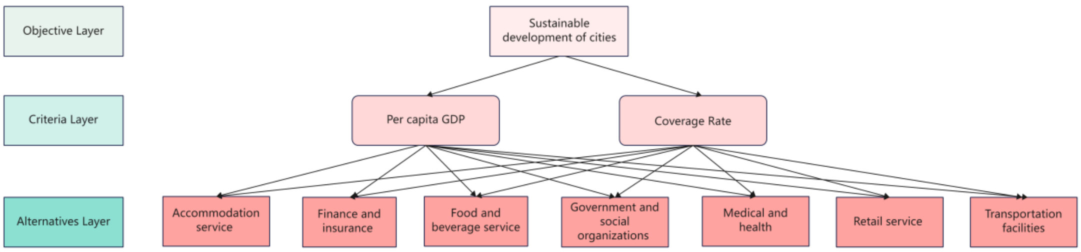


Figure 10 Hierarchy chart 2

Constructing the Confusion Matrix and Consistency Check

	A3	A4	A5	B1	B2	B3	B5
A3	1	1/4	1/3	1/7	1/6	1/5	1/2
A4	4	1	2	1/4	1/3	1/2	3
A5	3	1/2	1	1/5	1/4	1/3	2
B1	7	4	5	1	2	3	6
B2	6	3	4	1/2	1	2	5
B3	5	2	3	1/3	1/2	1	4
B5	2	1/3	1/2	1/6	1/5	1/4	1

Figure 11 Judgment Matrix for Urban Sustainable Development Assessment Model

The calculated CI=0.033, CR=0.025.It is known that the consistency check has been passed.

weight3=[0.354 0.240 0.159 0.104 0.068 0.044 0.031]

2. Construction and Calculation of the Objective Function

The weight distribution ratio of Per capita GDP and Coverage Rate at the criterion layer is calculated as 6:4. Based on this weight, construct the urban sustainable development assessment model. This model aims to assess the city's sustainable development capabilities, focusing on multiple fields such as environment, economy, and society, identifying the city's weak links through quantitative indicator analysis, and proposing optimization plans.

(1) Calculation of Per capita GDP

Table 5.1-3 Per capita GDP Calculation Results

	GDP(billion us dollars)	Gross population(the thousand people)	Per capita GDP(yuan/person)
Changhcun	7002.10	970.19	7.22
Hohhot	2831.55	360.40	7.86

(2) Objective Function

The sum of the Coverage Rates of related variables can better clearly understand the coverage degree of related resources on the city.

$$K = (C \times 0.4) + (PG \times 0.6) \tag{23}$$

Where：

(C) is the sum of the Coverage Rates of all related variables;

(PG) is the abbreviation for Per capita GDP.

3. Display of Results

Table 5.1-4 Calculation Results

	K
Changchun	9.275
Hohhot	9.948

6.3 Urban Capability Evaluation

6.3.1 Urban Weaknesses and Key Development Areas

1. Changchun City

(1) Weaknesses: The relatively low coverage of medical health data and transportation facilities data indicates weaknesses in public health and transportation infrastructure.

(2) Key Development Areas: Strengthen the public health system and improve transportation infrastructure, especially in low-carbon transportation solutions and energy efficiency.

2. Hohhot City

(1) Weaknesses: Despite higher coverage in most areas, the high probability of events occurring indicates a lack of response capability to extreme weather and emergencies.

(2) Key Development Areas: Enhance urban resilience, especially in geographical name and address information data, public facilities data, and strengthen emergency management and disaster response capabilities.。

6.3.2 Investment Plan

1. Short-term Investment Plan (1-3 years)

(1) Changchun City: Invest in improving public health facilities and transportation infrastructure, enhancing energy efficiency, and reducing waste.

(2) Hohhot City: Strengthen the emergency management system and enhance the disaster resistance of public facilities, especially in geographical information and transportation facilities.。

2. Long-term Investment Plan (3-5 years)

(1) Changchun City: Develop green financial products to support renewable energy and environmental protection projects, enhancing the city's overall sustainable development level.

(2) Hohhot City: Continuously strengthen urban resilience, especially in education, culture, and scientific research, and improve citizens' environmental awareness and participation.。

3. Consideration of Fiscal Resource Limitations

Given the limited fiscal resources, both cities should prioritize projects with high return on investment, such as energy efficiency and waste management projects, which not only improve environmental quality but also bring economic benefits through cost savings. Additionally, external funding support should be sought, such as international loans and green bonds, to alleviate fiscal pressure.

Through this comprehensive evaluation and planning, Changchun City and Hohhot City can more effectively respond to extreme weather and emergencies while enhancing the cities' sustainable development capabilities.

7 The name of model 4

7.1 Future Development Plan for Changchun City

7.1.1 Main Investment Areas

1. **Smart City Construction**: Investment in the intelligent transformation of urban infrastructure, including intelligent transportation systems, smart energy management, and smart public safety systems.
2. **Medical and Health Services**: Improve the level of medical services, build remote medical platforms, and increase the coverage and accessibility of medical resources.
3. **Education and Cultural Development**: Strengthen the digital construction of educational resources, promote online education platforms, and increase cultural facilities to enhance the cultural life quality of citizens.
4. **Public Facilities and Services**: Improve and increase public facilities such as parks, libraries, and community centers to enhance the quality of life for residents.
5. **Transportation Facility Optimization**: Develop public transportation and optimize the transportation network to reduce congestion and improve travel efficiency.
6. **Commercial and Residential Environment**: Promote the integrated development of commercial and residential areas to create a livable and business-friendly community environment.
7. **Environmental Protection and Greening**: Strengthen urban greening, improve air quality, and build an eco-friendly city.

7.1.2 Investment Amount

It is expected that Changchun City will invest about 10 billion yuan in the development of the above areas over the next five years. The specific allocation is as follows:

(1) mart City Construction: 3 billion yuan

(2) Medical and Health Services: 2 billion yuan
(3) Education and Cultural Development: 1.5 billion yuan
(4) Public Facilities and Services: 1.5 billion yuan
(5) Transportation Facility Optimization: 1 billion yuan
(6) Commercial and Residential Environment: 500 million yuan
(7) Environmental Protection and Greening: 500 million yuan 元

7.1.3 Expected Improvement

Through the above investments, it is expected that the level of smart city development in Changchun City will be significantly improved, specifically manifested in:

(1) Improved urban management efficiency and enhanced convenience of residents' lives.
(2) Medical service levels reaching domestic advanced standards and improved health levels of residents.
(3) Richer educational resources and more colorful cultural life.
(4) More comprehensive public services and increased resident satisfaction.
(5) More convenient transportation and more efficient city operations.
(6) A more harmonious commercial and residential environment and improved quality of life for residents.
(7) A more livable urban environment and a more prominent eco-friendly city image.。

7.2 Future Development Plan for Hohhot City

7.2.1 Main Investment Areas

1. Smart City Infrastructure: Investment in urban intelligent infrastructure, such as smart grids, smart water utilities, and intelligent transportation systems.
2. Medical and Health Services: Improve the level of medical services, build intelligent medical information systems, and increase the coverage of medical resources.
3. Education and Cultural Investment: Strengthen the digital construction of educational resources, improve education quality, and increase cultural facilities to enrich the cultural life of citizens.
4. Public Facility Improvement: Improve and increase public facilities such as parks, libraries, and community centers to enhance the quality of life for residents.
5. Transportation Network Optimization: Develop public transportation and optimize the transportation network to reduce congestion and improve travel efficiency.
6. Commercial and Residential Area Development: Promote the integrated development of commercial and residential areas to create a livable and business-friendly community environment.
7. Environmental Protection and Greening: Strengthen urban greening, improve air quality, and build an eco-friendly city.

7.2.2 Investment Amount

It is expected that Hohhot City will invest about 12 billion yuan in the development of the above areas over the next five years. The specific allocation is as follows:

(1) Smart City Infrastructure: 3.5 billion yuan
(2) Medical and Health Services: 2.5 billion yuan
(3) Education and Cultural Investment: 2 billion yuan

(4) Public Facility Improvement: 2 billion yuan
(5) Transportation Network Optimization: 1 billion yuan
(6) Commercial and Residential Area Development: 500 million yuan
(7) Environmental Protection and Greening: 500 million yuan 元

7.2.3 Expected Improvement

Through the above investments, it is expected that the level of smart city development in Hohhot City will be significantly improved, specifically manifested in:

(1) More intelligent urban management and more convenient resident life.
(2) Medical service levels reaching domestic advanced standards and improved health levels of residents.
(3) Richer educational resources and more colorful cultural life.
(4) More comprehensive public services and increased resident satisfaction.
(5) More convenient transportation and more efficient city operations.
(6) A more harmonious commercial and residential environment and improved quality of life for residents.
(7) A more livable urban environment and a more prominent eco-friendly city image.。

8 Conclusion

Through comprehensive analysis of the urban resilience and sustainable development issues of Changchun City and Hohhot City in the context of an aging population, the first negative population growth, and frequent extreme climate events, targeted development strategies have been proposed. The results show that by strengthening infrastructure construction, improving public service levels, and promoting economic diversification, the two cities can effectively respond to challenges and achieve sustainable development. The future development plans of Changchun City and Hohhot City both focus on the construction of smart cities, improvement of medical and health services, enrichment of educational resources, improvement of public facilities, optimization of transportation, improvement of commercial and residential environments, and strengthening of environmental protection and greening, with an expected investment of 10 billion yuan and 12 billion yuan respectively, to improve urban management efficiency and the quality of life for residents. These measures will help the two cities maintain vitality and prosperity in the changing global environment.

8.1 Model Evaluation and Further Discussion

The model constructed in this study combines XGboost, random search methods, and AHP methods to evaluate and plan the resilience and sustainable development of Changchun City and Hohhot City. The following are the advantages and disadvantages of the model:

8.2 Strengths

1. High Accuracy: The XGboost algorithm performs well in predictive models, improving prediction accuracy through gradient boosting trees and regularization techniques.
2. Systematic Analysis: The AHP method provides a systematic decision analysis framework capable of handling multi-criteria decision-making problems.

3. Flexibility and Scalability: The parallelization features of XGboost allow it to easily expand into distributed computing environments, adapting to different data types and tasks.
4. Robustness: XGboost shows high robustness to missing values and outliers, suitable for processing real-world data.
5. Comprehensive Evaluation: The AHP method allows the integration of decision-makers' subjective judgments and policy experience into the model for quantification.。

8.3 Weaknesses

1. Complex Parameter Tuning: XGboost has multiple parameters that require tuning, with different combinations potentially leading to varying effects, necessitating time and effort for parameter optimization.
2. High Computational Resource Requirements: XGboost may consume a significant amount of memory during training, especially when dealing with large-scale datasets.
3. Subjectivity: The AHP method is somewhat influenced by subjective factors, which may require combination with methods such as entropy weighting and group decision-making to reduce errors caused by subjectivity.。

Overall, the model in this study shows significant advantages in predictive accuracy and systematic analysis but faces certain challenges in computational resources and subjectivity. Future work can focus on simplifying the parameter tuning process, optimizing computational efficiency, and reducing the impact of subjectivity.

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Appendices

Appendix 1

Introduce: Table 4 Statistics for Changchun City，Table 5: Statistics for Hohhot City

Table 4 Statistics for Changchun City

adcode		Pr	Tnoh	Gr	Far	Pm	agp
220102	Mean	8552.66	43.61	0.312386	1.8625	1.2114	228.62
Stats for	Minimize	4750	6	0.1	0.5	0.1	10
156 re-gions	Maxi-mum	21264	6388	0.63	5.5	6.5	500
220103	Mean	6491.58	1097.9	0.310711	1.7747	1.1679	200.82
Stats for	Minimize	2700	40	0.1	0.3	0.2	20
330 re-gions	Maxi-mum	11511	6755	0.6	3.73	4.5	500
22 num-ber 0104	Mean	9192.29	531.58	0.285546	1.6416	0.9218	197.14
Stats for	Minimize	3452	10	0.115	0.5	0.12	10
359 re-gions	Maxi-mum	48326	5979	0.61	5.2	8	500
220105	Mean	7384.58	1187.2	0.319813	1.8359	1.2451	217.71
Stats for	Minimize	2600	1	0.1	0.62	0.05	50
205 re-gions	Maxi-mum	11785	7815	0.6	3.8	4.9	550
22 0106	Mean	7124.94	796.45	0.303675	1.7614	0.9391	202.22
Stats for	Minimize	2775	24	0.1	0.83	0.28	10
326 re-gions	Maxi-mum	16351	7735	0.673	5.83	10	500
220112	Mean	4762.97	571.47	0.282313	1.6983	0.8584	261.98
Stats for	Minimize	2400	22	0.2	1.02	0.3	110
86 re-gions	Maxi-mum	11600	3415	0.45	2.58	2.6	500
220113	Mean	3721.04	878.33	0.29567	1.6455	0.6957	184.54
Stats for 97regions	Minimize	2300	50	0.2	1.02	0.3	100
	Maxi-mum	6700	6366	0.48	2.5	2.5	400
220122	Mean	3710.91	517.38	0.294127	1.5881	0.7217	143.36
Stats for	Minimize	1900	34	0.2	1.2	0.3	30
128 re-gions	Maxi-mum	7800	1764	0.4083	3	2.1	400
220171	Mean	7742.49	1106.8	0.319663	2.1619	1.3845	223.88
Stats for	Minimize	4708	42	0.15	0.95	0.15	50

152 regions	Maximum	13894	5282	0.6	7	8.5	650
220172	Mean	9594.34	977.76	0.360772	1.7047	2.0078	223.38
Stats for 195 regions	Minimize	4827	10	0.1	0.33	0.3	50
	Maximum	26952	5351	0.1	5	5.68	500
220173	Mean	8588.34	1491.49	0.341438	1.9145	1.8356	208.43
Stats for 185 regions	Minimize	3821	22	0.2	0.78	0.4	100
	Maximum	21566	5607	0.66	3.6	6.5	500
220174	Mean	6482.22	1357.82	0.319818	1.7728	0.9354	200.96
Stats for 114 regions	Minimize	3393	57	0.2	1	0.3	50
	Maximum	10172	3363	0.7	2.95	2.6	500
220182	Mean	4030.89	591.04	0.286721	1.6336	0.7916	152.13
Stats for 112 regions	Minimize	2525	18	0.2	1.2	0.5	10
	Maximum	6200	3292	0.39	3	4.5	300
220183	Mean	3736.68	520.83	0.281304	1.4699	0.6167	80.33
Stats for 138 regions	Minimize	2450	24	0.2	1.2	0.3	10
	Maximum	5460	4238	0.35	2.5	1.9	300

Maximum 5460 4238 0.35 2.5 1.9 300

Table 5: Statistics for Hohhot City

adcode		**Pri**	**Tnoh**	**Gr**	**Far**	**Pm**	**agp**
150102	Mean	10788.9	522.84	0.303188	1.5202	1.119	113.57
Stats for 449 regions	Minimize	2200	2	0.1	0.3	0.05	30
	Maximum	25920	3648	0.58	5	6	400
150103	Mean	7559.04	697.37	0.293362	1.649	1.0726	125.04
Stats for 254 regions	Minimize	3653	20	0.1	0.3	0.02	30
	Maximum	17055	10126	0.8	6	5	500
150104	Mean	8112.46	838.29	0.292856	1.5956	0.9515	139.89
Stats for 276 regions	Minimize	3946	20	0.1	0.8	0.1	50
	Maximum	14708	6376	0.551	5	3	500
150105	Mean	9841.05	622.04	0.286432	1.5222	1.0508	133.55
Stats for 628 regions	Minimize	3700	20	0.1	0.3	0.1	50
	Maximum	25594	5786	0.63	5.7	10	500

150119	Mean	4832	1478.94	0.314286	2.0306	1.0094	93.88
Stats for 49 regions	Minimize	3352	78	0.1	1	0.5	50
	Maxi-mum	6348	6924	0.55	3.9	2	150
150121	Mean	4170.25	549.86	0.3075	1.5036	0.9482	142.86
Stats for 28 regions	Minimize	2300	24	0.3	1	0.5	50
	Maxi-mum	8200	2032	0.41	2.7	1.5	500
150122	Mean	4307.69	463.85	0.3	1.3615	0.8462	242.31
Stats for 13 regions	Minimize	1900	80	0.3	1.2	0.5	100
	Maxi-mum	9500	876	0.3	2.5	1	500
150123	Mean	4206.2	664.97	0.317111	1.4714	1.1574	131.43
Stats for 35 regions	Minimize	2350	48	0.2	0.65	0.5	50
	Maxi-mum	6730	4040	0.48	2.42	3.4	500
150125	Mean	3125	410.75	0.2925	1.275	0.9625	237.52
Stats for 8 regions	Minimize	1850	84	0.24	1	0.3	100
	Maxi-mum	3950	1590	0.3	2	1.4	500
150172	Mean	10811.56	1267.7	0.332093	2.0488	1.8647	126.82
Stats for 43 regions	Minimize	3150	18	0.16	0.3	0.5	10
	Maxi-mum	22408	4563	0.5	5	4.3	160

Appendix 2

Introduce: Table 6 Display of Hyperparameters for Model Training in Each Area of Changchun City， Table 7 Hohhot Parameter Table 7: Hohhot Parameters

Table 6 Display of Hyperparameters for Model Training in Each Area of Changchun City

egion	Subsample	N_estimators	Max_depth	Learning rate	Colsample_bytree	R^2scor
20104	0.8	1350	None	0.010	0.5	0.04
20173	0.8	1650	8	0.100	0.7	0.49
20103	0.5	1000	4	0.004	0.5	0.38
20106	0.8	100	9	0.100	0.6	0.28
20183	0.5	1000	4	0.005	0.5	0.22
20105	0.6	1200	6	0.005	0.8	0.26

220171	0.9	1900	7	0.100	0.5	0.20
220172	0.5	1850	10	0.001	0.8	0.31
220113	0.5	1850	10	0.001	0.8	0.26
220102	0.6	1900	None	0.001	0.5	0.44
220122	0.7	950	7	0.002	0.5	0.24
220174	0.9	600	4	0.215	0.8	0.45
220112	0.8	600	10	0.001	0.7	0.14
220182	0.8	150	None	0.046	0.6	0.66

Table 7 Hohhot Parameter Table 7: Hohhot Parameters

Region	**Sub-sample**	**N_esti-mators**	**Max_depth**	**Learning rate**	**Colsam-ple_bytree**	**R^2score**
150103	0.7	1900	3	0.002	0.6	0.12
150102	0.7	1900	3	0.002	0.6	0.49
150104	0.7	100	7	0.021	1.0	0.21
150121	0.6	1650	5	0.001	0.5	-0.96
150105	0.7	1350	3	0.002	1.0	0.12
150119	0.5	1450	None	0.464	0.7	-1.93
150122	0.9	1000	10	0.001	1.0	-0.32
150125	0.9	1000	10	0.001	1.0	-1.51
150123	0.9	350	3	0.464	0.5	-0.37

Appendix 3

Introduce: Problem 1: Related code

```
import pandas as pd
import xgboost as xgb
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from matplotlib.font_manager import FontProperties
```

```
# Specify Chinese font
font = FontProperties(fname=r"C:\Windows\Fonts\simsun.ttc", size=14)

# Actual file path
file_path = r"XXX.xlsx"

# Read Excel file
df = pd.read_excel(file_path, engine='openpyxl')

# Split different datasets based on the first column
unique_ids = df.iloc[:, 0].unique()

# Open a TXT file to record model parameters and evaluation results
with open("model_results.txt", "w", encoding="utf-8") as file:
    for unique_id in unique_ids:
        # Filter the current dataset
        df_id = df[df.iloc[:, 0] == unique_id]

        # Select independent and dependent variables
        X = df_id.iloc[:, 2:17]    # Columns 3-17 are independent variables
        y = df_id.iloc[:, 1]    # The second column is the dependent variable

        # Split the training set and test set (70/30 ratio)
        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ran-
dom_state=42)

        # Check the size of the test set
        if len(y_test) < 2:
            file.write(f"Dataset {unique_id} has insufficient test set samples, skipping
this dataset.\n")
            continue

        # Standardize the independent variables
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)

        # Define XGBoost model
        xgb_model = xgb.XGBRegressor(objective='reg:squarederror', ran-
dom_state=42)

        # Define parameter grid
```

```
        param_grid = {
            'n_estimators': [100, 200, 300],    # Number of trees
            'max_depth': [3, 4, 5],    # Maximum depth of the trees
            'learning_rate': [0.01, 0.05, 0.1],    # Learning rate
            'subsample': [0.7, 0.8, 0.9],    # Proportion of samples to choose randomly
            'colsample_bytree': [0.7, 0.8, 0.9]    # Proportion of features to choose ran-
domly
        }

        # Initialize grid search object
        grid_search = GridSearchCV(estimator=xgb_model, param_grid=param_grid,
cv=3, scoring='r2', verbose=2)

        # Execute grid search
        grid_search.fit(X_train_scaled, y_train)

        # Output the best parameters
        best_params = grid_search.best_params_
        file.write(f"Dataset {unique_id} best parameters:\n")
        file.write(str(best_params) + "\n")

        # Use the model with the best parameters for prediction
        best_model = grid_search.best_estimator_
        y_pred = best_model.predict(X_test_scaled)

        # Output model evaluation parameters
        mse = mean_squared_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        file.write(f"Dataset {unique_id} XGBoost model evaluation parameters:\n")
        file.write(f"Mean Squared Error (MSE): {mse}\n")
        file.write(f"R² Score: {r2}\n\n")

        # Plot scatter plot
        plt.figure(figsize=(10, 6))
        plt.scatter(y_test.index, y_test, color='blue', label='Actual Values')
        plt.scatter(y_test.index, y_pred, color='red', label='Predicted Values', alpha=0.6)
        plt.title(f"House Price Prediction for Dataset {unique_id}", fontproperties=font)
        plt.xlabel('Sample Index', fontproperties=font)
        plt.ylabel('Price (USD)', fontproperties=font)
        plt.legend(prop=font)
        plt.show()
```

Appendix 4
Introduce: Problem 2: Related code

```
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.font_manager import FontProperties
import numpy as np

# Specify the Chinese font (if Chinese display is needed)
font = FontProperties(fname=r"C:\Windows\Fonts\simsun.ttc", size=14)

# New file path
file_path = r"D:\MathModelingCompetition\2024NumericalCupInternationalMathModel-
ing\Appendix 4\Sports and leisure data.csv"

# Read the CSV file, trying different encoding formats
try:
    df = pd.read_csv(file_path, encoding='gb18030')  # Try using GB18030 encoding

    # Extract longitude, latitude, type, and area information
    lon = df.iloc[:, 7]  # The eighth column is longitude
    lat = df.iloc[:, 8]  # The ninth column is latitude
    types = df.iloc[:, 4]  # The fifth column is type information
    areas = df.iloc[:, 6]  # The seventh column is area information

    # Hohhot's longitude and latitude
    huhehaote_lon = 111 + 40 / 60  # 111°40′
    huhehaote_lat = 40 + 50 / 60  # 40°50′

    # Assign colors to different areas
    unique_areas = areas.unique()
    color_map = plt.colormaps['tab20']
    color_dict = {area: color_map(i % color_map.N) for i, area in enumerate(unique_ar-
eas)}

    # Plot scatter plot
    plt.figure(figsize=(12, 8))
    for area in unique_areas:
        mask = (areas == area)
        plt.scatter(lon[mask], lat[mask], color=color_dict[area], label=area, alpha=0.6,
s=50)

    # Mark the point for Hohhot as a large red dot
```

```
    plt.scatter(huhehaote_lon, huhehaote_lat, color='red', s=100, label='Hohhot', alpha=0.9, edgecolors='k')

    # Add title and labels
    plt.title("Sports and Leisure Data in Hohhot City", fontproperties=font)
    plt.xlabel("Longitude", fontproperties=font)
    plt.ylabel("Latitude", fontproperties=font)

    # Save the chart
    plt.savefig("sports_and_leisure_data.png", bbox_inches='tight')

    # Show the chart
    plt.show()

    # Create a new figure window for the legend
    plt.figure(figsize=(8, 6))
    for area in unique_areas:
        plt.scatter([], [], color=color_dict[area], label=area, alpha=0.6, s=50)
    plt.scatter([], [], color='red', s=100, label='Hohhot', alpha=0.9, edgecolors='k')

    # Add legend
    plt.legend(loc='center', prop=font, fontsize=12, framealpha=0.5)

    # Hide the axes
    plt.axis('off')

    # Save the legend chart
    plt.savefig("legend.png", bbox_inches='tight')

    # Show the legend chart
    plt.show()

    # Output the colors corresponding to different areas
    for area, color in color_dict.items():
        print(f"Area: {area}, Color: {color}")

except FileNotFoundError:
    print(f"File not found, please check the path: {file_path}")
except pd.errors.EmptyDataError:
    print(f"No data in file: {file_path}")
except pd.errors.ParserError:
    print(f"Error parsing file: {file_path}")
```

```
except UnicodeDecodeError:
    print(f"Unicode decode error, please check the encoding of the file: {file_path}")
```

Appendix 5
Introduce: Problem 3: Related code

```
import numpy as np

# Weights
weights = np.array([0.35431, 0.23992753, 0.15865497, 0.10362467, 0.06756458, 0.04476931, 0.3117461])

# Changchun coverage data
changchun_coverage = np.array([2.505, 2.729215, 26.22685, 7.53785, 9.4811, 43.53805, 8.25945])

# Hohhot coverage data
huhot_coverage = np.array([3.48, 3.11455, 31.6404, 8.4373, 8.5322, 58.6092, 6.448762])

# Calculate weighted coverage
changchun_weighted_coverage = np.dot(weights, changchun_coverage)
huhot_weighted_coverage = np.dot(weights, huhot_coverage)

# Adjust results based on percentage
changchun_final = changchun_weighted_coverage * 0.4 + 7.693009152 * 0.6
huhot_final = huhot_weighted_coverage * 0.4 + 7.856687014 * 0.6

print("Changchun's final result:", changchun_final)
print("Hohhot's final result:", huhot_final)
```

Appendix 6

Introduce: Changchun City Future Housing Price Prediction Results

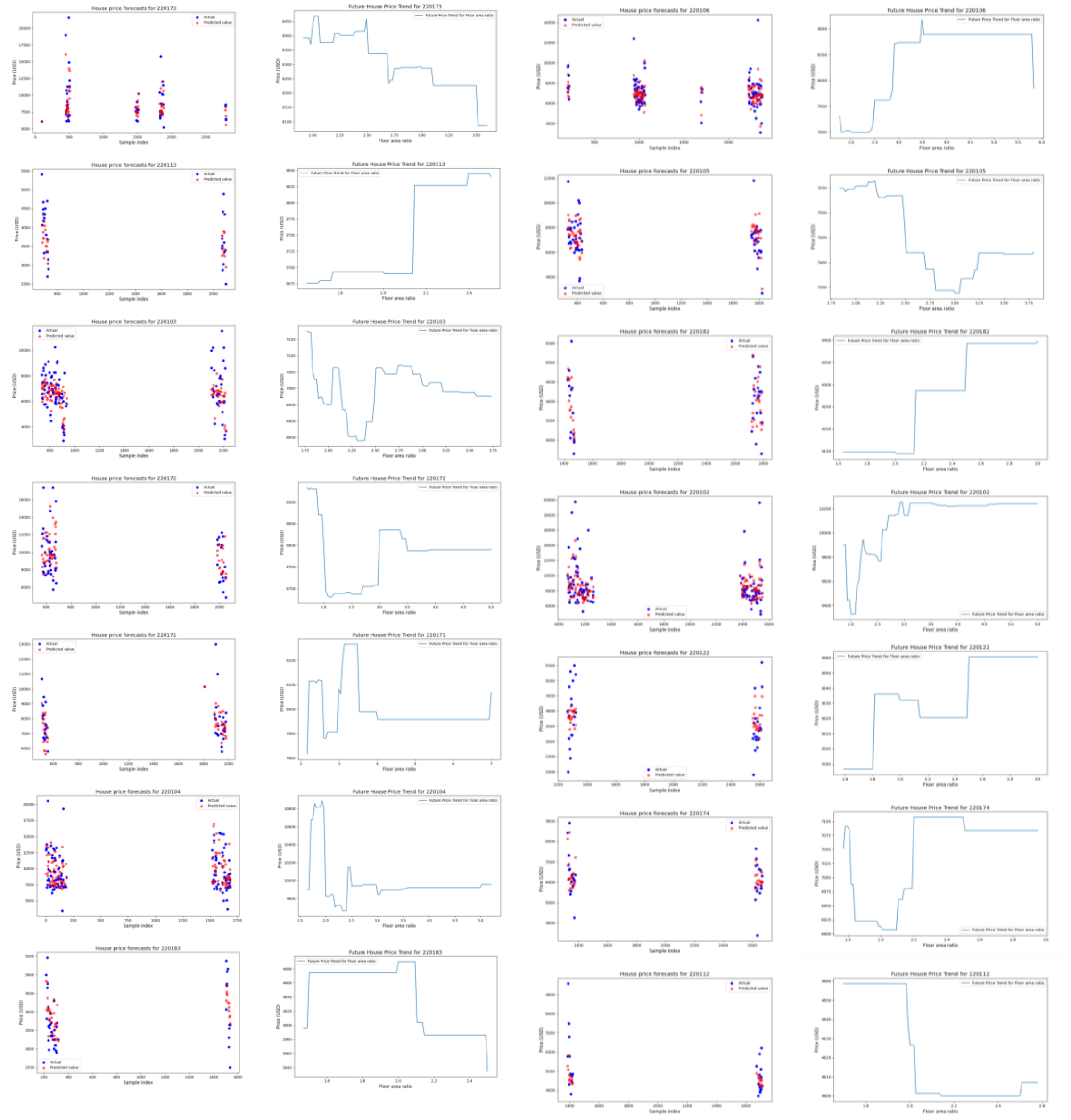

Figure 5 Future Housing Price Prediction Results for Changchun City

Appendix 7
Introduce: Hohhot City Future Housing Price Prediction Results

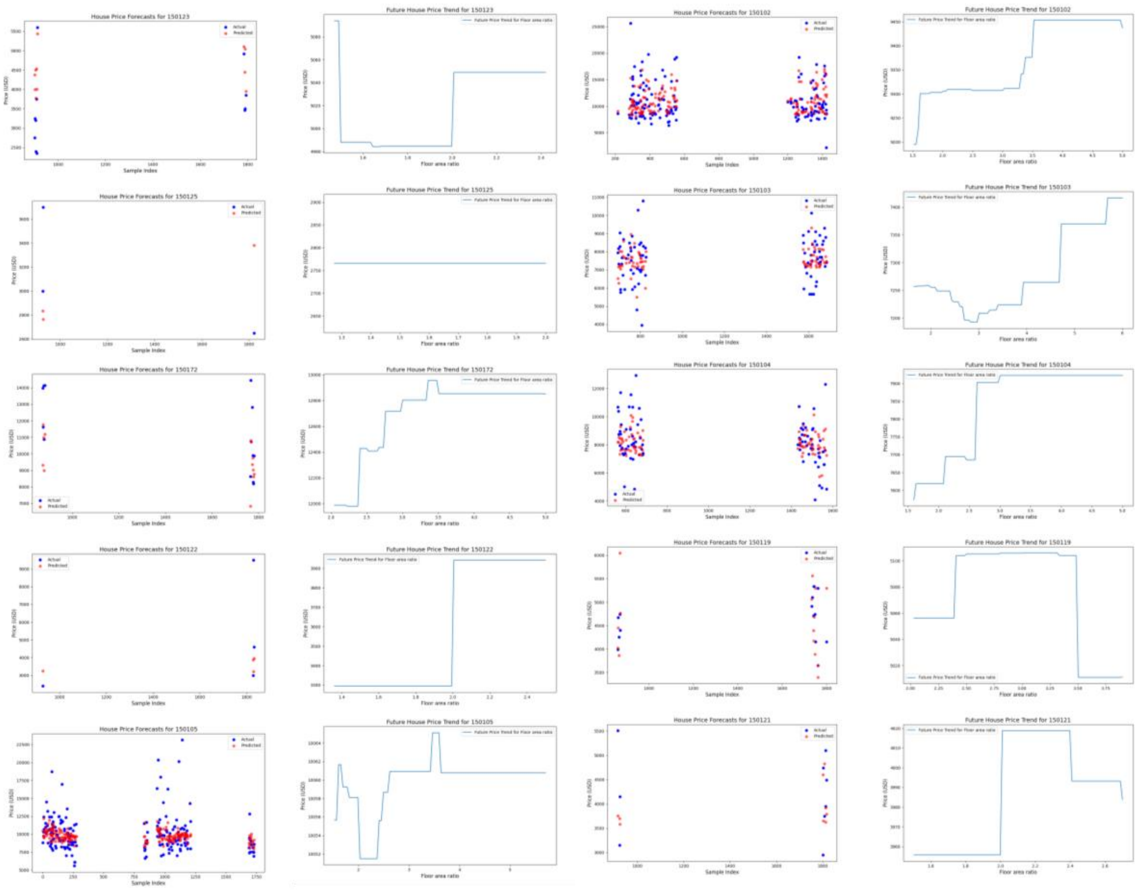

Figure 6 Future Housing Price Prediction Results for Hohhot