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Article

Simulation of the Urban Jobs–Housing Location Selection and Spatial Relationship Using a Multi-Agent Approach

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Abstract: The jobs–housing balance concerns the spatial relationship between the number of jobs and housing units within a given geographical area. Due to the separation of jobs and housing, spatial dislocations have occurred in large cities, which have resulted in a significant increase in commuting distance and time. These changes have ultimately led to an increase in pressure on urban traffic, and the formation of tidal traffic. In this study we introduce a multi-agent approach to examine the jobs–housing relationship under the maximum location utility of agents. The jobs/housing ratio measures the balance of the of jobs–housing relationship, as well as comparing and analyzing jobs–housing separation in Beijing by district, county, and street scales. An agent-based model was proposed to simulate spatial location selection behavior of agents by considering environmental and economical influences on residential decisions of individuals. Results show that the jobs–housing relationship imbalance in Beijing has been mainly aggravated due to rapid population growth in the 6th Ring Road. An imbalance in the jobs–housing relationship has arisen due to a mismatch with the number of households available compared to the number of jobs; the surrounding urban areas cannot provide the required volume of housing to accommodate the increase in workers. Six sets of experiments were established to examine resident agents and enterprise agents. Differences in resident agents' income level had a greater impact on residential location decision-making, and housing price was the primary factor affecting the decision of residents to choose their residential location. The spatial distribution of jobs and housing in Beijing under the maximization of micro-agent location utility was obtained in this study. Results indicated that the imbalance in the jobs¬-housing relationship in central Beijing has improved and, compared with the initial distributions, the number of jobs–housing balance areas in Beijing has increased.

Keywords: jobs–housing relationship; agent-based modeling; location decision-making; Beijing

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1. Introduction

Car dependence, traffic congestion, long commuting distance, and associated air pollution and Greenhouse Gas (GHG) emissions in metropolises have become a serious global area of concern [1,2]. At the same time, rapid urbanization and population growth, rising incomes, increased car ownership, land use changes, and weak traffic management have resulted in an increase in commuting time in cities [3–6]. In order to deal with these issues, different counter measures have been proposed. The jobs–housing balance has been considered by planners, researchers, and policy makers to be the most effective counter measure [7–14]. This balance reflects the distribution of both residential and employment opportunities within an urban area, being the "spatial relation between the number of jobs and housing units within a given area" [15]. The jobs–housing balance can also be used as a ratio to measure jobs and housing opportunities via spatial units, such as Traffic Analysis Zones (TAZ) [16,17]. If a spatial unit achieves a certain ratio of jobs and housing opportunities, it is in a "quantitative balance"; a "quantitative imbalance" is achieved when this is not the case [1]. More generally, commuting time can be a proxy for the jobs–housing balance. An imbalance is suggested whether workers live far (in either space or time) from opportunities or not. The resulting jobs–housing imbalance (JHI) has been analyzed theoretically and empirically by urban economists, geographers, and planners, and three issues have been identified: (i) longer commuting distance—JHI can induce a longer total commuting, e.g., "wasteful" commuting; (ii) single-occupant commuting—JHI increases the rate of solo-driving trips; and (iii) social exclusion—JHI influences commuting of both workers and job-seekers who do not have their own cars. As these issues can be related to traffic congestion and deteriorating air quality, the jobs–housing imbalance has been examined as solutions are sought to address these social and environmental related problems [18].

Empirical studies have quantified the spatial relationship between jobs and housing using different geographical methods. The ratio of the number of jobs to the number of working people within a given region is probably one of the most convenient, simple, and prevalent measurements used. This measurement has previously been defined by Boussauw et al. [19,20]. Currently, different ratios reflecting a suitable balance of jobs to housing have been proposed. Margolis [16] used a ratio of 0.75–1.25 for the community level; Cervero [21] proposed a reasonable ceiling of 1.5 at the nationwide level; and Peng [15], based on traffic analysis zones, suggested a range of 1.2–2.8. Other measurements include theoretical minimum/maximum commuting distance, excess commuting, commuting potential, and observed or reported individual-level or aggregated commuting distance [22–26]. Cervero [9] emphasized that the balance between an ideal job and housing is an abstract concept that is difficult to measure, and it has long been thought that people tend to gather in places where there are more jobs; residents therefore believe that jobs are more likely to be found in neighborhoods where housing is concentrated [27], constituting an analytic parameter for these measurements. Boussauw et al. [19] found that that the spatial proximity represents, for example, the jobs–housing balance or the number of potentially accessible jobs, and it can be used as non-linear predictors for reported commuting distances. This finding was confirmed by Horner who thought that the balance of jobs–housing, excess commuting distance, and job accessibility were interrelated in urban areas [28,29]. At the same time, a number of investigations were undertaken on spatial models of the interactions of jobs and housing site selection. For example, Hincks and Wong [30] empirically examined the spatial process of housing and the interaction with the labor market using a case study in north west England, and Sener et al. [31] analyzed housing choices using a generalized spatially correlated logit model based on survey data from San Francisco, USA. These studies adopted traditional 'top-down' methods, which are limited in reflecting and expounding individual behavior leading to spatial population dynamics [32–37]. Due to spatial population dynamics based on individuals looking for work and choosing where to live, it is therefore hard to simulate complicated individual behavior using these models [38].

The urban ecosystem is complex, involving multiple factors such as population, economy, transportation, and the environment. There are complex inter-relationships between internal factors that influence and/or restrict each other. Among many simulation methods of complex systems, agent-based models (ABMs) are an important tool to simulate complex systems which have increased in popularity [39–42]. ABMs utilize a 'bottom-up' approach to simulate the complex behaviors of interacting individual agents [43–46]. These models are advantages by dynamically connecting social and economic factors, and simulating the process of individual decision making and interactions [47,48]. ABMs can describe the behavior of individual agents, which can be governments, the environment, individuals or enterprises, depending on the specific conditions. ABMs also often focus on decision-making processes, such as which objectives to examine and decision rules. Therefore, ABM approaches can potentially be used in modeling spatial dynamics evolving from individual behavior [49–51]. Liu and Ye [49] explored the evolvement of firms' environmental behavior and influencing factors using an adaptive agent-based modeling approach, and the results revealed that firms' environmental behavior followed this evolvement path: defensive behavior, preventive behavior, and enthusiastic behavior using empirical data from 167 firms in China. Adrestani et al. [50] proposed an agent-based model of residential segregation, which contributes to the same realistic modelling direction for analyzing the effect of residential location decision of individual residents on the spatial ethnic mosaic pattern of the central Auckland region (New Zealand metropolis). Yue et al. [51] built a simulation model of the energy-saving behavior of urban residents using agent-based modeling, and analyzed the subsequent effect of behavioral outcomes due to the short- and long-term influence of energy-saving behavior and intentions under different policy situations. Therefore, agent-based models (ABMs) are ideally suited for simulating individual behavior differences in a complex system.

With the large-scale agglomeration of populations in some large cities, and the rapid expansion of urban space, serious large-scale urban diseases such as unbalanced occupations, traffic congestion, and environmental pollution have emerged, which have severely restricted the sustainable development of the region and the construction of ecological civilization. As a typical single-center layout city in China, Beijing has a large-scale agglomeration of urban population and a rapid expansion of urban space. Serious urban issues, such as jobs–housing separation (JHS), traffic congestion, and environmental pollution, have significantly restricted the sustainable development of Beijing. Therefore, in order for Beijing to successfully develop in the post-Olympic era, solutions to solve urban traffic congestion, to relieve the current situation of JHS, and to shorten commuting time and distance are urgently needed. In this study, we propose an ABM to simulate spatial location selection behavior of agents by considering the impact of environment and economy factors on employment behavior and the residential decisions of individuals. This approach will also simulate residential decisions made by individuals. The difference of resident agents' income level has a significant impact on residential location decision-making, and housing price is the primary factor affecting the decision of residents to choose their residential location. Based on the simulation results of location selection of agents, the density simulation results of resident population and employment population on a street level in Beijing, as spatial units, will be obtained. Using this approach, the spatial distribution of jobs–housing in Beijing under the maximization of the micro-agent location utility will also be identified. The spatial relationship distribution of jobs–housing in Beijing and the imbalance of the jobs–housing relationship in the central city has improved. Compared with the initial distribution, the number of jobs–housing balance areas in Beijing has increased. Our aim is to simulate the adaptive behavior of each agent on the jobs–housing environment by constructing the location selection method framework of agents. Moreover, we used the modular and hierarchical modelling characteristics of the Anylogic platform to analyze the urban jobs–housing location selection and spatial relationship. Our study is an exploration of a complex multi-agent system model on the jobs–housing relationship, and results provide suggestions for improving spatial relationships of jobs and housing to achieve a balance. At the same time, our study has a certain theoretical and practical significance to scientifically formulate policy measures for improving the jobs–housing relationship and green low-carbon transportation development strategies.

2. Materials and Methodology

2.1. Study Area

In this study, Beijing was selected as a case-study, and a complex system model was developed to support intelligent simulation of the region jobs–housing relationship. Beijing is the capital of China and one of the most developed metropolitan areas. Beijing is located on the North China Plain, covering an area of 16,411 km^2; this city has a gradual altitude decline from the northwest to the southeast. Beijing administers 16 districts and two counties, with Tiananmen Square as the city center (Figure 1). The permanent population of Beijing increased from 15.4 to 21.54 million between 2005 and 2018, of which approximately 86.5% are situated in urban areas [52]. GDP in Beijing increased from 714.1 to 3032.0 billion CNY over the same period [53]. Beijing's serious commuting problems have been frequently reported in recent years. Data from the Beijing Third (2005) and Fifth (2014) Travel Surveys showed that in the 10-year period between 2005 and 2014, the average commuting time by bus and subway increased by 40.9 and 38.3 min, respectively [54,55]. Average one-way commuting time in Beijing has reached 52.9 minutes, ranked as the highest in China. Jobs–housing separation is considered a main reason to increase the commuting burden of Beijing's residents. The phenomenon of jobs–housing separation and spatial dislocations have occurred in cities, increasing the pressure on urban traffic and forming tidal traffic.

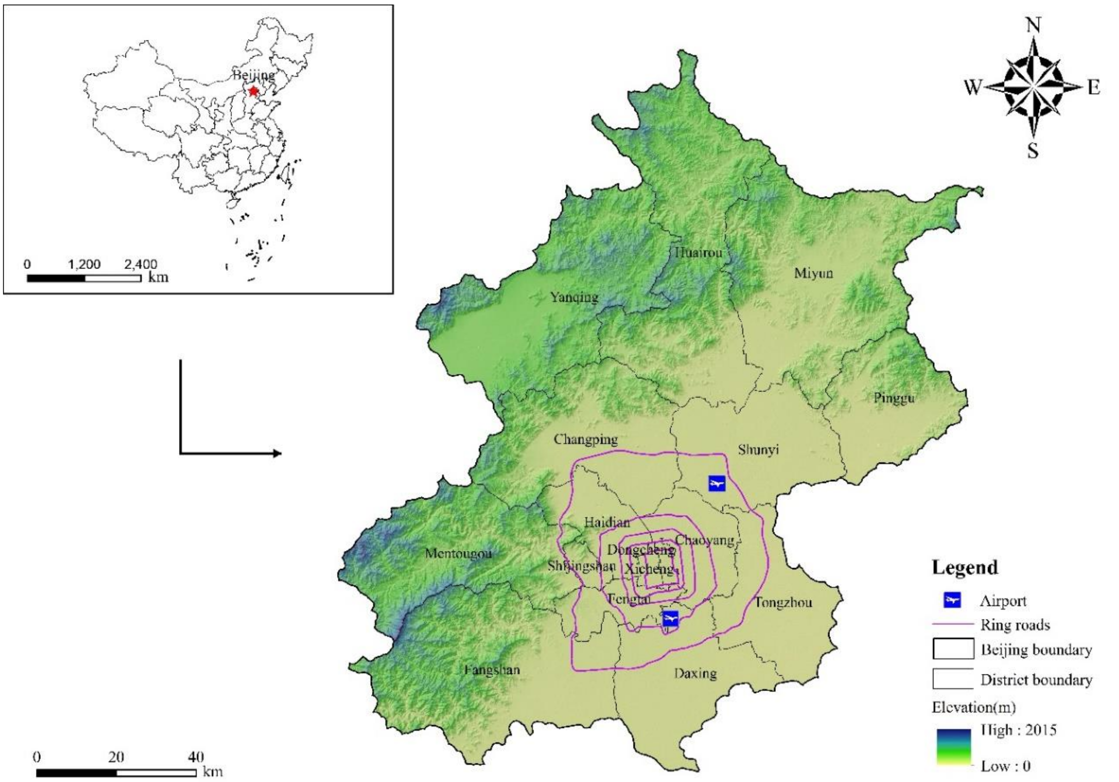

Figure 1. Location of Beijing in China.

2.2. Methodology

2.2.1. Analysis Method of the Urban Jobs–Housing Relationship

A region with a balanced jobs–housing relationship is relatively independent and self-sufficient, providing a stable environment where people can undertake a range of activities, such as employment, housing, entertainment, and leisure activities. The space mismatch hypothesis, proposed in 1968 by Kain [56], expounded the spatial mismatch between the number and the quality of jobs and residences, providing clarity on the concept of the job–housing relations balance. Generally, the job–housing relation balance has two levels of meaning: (i) the balance of quantity—indicating that the number of jobs in a certain area is equal to the number of living units; and (ii) the balance of quality—where job skills are matched with employment opportunities. The average income of residents is also matched with house price.

In order to measure the balance of the number of jobs–housing relationships, urban jobs–housing relationships are generally measured using the jobs/housing ratio (JHR). This ratio assumes that in a certain area, one member of one household on average is employed, and each household has its own residence. When $JHR = 1$, the job–housing relationship in the region is in balance; when $JHR > 1$, there is not enough housing in the area to satisfy demand, resulting in people living away from the area; and when $JHR < 1$, housing supply is greater than demand. When JHR is both <1 and >1, the region is in an imbalanced state in relation to jobs and housing. The equation for the jobs–housing ratio is:

$$JHR_i = \frac{J_i}{R_i} \tag{1}$$

where JHR_i is the jobs–housing ratio of the ith street, J_i is the number of jobs for the ith street, and R_i is the total number of residents of the ith street.

Data required for analysis was readily available, it has strong operability, and it can be calculated and analyzed on the basis of existing data. However, due to the lack of a standard value range that uses JHR to determine whether the regional jobs–housing relationship is balanced, our study was partially based on previous analysis by Margolis [16] and Wang et al. [57]. By considering the current ratio of the number of households and the number of jobs in Beijing, the JHR value (0.75–1.25) is considered to be in a balanced state, and the area beyond Beijing is considered to be unbalanced. The jobs–housing imbalance (JHI) presented in this study is a concept that is relative to the jobs–housing balance, mainly referring to the jobs–housing relation in the region when the number of housing provided to employees in the region is seriously mismatched with the number of jobs. From the perspective of the quantitative balance, the JHR calculation can reflect the degree of jobs–housing imbalance/balance in the region to a certain extent.

2.2.2. Behavior Setting of Agents

Resident Agents

The resident agent examined in this analysis enabled agents to select their own residence and workplace according to the maximum location benefit. Many factors are considered to affect the location decision of residents, including some internal factors, such as economic income [58,59] and family structure [60–63]. Agents with higher incomes generally have more choices. There are also some external factors that will affect the decision-making of the agent, such as the natural environment [64], infrastructure [65,66], and house prices [67–70]. The natural environment and infrastructure conditions around locations are also an important factor considered by the agent. The agent usually prefers the location with beautiful surroundings and convenient facilities. However, due to significant house price differences in the city, economic income can directly affect residents' decisions on residential location [69]. With consideration of data from the sixth nationwide population census data, we divided the average income level of urban households into five equal parts (Table 1). House price and living environment are important factors affecting the spatial location choice of resident agents, with house price directly determining the purchase intention of the residents. Resident agents with different income levels have different sensitivity to house price. In addition, different types of resident agents also have different preferences for the living environment, including nature, transportation, education, medical treatment, and commerce. As a result, the spatial location choice behavior of residents is closely related to the spatial morphological characteristics of various living infrastructures. By considering the availability and quantification of data, we selected house price, distance from green space, distance from water bodies, distance from ring roads, distance from first-class roads, distance from subway stations, distance from hospitals, density of bus stations, commercial density, density of primary schools and density of middle schools as the main external factors affecting residents' spatial choice behavior. The original vector data of these factors were spatially analyzed using ArcGIS software (Figure A1). A resident agent chooses an optimal residential location according to the maximum location efficiency. The behavior rules of the resident agents are shown in Figure A2. In this study, we chose income and family structure as indicators to reflect the characteristics of the resident agents' own attributes.

Table 1. The division of the resident agents.

Code	Income Level	Proportion
P1	High income	0.178
P2	Medium and high income	0.202
P3	Medium income	0.147
P4	Medium and low income	0.285
P5	Low income	0.188

In the study, we used an urban job–housing space decision-making model to select resident agents' residential location. Firstly, 6000 sample points were randomly generated as the analysis sample of resident agents (Figure A3). The spatial preference probability of each type of resident agents was then calculated and the results were tested (Figures A4 and A5).

Spatial decision behavior simulation method framework for resident agents is shown in Figure 2. Firstly, we converted the basic vector data (spatial data) into ASCII format in ArcGIS based on the framework of the method; Then we input the ASCII format data into Anylogic platform and based on the behavior rules of Agents (Figures A2 and A8), the simulation results are obtained by running in Anylogic platform, the results' data are also in ASCII format. Finally, the data results of ASCII format are input into ArcGIS platform, and the simulation results are displayed and analyzed. Assuming that the income level of resident agents is I, the maximum utility function under income constraints is [71]:

$$\begin{array}{c} \max U = \max u(A,B) = A^a \times B^b; \quad a,b > 0 \\ s.t \quad I = WN = p_A A + p_B B + C \end{array} \tag{2}$$

where p_A and p_B are different product prices, A and B are quantities of products, and C is commuting cost.

When C= 0, the optimal consumption decision is:

$$\begin{cases} p_A * A = \frac{a}{a+b} I \\ p_B * B = \frac{b}{a+b} I \end{cases} \tag{3}$$

when $a_1 I = \frac{a}{a+b}, a_2 = \frac{b}{a+b}$, so $a_1 + a_2 = 1$.

Furthermore, the resident agents degree of satisfaction with current location is calculated. The fixed space location of housing determines its value and use value. The housing price is divided into two parts (the basic price and the environmental price of housing):

$$P_h = P_{h1} + P_{h2} \tag{4}$$

where P_h is the total housing price, P_{h1} is the basic price of housing, and P_{h2} is the environmental price of housing.

In general, resident agents are keen to pursue ideal housing prices and live in a better environment, and their investment depends entirely on the preferences of consumer portfolio decisions.

When resident agents have Cobb-Douglas preferences for the basic and environmental prices of housing, the resident agents optimal consumption decision is: $a_1 I$ for basic housing prices, $a_2 I$ for environmental housing prices.

Under a certain income level, the residential pressure of resident agents on their residential location is as follows:

$$Y(A,T) = \beta_{h1}|a_1 * I(A,T) - P_{h1}(A,T)| + \beta_{h2}|a_2 * I(A,T)| - E_A * \overline{P}_{h2} \tag{5}$$

where $Y(A,T)$ is residential pressure of resident agents in location A at T-time, β_{h1} and β_{h2} are the weights of residential pressure caused by basic prices and environmental prices of housing, $I(A,T)$ is the income level of resident agents in location A at T-time, $P_{h1}(A,T)$

is the basic housing price of resident agents, and E_A is the habitability index of resident agent's current residence location. The expression of the index is as follows:

$$E_A = \mu_1 * P_{ta} + \mu_2 * P_{col} + \mu_3 * P_{goe} \tag{6}$$

where μ_i is the preference coefficient (preference for transportation, life and environment, respectively), P_{ta} is traffic accessibility, P_{col} is convenience of life, and P_{goe} is the gracefulness of the environment.

The formulas for calculating traffic accessibility (P_{jt}), living convenience (P_{sh}) and environmental gracefulness (P_{hj}) in Equation (6) are as follows:

$$P_{jt} = \mathrm{k}_1 e^{-\alpha_1 D_d} + \mathrm{k}_2 e^{-\alpha_2 D_t} + \mathrm{k}_3 e^{-\alpha_3 D_h} \tag{7}$$

$$P_{sh} = \varepsilon_1 e^{-\lambda_1 D_x} + \varepsilon_2 e^{-\lambda_2 D_y} + \varepsilon_3 e^{-\lambda_3 D_s} \tag{8}$$

$$P_{hj} = \eta_1 e^{-\theta_1 D_r} + \eta_2 \sum_{i=1}^{n} \frac{N}{(2r+1)^2} \tag{9}$$

where k_i is the spatial attenuation coefficient of trunk road, subway, and ring road; ε_i is the distance of school, hospital, and business center; α_i and θ_i are weights of each factor; λ_i is distance attenuation coefficient of each factor; D_r is distance to water body; N is number of green space units in adjacent units; and n is neighborhood radius.

$\overline{P}_{h2}$ is the average unit environmental value in residential area, and the formula is:

$$\overline{P}_{h2} = \frac{\sum_{i=1}^{m} a_2 I(A,T)}{\sum_{i=1}^{m} E_{Ai}} \tag{10}$$

where i is the number of agents in the resident agents neighborhood.

Then the probability $P(A,T)$ of selecting candidate residential location at T time is:

$$P(A,T) = 1 - (\partial_1 + e^{-\partial_2 Y(A,T)}) \tag{11}$$

where $P(A,T)$ is the probability of resident agents choosing a candidate residential location at T time, and ∂_i is a constant.

Enterprise Agents

Enterprise agents studied in this analysis selected their own production and operation site according to the maximum location benefit. Many factors are considered to affect the location decision of enterprises, including some internal factors, such as the nature, scale, and self-organization structure of the enterprise [71–74]. There are also some external factors that will affect decision-making of enterprise agents, such as land price [75,76], infrastructure [77–79], and population concentration [80–83]. After considering enterprise agents' data availability and quantification, we chose house price, GDP, population density, commercial density, distance from industrial areas, and distance from science parks as the main external factors affecting the spatial choice behavior of enterprises (Figure A6). ArcGIS was then used to analyze the original vector data of these factors in space. At the same time, different influence areas were divided according to distance and density, and corresponding distance and density load raster layers were generated. GDP, population density, the number of migrants, and the proportion of tertiary industry were social and economic factors. GDP and population density were rasterized data obtained by spatial interpolation of ArcGIS based on township point data, while the number of migrants and the tertiary industry's weighted data were based on district and county surface data. This data was spatially rasterized to achieve data spatialization. In this study we divided enterprise agents into four main types based on the point-based data (Table 2 and Figure A7). In order to maximize the utility of enterprise agents, it was necessary to judge the satisfaction of the enterprise to the location. The behavior rules of the enterprise agents are shown in Figure A8.

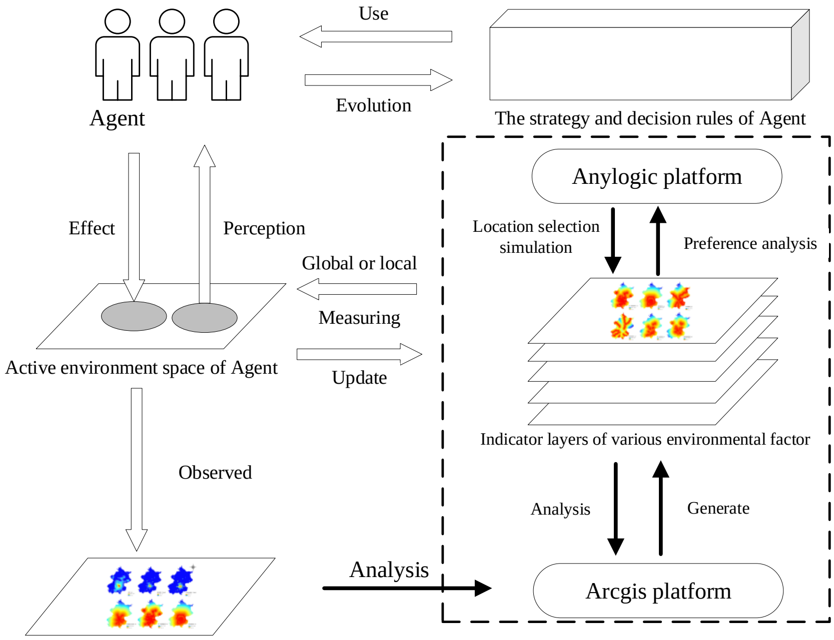

Figure 2. Spatial decision behavior simulation method framework for resident agents.

Table 2. The division of enterprise agents.

Code	Agent Type	Proportion
q1	Industrial Manufacturing (IM)	0.188
q2	Social Service (SS)	0.627
q3	Financial Services (FS)	0.124
q4	Technological Innovation (TI)	0.061

The logical regression model is a common method used in the simulation of location selection. In this study, we constructed a general least squares global model to quantify the enterprise agent's spatial choice preference. Firstly, the research area was divided into several grids, and the location selection of agents was expressed using binary variables. The relationship between Y (dependent variable) and X (independent variable) was also given. The estimated values of model parameters were calculated and tested using the receiver operating characteristic (ROC) curve. The spatial preference probability of each type of enterprise agent was calculated and the results were tested (Figures A9 and A10).

The formula is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + e \tag{12}$$

$$Q = \sum_{n=1}^{n} e^2 = \sum_{n=1}^{n} (Y - \beta_0 - \beta_1 X_1 - \cdots - \beta_n X_n)^2 \tag{13}$$

where Y is the value of binary variables selected by Agents location; X_n is the nth external factor; β_0 is the constant term; β_n is the regression coefficient of the nth external factor; e is the error; and Q is the sum of squares of errors.

Taking Q as the parameter function to be evaluated, the partial derivative of Q is obtained. When the partial derivative is 0, the point is the function extreme point. The formula is as follows:

$$\begin{cases} \frac{\partial Q}{\partial \beta_0} = 2\sum_{n=1}^{n} (Y - \beta_0 - \beta_1 X_1 - \cdots - \beta_n X_n)(-1) = 0 \\ \vdots \\ \frac{\partial Q}{\partial \beta_n} = 2\sum_{n=1}^{n} (Y - \beta_0 - \beta_1 X_1 - \cdots - \beta_n X_n)(-X_n) = 0 \end{cases} \quad (14)$$

2.3. Data Sources

Data sources used in this study mainly included: (1) Macro statistical data: part of the economic and demographic data derived from the Beijing Statistical Yearbook [53]. Demographic data was collated from the sixth nationwide population census data and the street population data (2014), and employment data was collected from the second and third nationwide economic census data (2008 and 2014). (2) Geospatial data: spatial distribution data, including housing price, green space, water body, ring roads, first-class roads, subway stations, bus stations, hospitals, schools, business centers, industrial zones, and science parks in Beijing were derived from the National Earth System Science Data Center, Data Center for Resources and Environmental Sciences of Chinese Academy of Sciences, Geospatial Data Cloud Platform. All spatial data in this study were 500 × 500 m raster data.

3. Results and Discussion

3.1. Analysis of the Urban Jobs–Housing Relationship

Analysis of the status of the JHS in Beijing (2010 and 2014) on district and county scales indicated that the jobs–housing relationship was in a balanced state in 2010. The number of jobs in the whole city was matched with the number of residential buildings. However, by 2014 the status of the jobs–housing relationship had intensified (Table 3). Most areas in the 6th Ring Road could not provide the number of residential buildings required for the number of jobs, leading to an imbalance in the jobs–housing relationship.

Table 3. Jobs/housing ratio (JHR) results in various regions of Beijing.

Region	2010		2014	
	JHR	Status	JHR	Status
The whole city	1.20	Balance	1.30	Imbalance
Dongcheng	2.09	Imbalance	2.52	Imbalance
Xicheng	2.22	Imbalance	2.32	Imbalance
Chaoyang	2.11	Imbalance	1.37	Imbalance
Fengtai	1.00	Balance	0.97	Balance
Shijingshan	0.89	Balance	1.24	Balance
Haidian	1.89	Imbalance	1.94	Imbalance
Fangshan	0.62	Imbalance	0.72	Imbalance
Tongzhou	0.70	Imbalance	0.73	Imbalance
Shunyi	1.37	Imbalance	1.54	Imbalance
Changping	0.59	Imbalance	0.67	Imbalance
Daxing	0.71	Imbalance	0.74	Imbalance
Mentougou	0.80	Balance	0.86	Balance
Huairou	0.83	Balance	1.04	Balance
Pinggu	0.74	Imbalance	0.88	Balance
Miyun	0.68	Imbalance	0.83	Balance
Yanqing	0.56	Imbalance	0.81	Balance

At the same time, within the urban area of Beijing (within the 5th Ring Road), a serious imbalance in the jobs–housing relationship was caused by the over-concentration of industry and a lack of housing supply. Results indicated that suburban urbanization affected the area situated between the 5th and 6th Ring Road (termed the suburbs). Therefore, due to the increase in industrial development and a lack of housing construction, or the construction of large-scale residential areas, a serious imbalance in the jobs–housing relationship was formed in this region.

Results from district and county scales (Figure 3) indicate that the jobs–housing relationship of the central urban area (Dongcheng and Xicheng) was still in an obvious state of imbalance. This area greatly exceeds the limit, indicating that it was impossible to provide accommodation for employed people in the area. This lack of housing resulted in workers having to live in other external areas. Results for Chaoyang district and Haidian district in 2014, compared with results in 2010, recorded contrary findings for the imbalance of the jobs–housing relationship. Although the imbalance in the jobs–housing relationship eased by 2014 in the Chaoyang district, the imbalance in the relationship was still poor. Results for Haidian district recorded the imbalance to have intensified over the same time period. The five districts and counties of the urban development new district are in an unbalanced state of jobs–housing relationship and, compared to 2010, the status of the imbalances have intensified. The five districts and counties in the ecological conservation development zone are in a balanced state of jobs–housing relationship. Compared with 2010, the jobs–housing relationship between the three regions of Yanqing County, Miyun County, and Pinggu District has eased.

In order to further analyze the jobs–housing relationship on street and township scales in each district and county, the jobs–housing ratio for streets and townships in each district and county were calculated using relevant population and economic data in Beijing in 2010 and 2014 (Figure 4). Results for the top ten balanced and unbalanced streets in Beijing (Table 4) indicated that parks and historical and traditional cultural areas of Nanyuan, Beiyuan, Tiantan, Tsinghua Park, and Yushu Street in the 6th Ring Road of Beijing were all in a relatively balanced state for the jobs–housing relationship. Due to a lack of sufficient jobs and some residents having to choose employment in other external areas, some larger residential areas in Beijing (for example Tiantongyuan, Huilongguan, and Huoying) recorded an obvious imbalance in the jobs–housing relationship [57]. Streets in Haidian, Dongzhimen, and Jianwai were also found to be in an unbalanced state, mainly due to these areas not being able to provide enough housing for workers, with some people having to live outside the area. Due to the close proximity to the central city, most of the districts (streets) such as Chaoyang, Haidian, and Fengtai formed regional industrial-intensive areas, which have subsequently become the main employment areas. As these areas cannot provide enough living space for employees, they are in an unbalanced position. As these areas, combined with the central urban area, constitute the current main urban area of Beijing, they indicate a state of imbalance for the main urban areas of Beijing for the jobs–housing relationship. Although these areas have become the core area of the urban economy due to their good industrial development advantage, the limited size of this area has resulted in predominantly economic development. As the limited land resources are used more for economic development, land available for new housing is insufficient, resulting in the inability to provide sufficient housing in the region, therefore resulting in a mismatch between the number of housing and the number of jobs in the region.

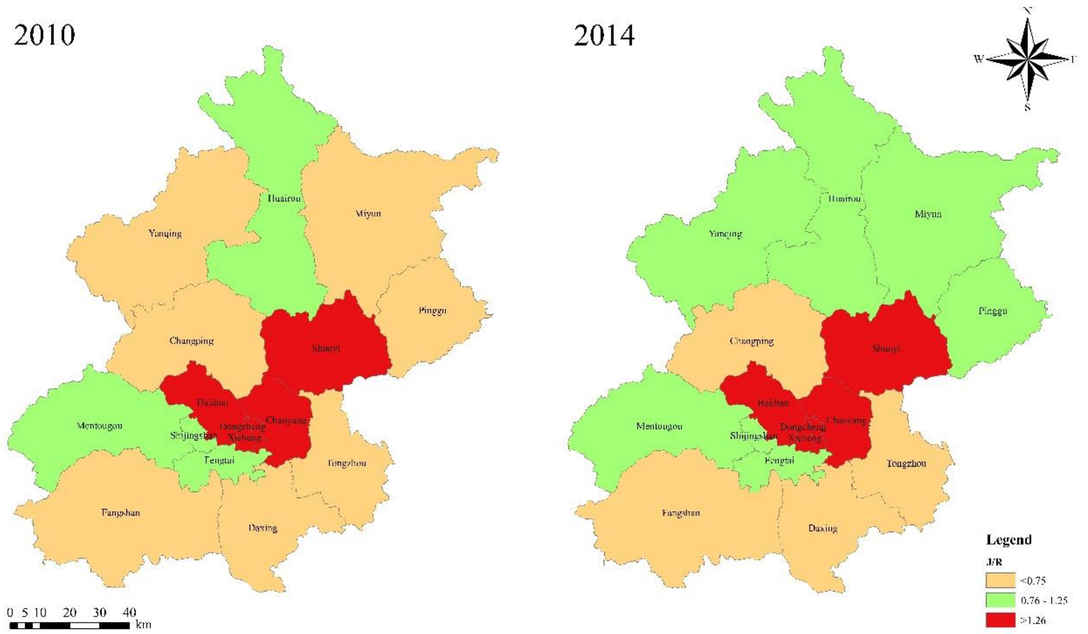

Figure 3. Distribution of JHR from the district and county scales in Beijing in 2010 and 2014.

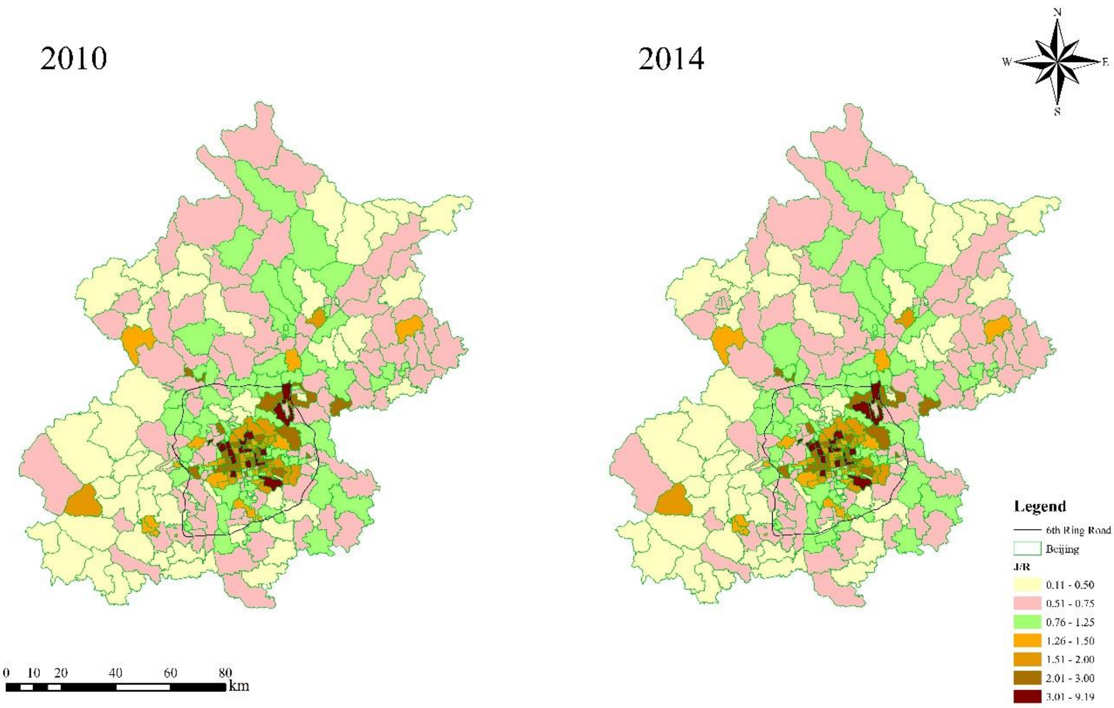

Figure 4. Distribution of JHR from the street and township scales in Beijing in 2010 and 2014.

3.2. Simulation Results of Location Selection for Various Agents

3.2.1. Results of Location Selection for Resident Agents

In this study, six groups of simulation experiments were established, and it was assumed that agents could obtain the same information resources. Location selection simulation results of residents' agents (Figure 5) indicated that '1' represents the selected area and '0' represents the unselected area. During the operation of the model (Figures 5 and 6), resident agents gradually moved for the maximum location efficiency and locate the optimal location.

Table 4. The top of ten streets with a JHR balance and imbalance in Beijing.

Code	Jobs–Housing Balance		Jobs–Housing Imbalance	
	Streets	**JHR**	**Streets**	**JHR**
1	Nanyuan	0.93	Dongxiaokou	0.15
2	Guangning	0.96	Huoying	0.15
3	Beiyuan	0.97	Tiantongyuan	0.15
4	Sanjianfang	0.98	Beiqijia	0.27
5	Qinghe	0.99	Huilongguan	0.32
6	Chunshu	1.03	Haidian	4.54
7	Tiantan	1.06	Dongzhimen	4.67
8	Qinghuayuan	1.08	Zhanlanlu	7.37
9	Wenquan	1.10	Maizidian	8.41
10	Dongfeng	1.12	Jianwai	9.19

According to the location selection simulation results of agents (Figures 5 and 6), the location distribution of resident agents gradually changed from dispersion type to aggregation type (T1–T6), gradually forming a relatively concentrated population spatial pattern. When T = 5, the surrounding area of the central city for agents tended to be stable state. At the same time, we simulated the resident agent's location selection utility of different experiments [71]. The results showed that the location utility was optimal under T5.

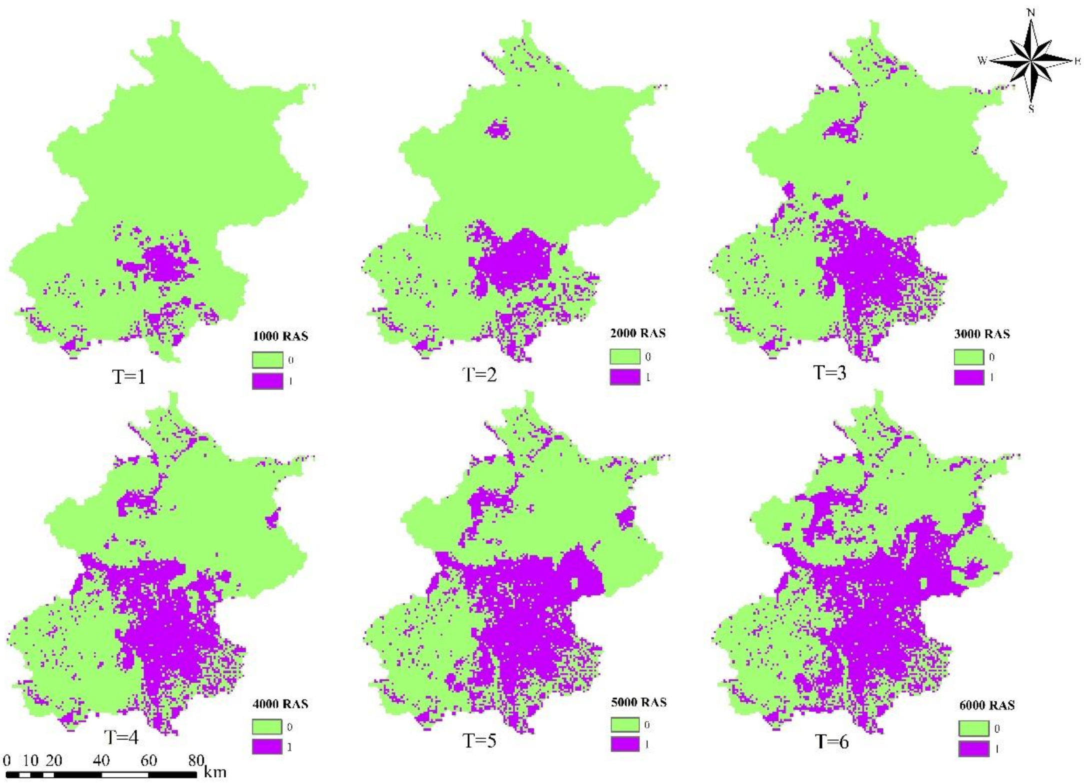

Figure 5. Location selection simulation results of resident agents.

Furthermore, in this study we also simulated and analyzed the impact of income level differences on the location choice of resident agents. Simulation results indicated that resident agents with middle and high incomes were mainly concentrated in the urban area and areas with a better environment; low-income residents were mainly concentrated in the new city area and the urban development new area (Figure 7). This finding indicates that the difference of resident agents' income level has a greater impact on residential location decision-making, and house price is the primary factor affecting the decision of residents to choose their residential location. Although the model simulation results are constantly evolving in each grid unit, the results are generally stable, and the simulation results are similar to the real residential spatial location distribution pattern that reflects reality.

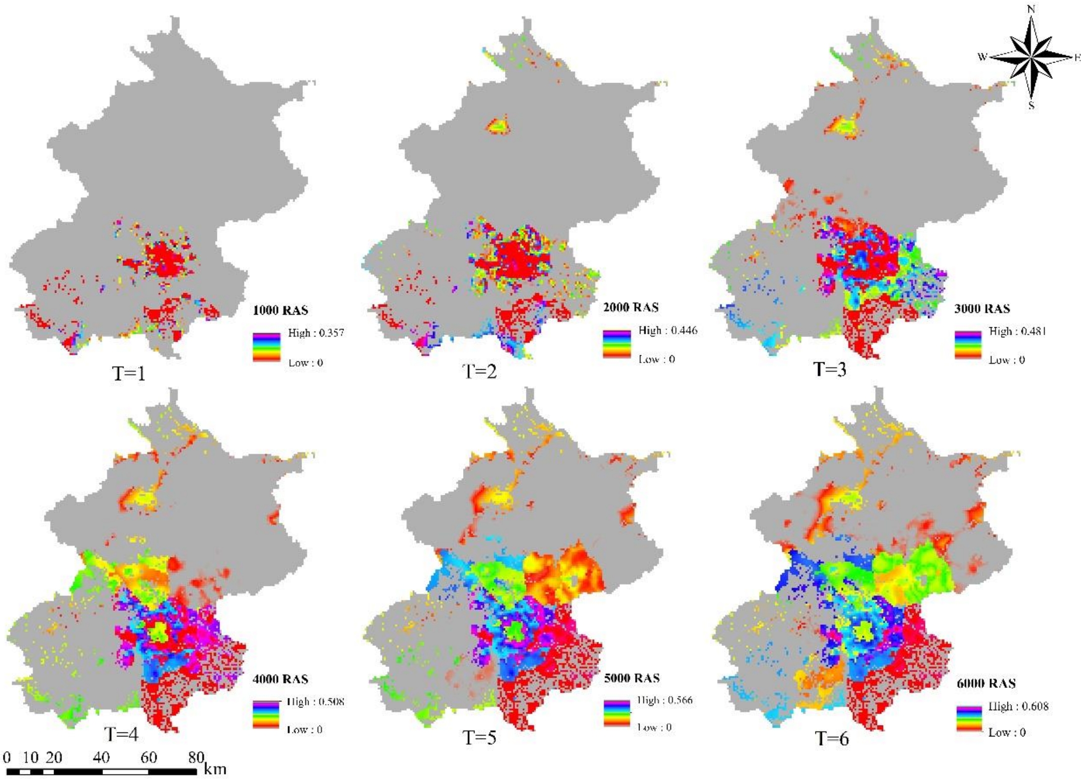

Figure 6. Results of spatial selection probability for resident agents.

3.2.2. Results of Location Selection for Enterprise Agents

In this study, we established six sets of experiments (Q1–Q6). It was assumed that agents could obtain the same information resources in a certain area and make location decisions according to their own attributes. Location selection simulation results of enterprise agents (Figure 8) recorded values of '1' for selected areas of enterprise agents and a '0' for unselected areas. Probability results for selection of the spatial location were also calculated (Figure 9). During model operation (Figures 8 and 9), enterprise agents gradually moved towards the maximum location efficiency, being located in optimal locations.

According to the location selection simulation results of enterprise agents (Figures 8 and 9), the location distribution of enterprise agents gradually changed from a dispersion type to an aggregation type (Q1–Q6); a relatively concentrated employment space pattern was gradually formed. When Q = 5, the surrounding area of the central urban area for enterprise agents tended to be stable state. When Q = 6, the process of location selection for enterprise agents was slow, and the change of agents' behavior was small. After comprehensive consideration, the optimal simulation result was identified as Q = 5.

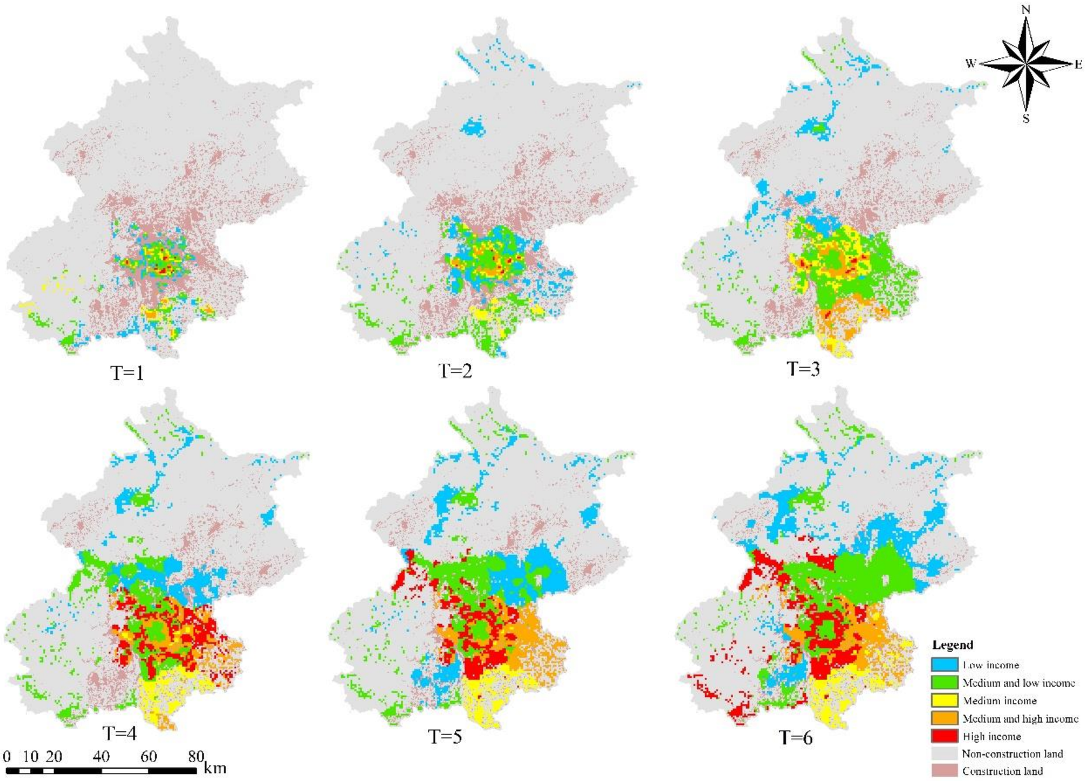

Figure 7. Spatial location distribution simulation of different types of resident agents.

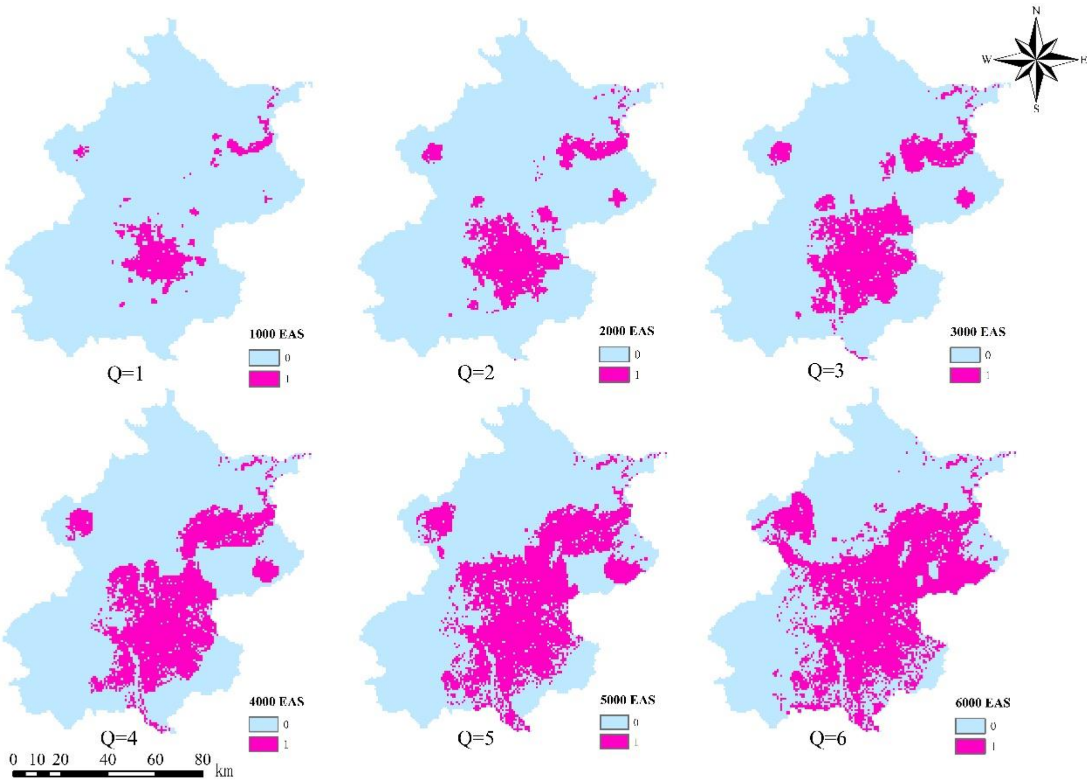

Figure 8. Location selection simulation results of enterprise agents.

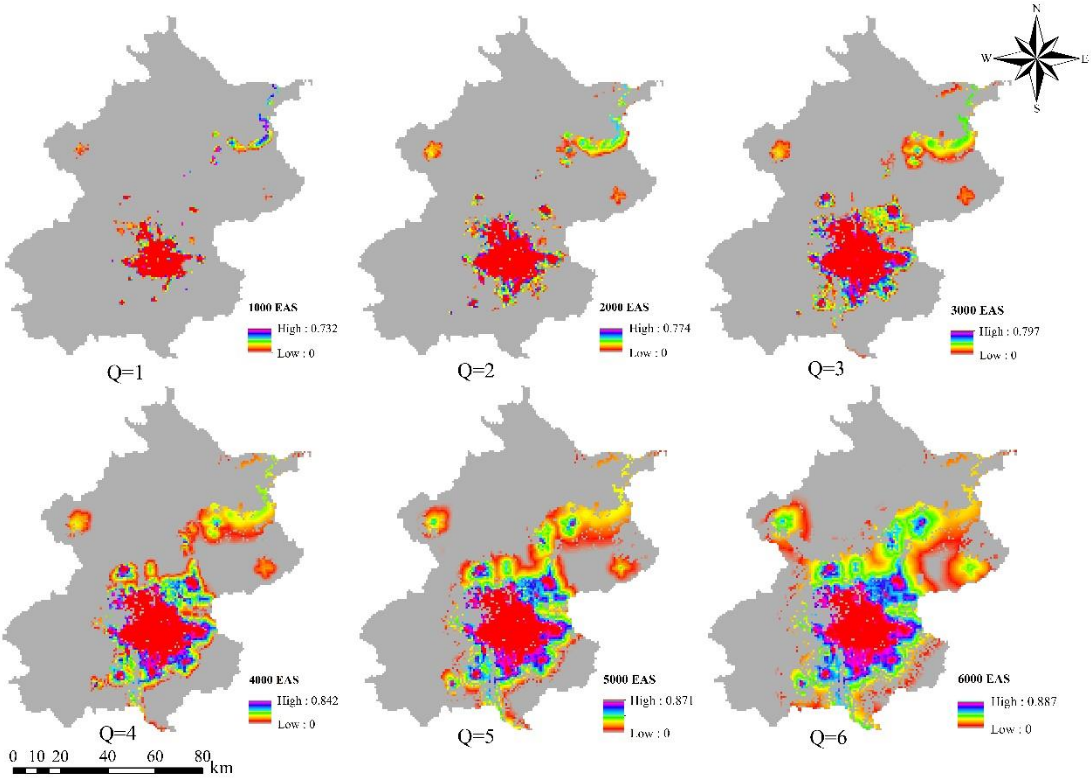

Figure 9. Spatial selection probability results for enterprise agents.

Furthermore, in this study we also simulated and analyzed the location selection results of different types of enterprise agents. Simulation results suggested that financial and technological innovation service enterprises were mainly concentrated in urban areas and key science park areas; although social service enterprises were more geographically dispersed, they were mainly concentrated in the 6th Ring Road. The location of industrial manufacturing enterprises was mainly distributed outside the 6th Ring Road, concentrated in the urban development new zone (Figure 10). Our results showed that although the model simulation results are constantly evolving in each grid unit, results were generally stable. The simulation results were also similar to actual enterprise spatial location distribution patterns, thereby generally reflecting the law of reality.

3.3. Simulation Results of Urban Jobs–Housing Spatial Relationship

Separation or jobs–housing balance are two key issues that reflect the spatial relationship of urban jobs–housing, an area that has increased in importance recently [84]. Jobs–housing separation (JHS) is based on the assumption of spatial dislocation theory to propose the basic problem of dislocation of jobs–housing space [84,85], and its essence reflects the imbalance of urban jobs–housing space. The balance of jobs–housing reflects a balanced relationship between residence and employment in a geographical space. The area of jobs–housing balance refers to urban residents who can attend their place of employment from their place of residence within a given commuting distance or time. In the area of jobs–housing balance, residents can be employed near to their place of work, conforming to an ideal state of the spatial relationship of jobs–housing [86]. Based on the simulation results of location selection of resident agents and enterprise agents, the density simulation results of resident population and employment population with the streets of Beijing as spatial units were obtained using ArcGIS (Figures 11 and 12). By using this data, the spatial distribution of jobs–housing in Beijing under the maximization of micro-agent location utility was obtained (Figure 13).

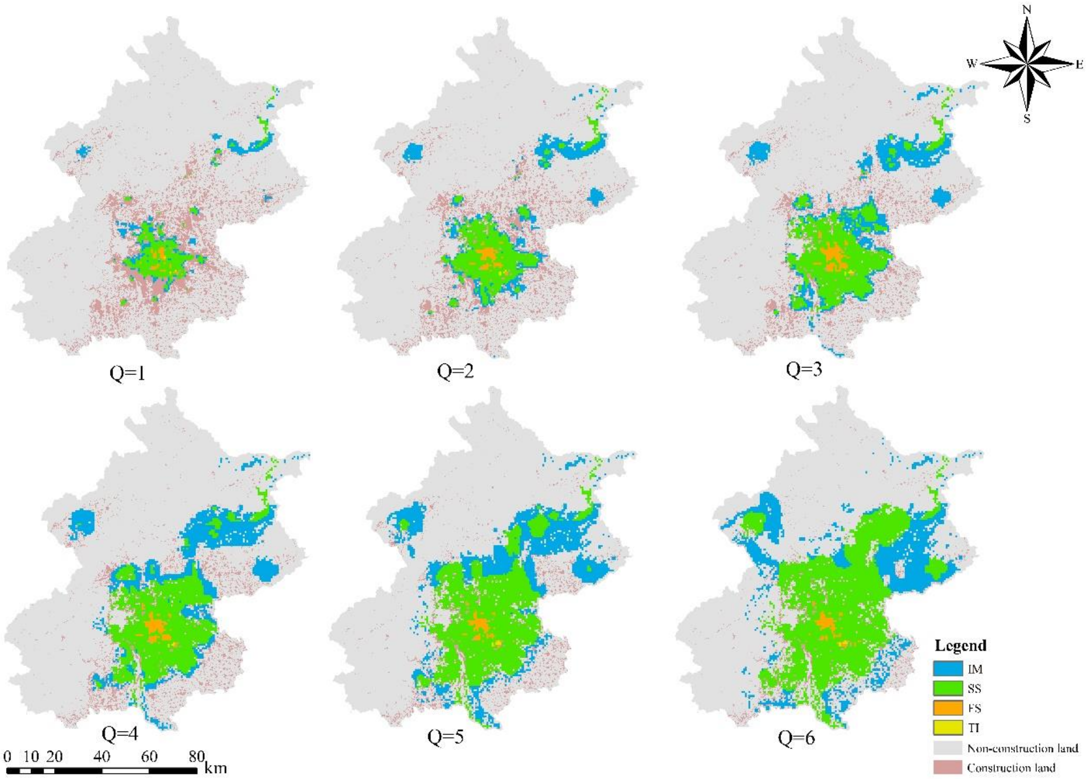

Figure 10. Spatial location distribution simulation of different types of enterprise agents.

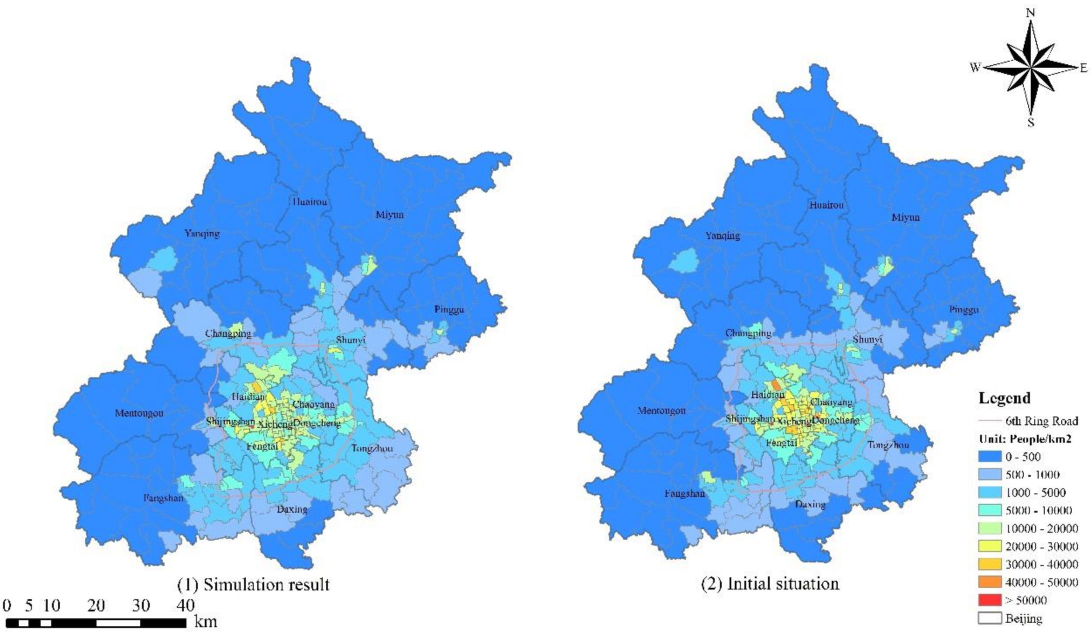

Figure 11. Simulation results of residential spatial distribution.

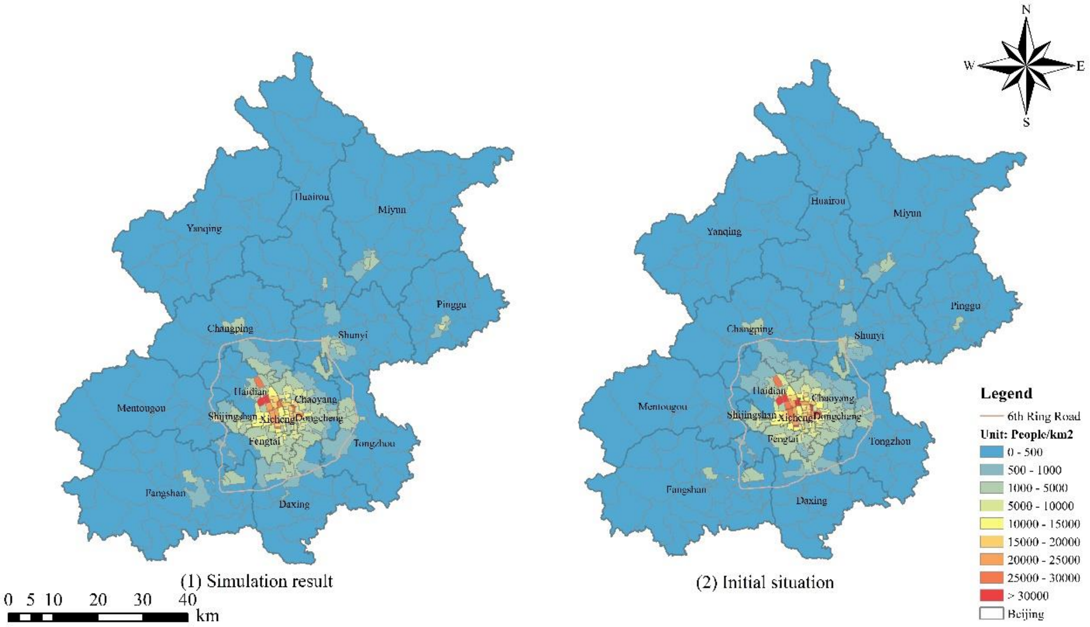

Figure 12. Simulation results of employment spatial distribution.

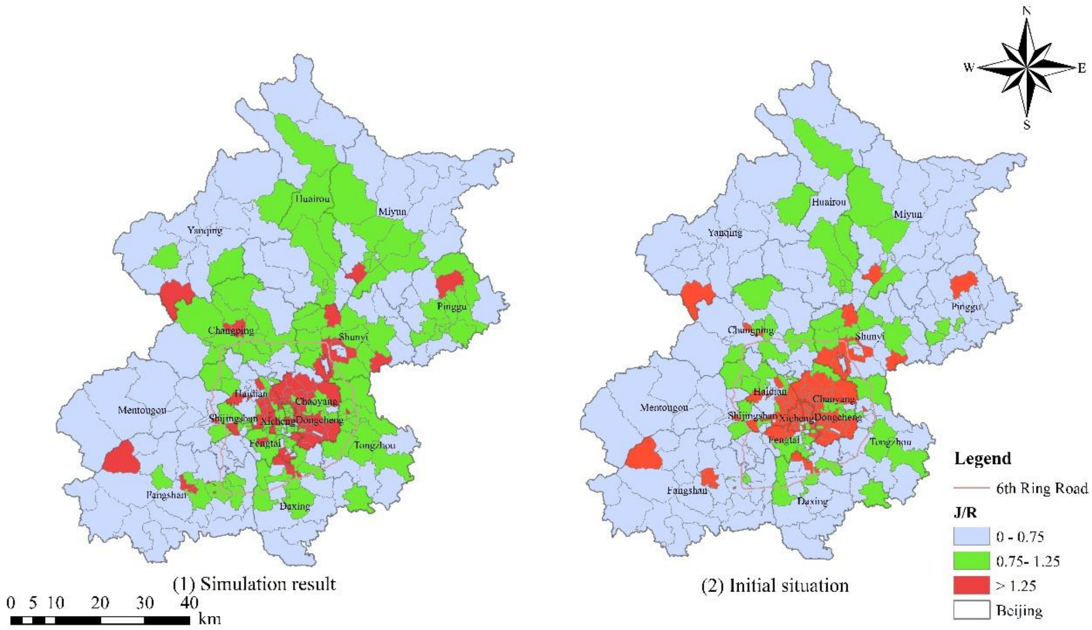

Figure 13. Simulation results of jobs–housing spatial distribution.

With the acceleration of urbanization processes, Beijing's urban space has continued to expand to the periphery, and large-scale residential areas have emerged in the suburbs of the city. These changes have intensified the high-density concentration of the resident population in urban suburbs. At the same time, due to the strong dependence of residential areas on urban commercial centers and employment centers, corresponding economic services and employment supply in these areas have not achieved coordinated development. The construction of large-capacity travel tools and facilities connecting urban areas have also not yet synchronized development. As the commuting time/distance of suburban residents has continued to increase, this has resulted in an intensification of the JHS, thereby forcing residents who commute to use the road network between residential and employment areas, resulting in serious traffic congestion during peak hours. Compared with the initial distribution, simulated employment, and resident population in the central urban area of Beijing have been alleviated and, based on the results of the simulated population density distribution (Figure 11), the employment center and surrounding areas have a relatively high population density and residents can consider choosing local employment.

At the same time, spatial distribution results for the employed population (Figure 12) indicated that employment in Beijing is mainly concentrated in the central urban area, and the population density in the commercial center areas of the four districts of Dongcheng, Xicheng, Haidian, and Chaoyang (the employment aggregation center of Beijing) is more than 20,000 people/km^2. Employment density of industrial enterprises in the central city is relatively small, and the region mainly comprises service-oriented and technology-based enterprises. From the simulation results of the spatial relationship distribution of jobs–housing in Beijing (Figure 13), the imbalance of the jobs–housing relationship in the central city has improved. Compared with the initial distribution, the number of jobs–housing balance areas in Beijing has also increased.

4. Conclusions

In this study we introduced a multi-agent approach to examine the jobs–housing relationship under the maximum location utility of residents and enterprises. The jobs/housing ratio was initially used to measure the balance of the number of jobs–housing relationships. JHS of Beijing in 2010 and 2014 was then compared and analyzed using district, county, and street scales. Results from this analysis identified that rapid population growth in the 6th Ring Road, a mismatch between housing and jobs, and the surrounding urban areas not being able to provide sufficient housing has resulted in an imbalance in the jobs–housing relationship in Beijing. The jobs–housing relationship of the central urban areas (Dongcheng and Xicheng) is still in an obvious imbalance, and it greatly exceeds the limit, indicating that it is impossible to provide corresponding accommodation for people in the area. From street and township scales, parks, historical, and traditional cultural areas of Nanyuan, Beiyuan, Tiantan, Tsinghua Park, and Yushu Street in the 6th Ring Road are all in a relatively balanced state. For some large residential areas in Beijing (such as Tiantongyuan, Huilongguan, and Huoying), an obvious imbalance in the jobs–housing relationship exists due to a lack of jobs; some residents living in these areas have to work in other external areas. Due to a lack of housing, forcing people to live in other areas, the streets of Haidian, Dongzhimen, and Jianwai are also in an unbalanced state.

An agent-based model was proposed to simulate spatial location selection behavior of agents by considering the influence of environment and economy on the residential decisions of individuals. Simulation results for six resident agents and enterprise agents experiments examining the spatial location selection process of residents in Beijing were analyzed. Resident agents with a middle and high income were mainly concentrated in the urban area, and areas with better environmental characteristics. Low-income residents, however, are mainly concentrated in the new city area and the urban development new area. This result indicated that the difference of resident agents' income level has a significant impact on residential location decision-making, and housing price is the primary factor affecting the decision of residents to choose their residential location. At the same time, financial and technological innovation service enterprises are mainly concentrated in urban areas and the key science park areas; although social service enterprises are more geographically dispersed, they are mainly concentrated in the 6th Ring Road. The location of industrial manufacturing enterprises are mainly distributed outside the 6th Ring Road, concentrated in the urban development new zone. The spatial distribution of jobs–housing in Beijing under the maximization of micro-agent location utility was also obtained. The spatial relationship distribution of jobs–housing in Beijing and the imbalance of the jobs–housing relationship in the central city has improved. Compared with the initial distribution, the number of jobs–housing balance areas in Beijing has increased.

The current situation of serious urban issues, such as jobs–housing separation (JHS), traffic congestion, and environmental pollution, have significantly restricted the sustainable development. The reasonable urban jobs–housing adjustment policy not only improves traffic congestion, but also improves urban residents' commuting efficiency and reduces commuting time. Local governments can accelerate the implementation of policy combinations to encourage the closest residence or employment, thereby achieving a real sense of a jobs–housing relationship balance. These include the establishment of urban sub-centers, the orderly promotion of the transfer of all or part of municipal administrative institutions to sub-centers, minimization of traffic congestion caused by commuting, and promotion of job–housing balance. Meanwhile, the construction of new surrounding areas should be accelerated, focusing on creating a non-capital function decentralized centralized load-bearing area, effectively alleviating diseases in large cities, and focusing on alleviating the pressure on urban populations. At the same time, it is necessary to speed up the implementation of the means and programs that focus on adjusting the jobs–housing relationship, reduce the travel demand of residents from the source, shorten the commute time and distance of commuters, alleviate the pressure of tidal traffic, and achieve the purpose of controlling the demand for urban travel, and achieve jobs–housing balance from urban transport.

There are some potential limitations of this study. We used ABM models to simulate the local jobs–housing relationship based on different scenarios. In order to facilitate the construction of the model we simplified the behavior rules and decision-making of agents. In real life, behavior rules and decisions of micro-agents are affected by urban spatial planning, land use control, financial regulation, etc. Future research based on our findings can continue to improve this model, thereby improving the accuracy and the reference of simulation results. In addition, due to government control and supervision of people, the behavior of enterprises can be affected by many factors. Future studies need to combine the situation of the local jobs–housing relationship adjustment policy and government control to analyze its impact on the behavior of enterprise agents.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

C	commuting cost
D	distance to water body
e	the error
E	the habitability index
I	income level
J	the number of jobs
N	number of green space units in adjacent units
P	product prices
$\overline{P}$	the average unit environmental value in residential area
Q	the sum of squares of errors
R	the total number of residents
U	utility
X	external factor
Y	the value of binary variables selected by Agents location
Subscripts	
i	the ith street
h	the total housing price
$h1$	the basic price of housing
$h2$	the environmental price of housing
ta	traffic accessibility
col	convenience of life
goe	the gracefulness of the environment
n	the nth external factor
Abbreviations	
ABMs	agent-based models
CNY	Chinese Yuan
FS	financial services
GDP	gross domestic product
GHGs	greenhouse gases
IM	industrial manufacturing
JHI	jobs–housing imbalance
JHR	jobs–housing ratio
JHS	jobs–housing separation
ROC	receiver operating characteristic
SS	social service
TAZ	traffic analysis zones
TI	technological innovation

Appendix A

Supplementary material to: Simulation of the urban jobs–housing location selection and spatial relationship using a multi-agent approach.

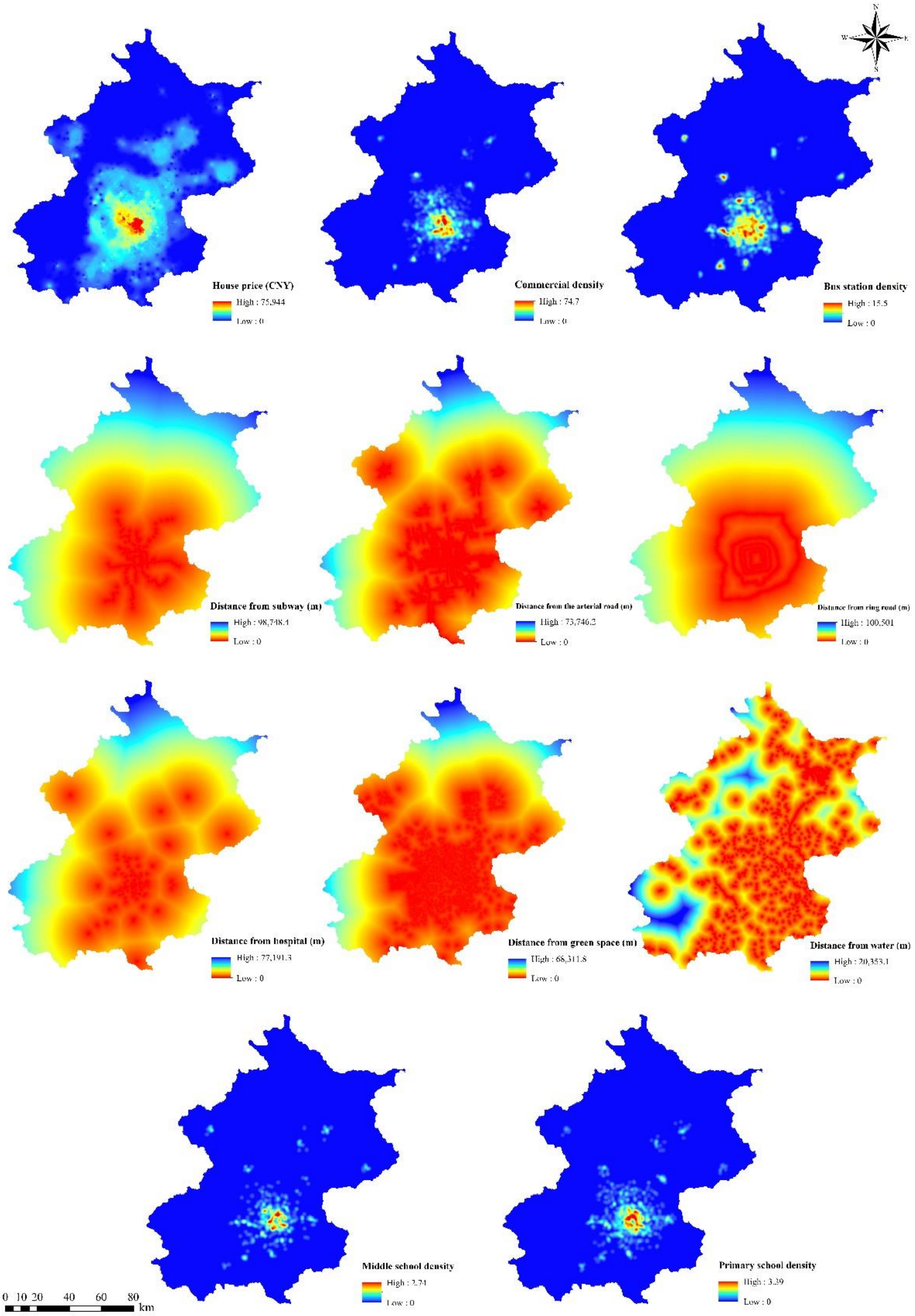

Figure A1. Spatialization of external elements of resident agents.

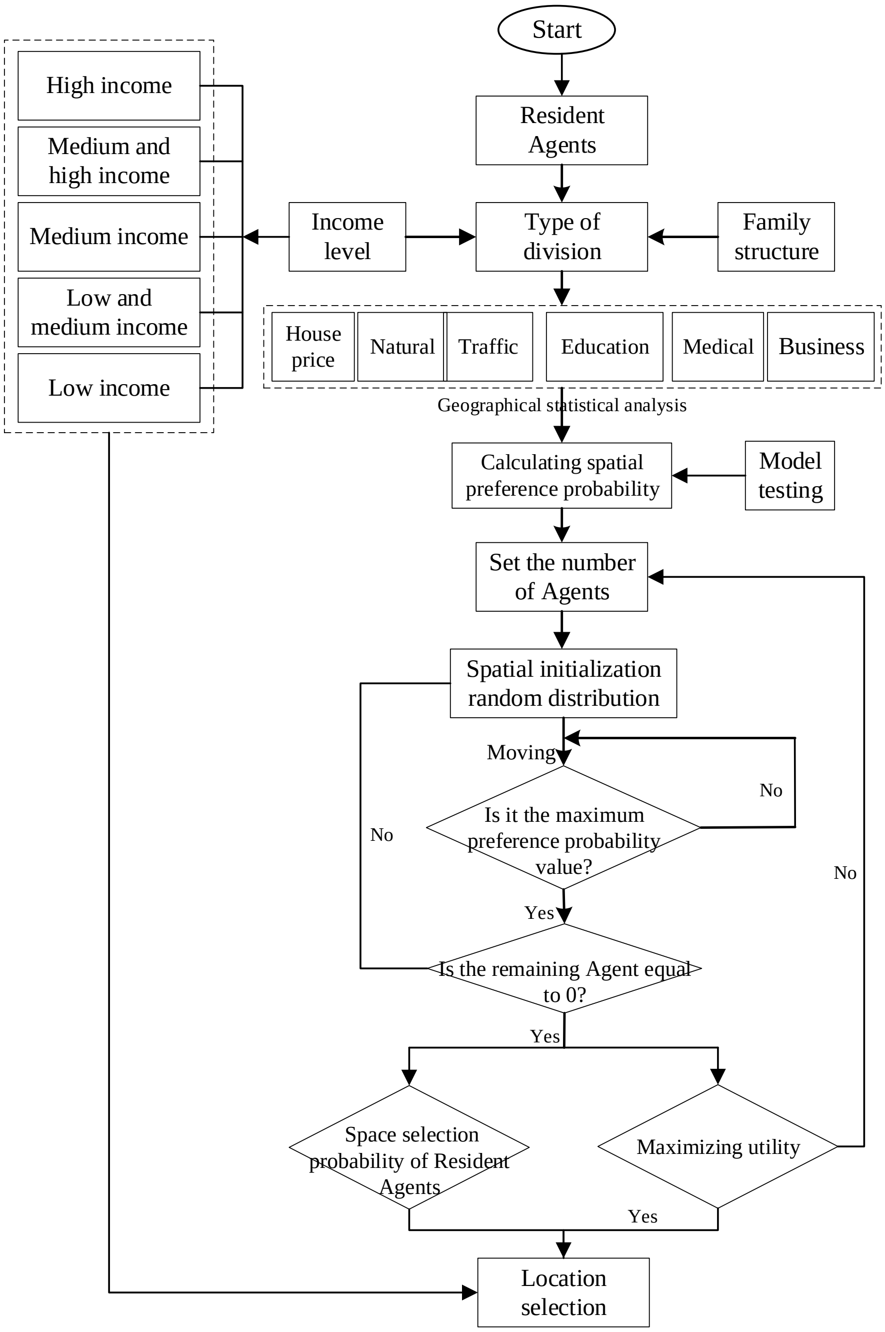

Figure A2. Rules of behavior for resident agents.

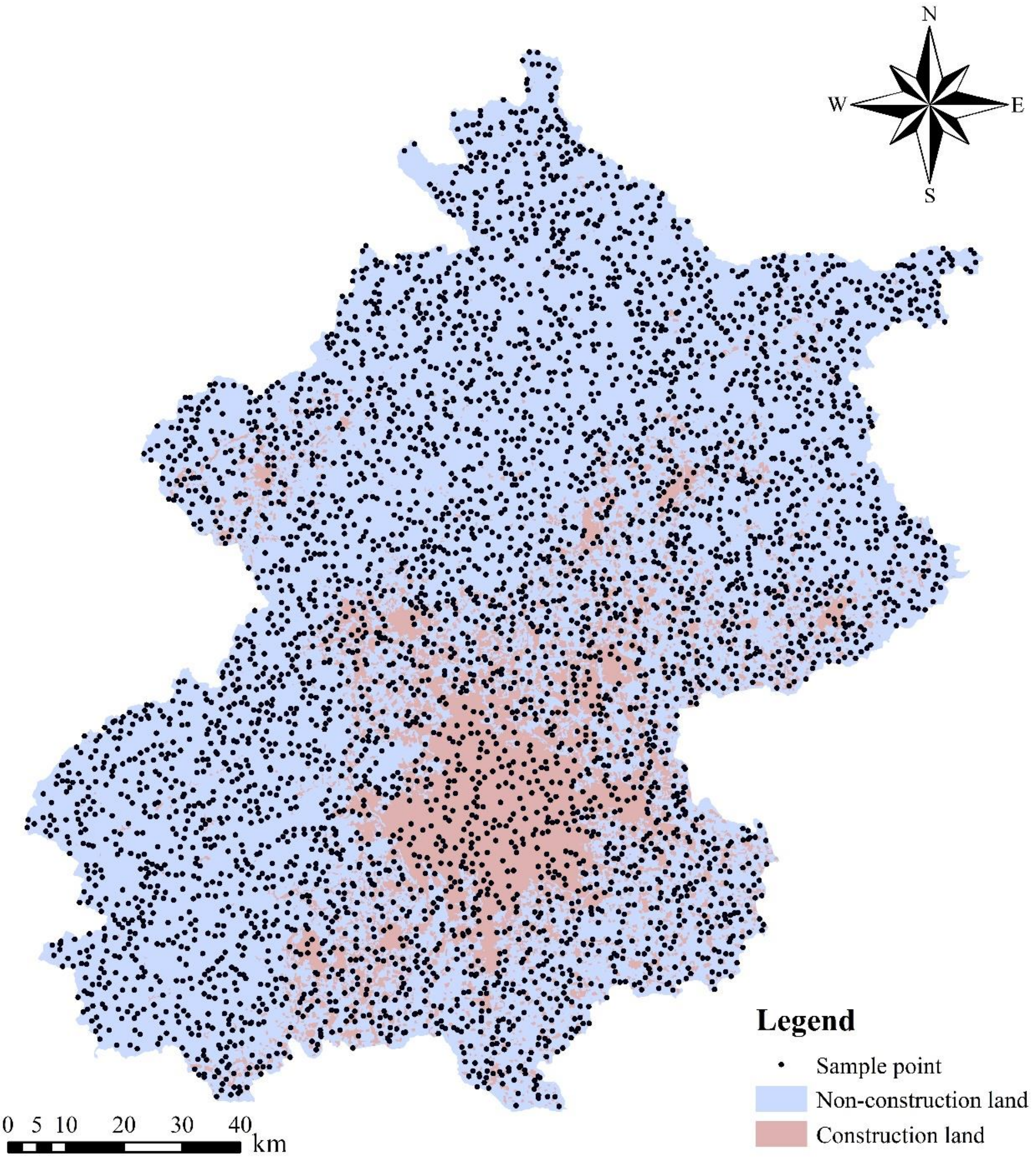

Figure A3. Distribution of sample points.

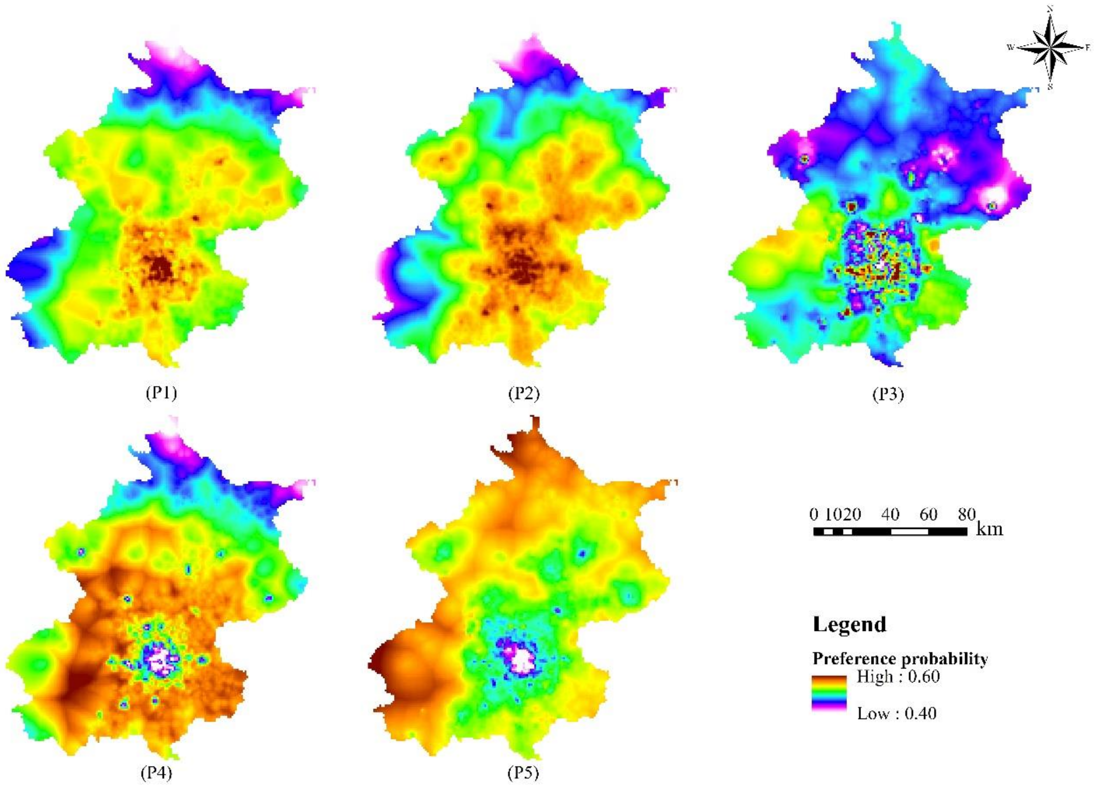

Figure A4. Preference probability of resident agents (**P1**–**P5**).

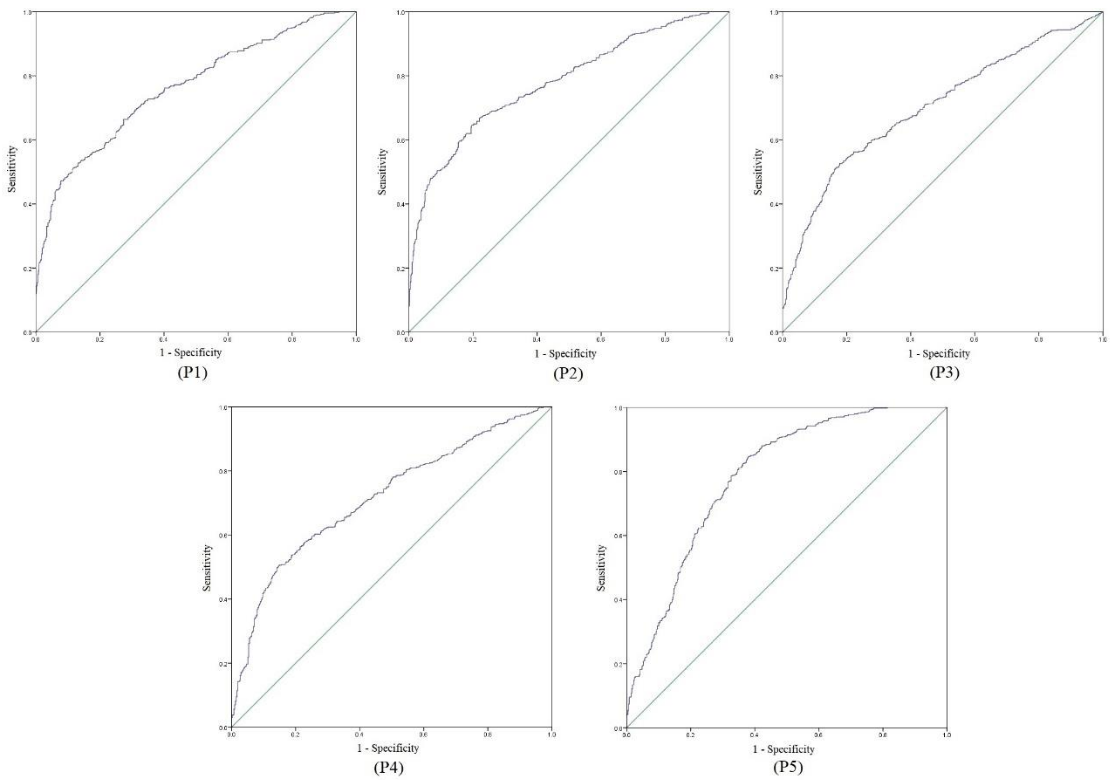

Figure A5. Receiver operating characteristic (ROC) curve of spatial preference probability for each type of resident agents (**P1**–**P5**).

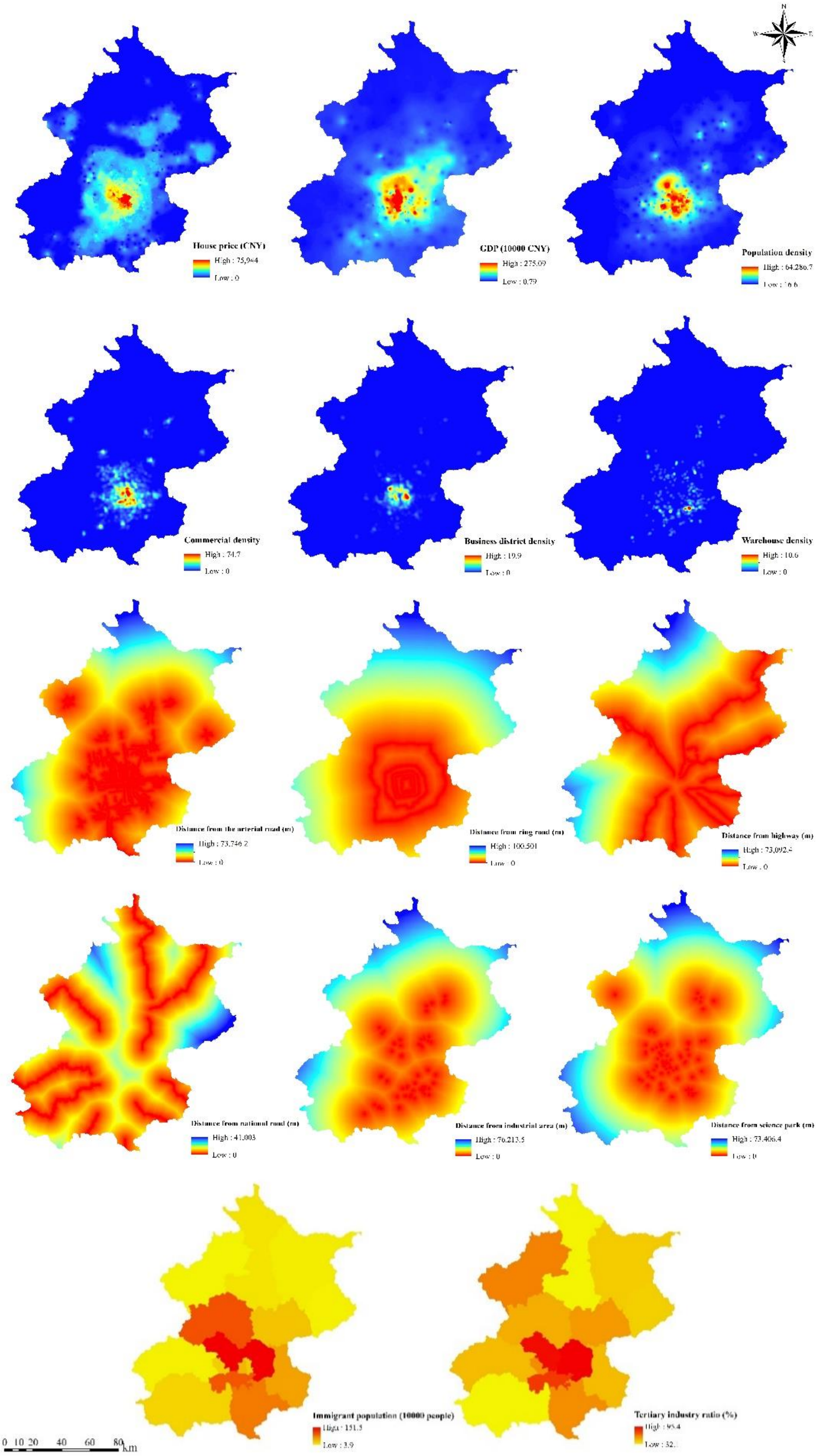

Figure A6. Spatialization of external elements of enterprise agents.

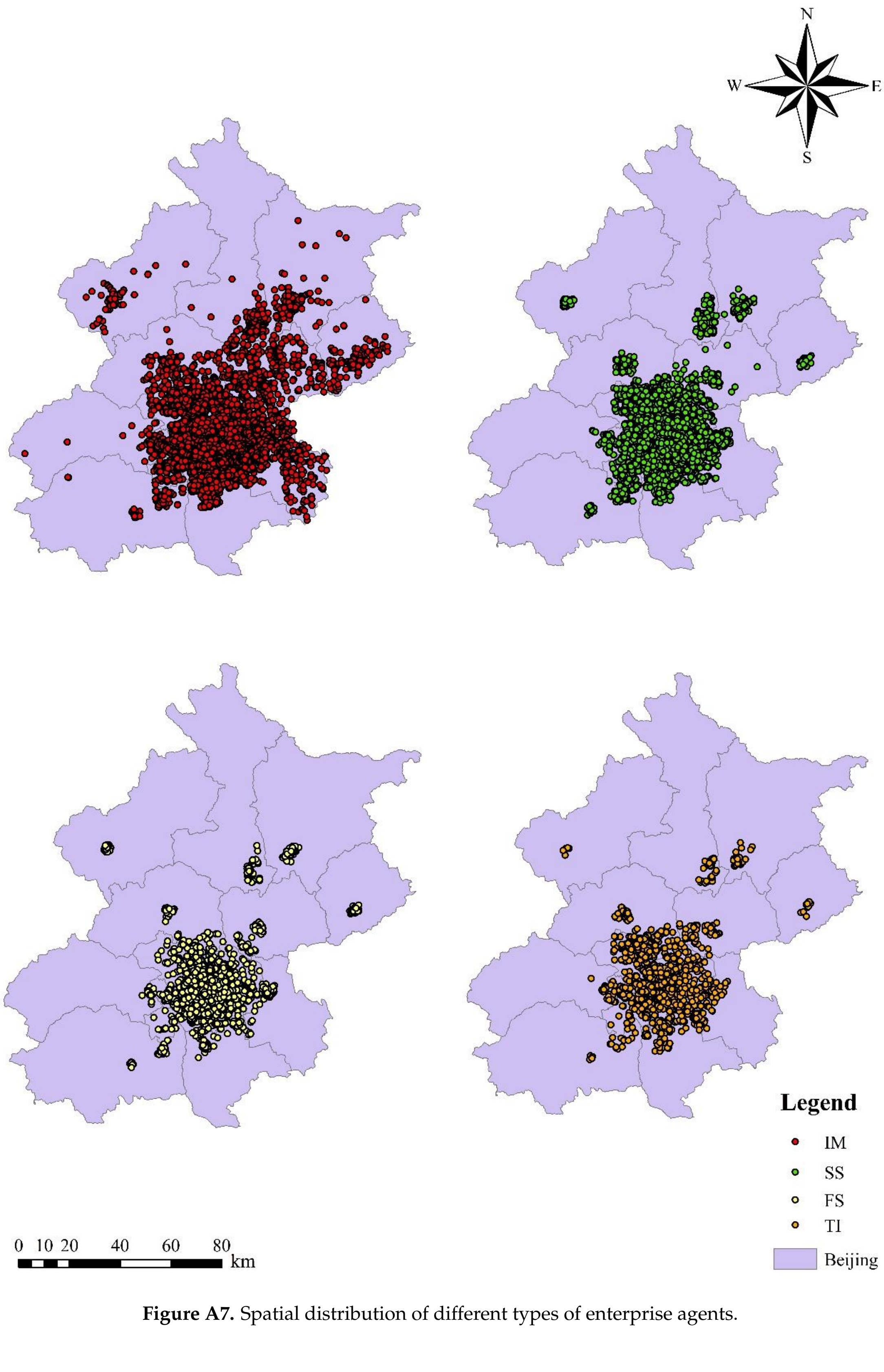

Figure A7. Spatial distribution of different types of enterprise agents.

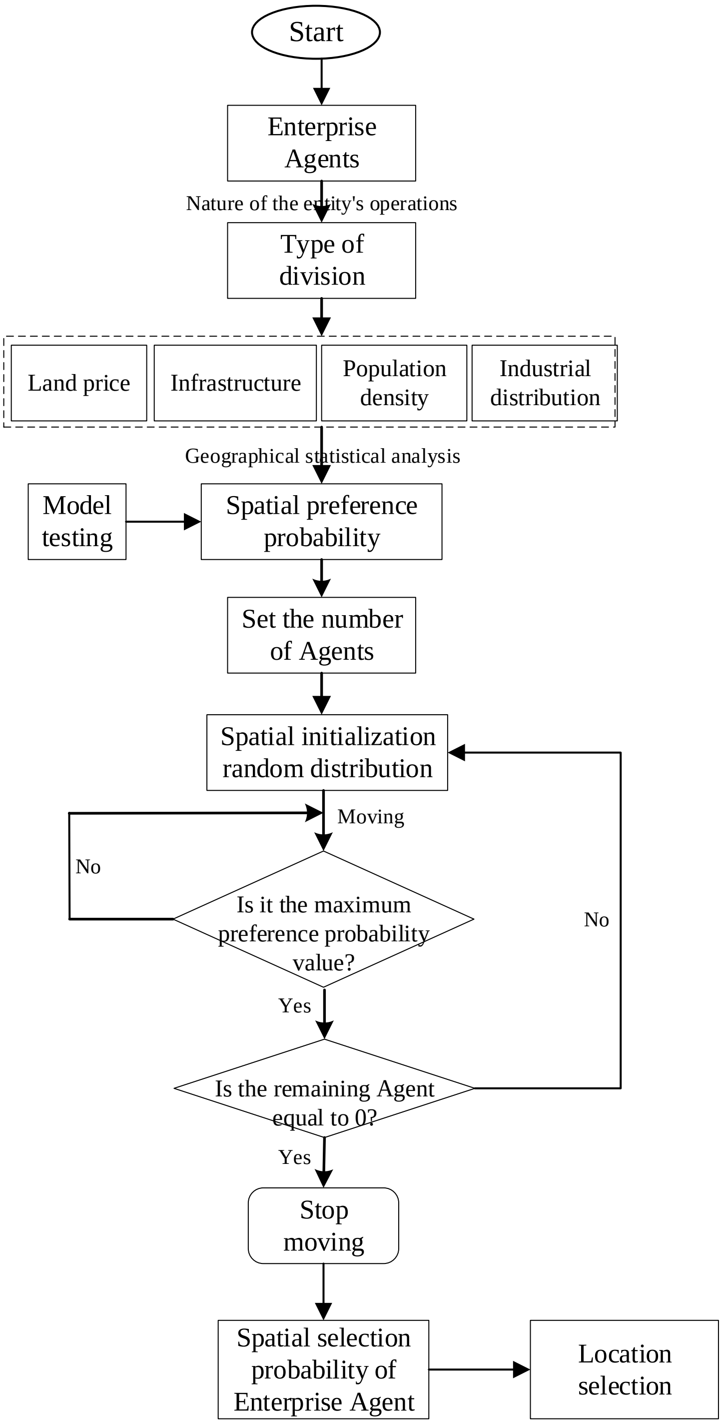

Figure A8. Rules of behavior for enterprise agents.

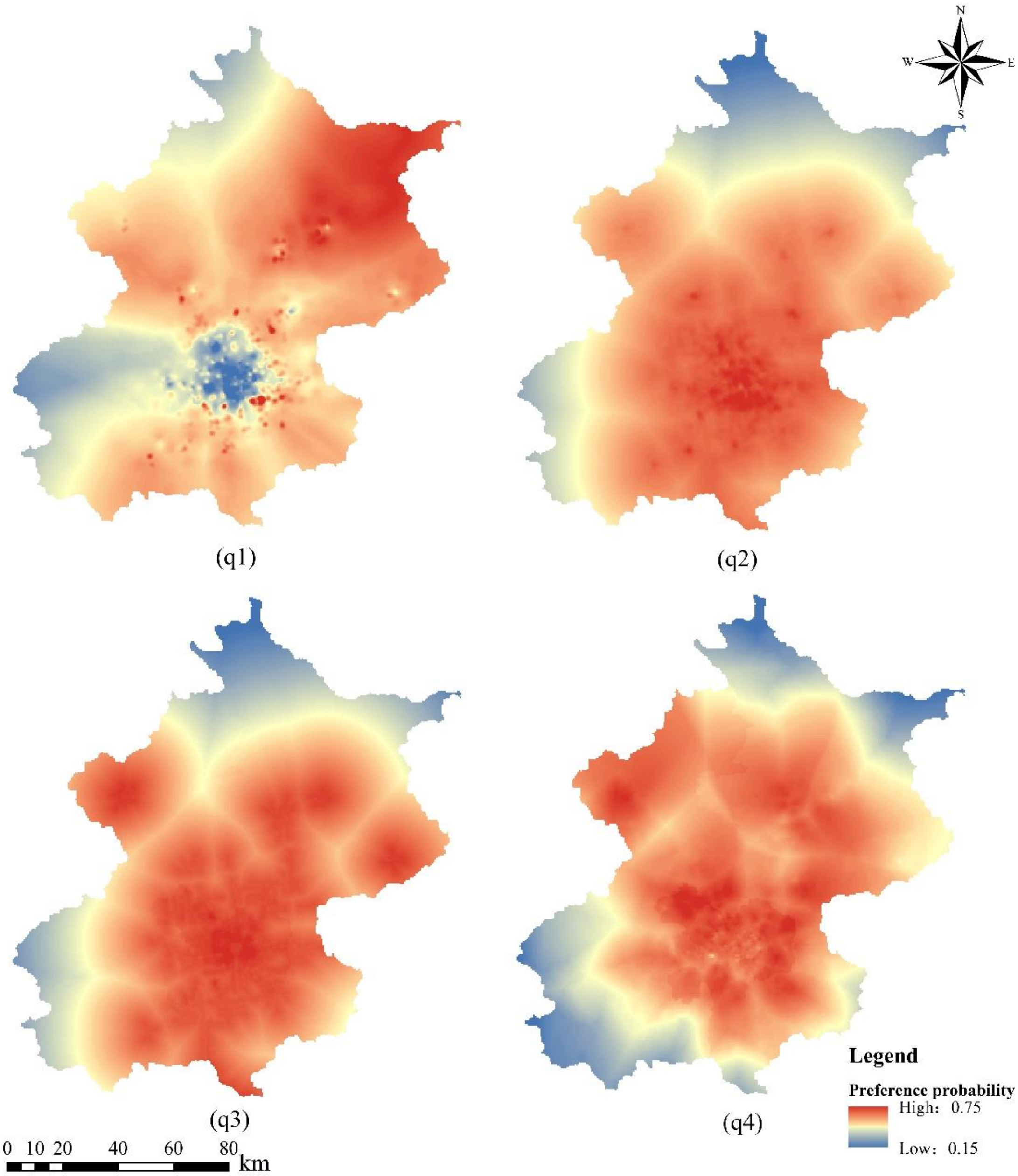

Figure A9. Preference probability of enterprise agents (**q1**–**q4**).

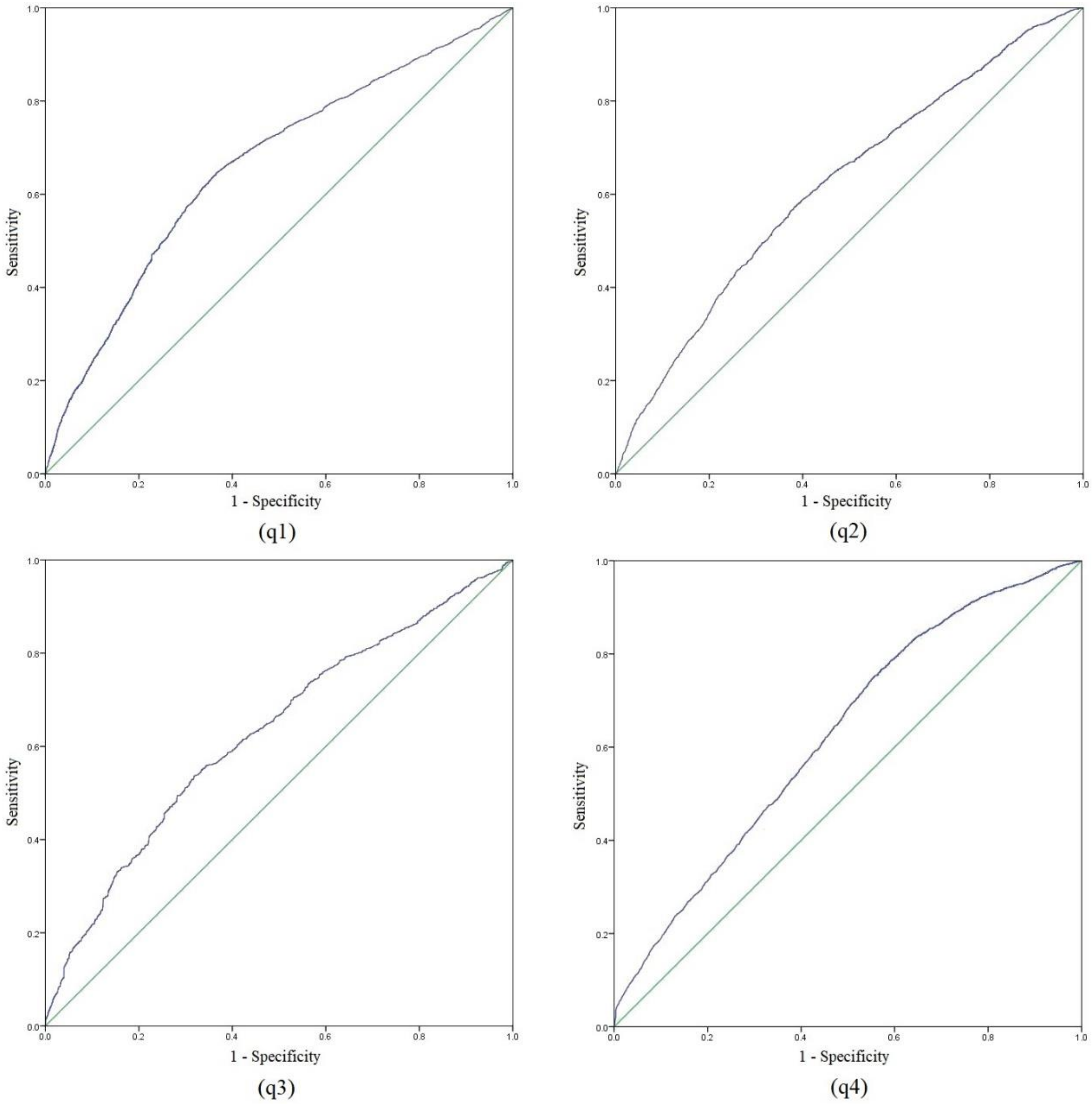

Figure A10. ROC curve of spatial preference probability for each type of enterprise agents (**P1**–**P4**).

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