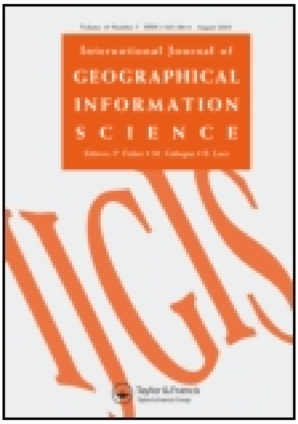

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Simulation of spatial population dynamics based on labor economics and multi-agent systems: a case study on a rapidly developing manufacturing metropolis

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Spatial population dynamics affects resource allocation in urban planning. Simulation of population dynamics can provide useful information to urban planning for rapidly developing manufacturing metropolises. In such a metropolis with a concentration of immigrant labor forces, individual employment choices could have a significant effect on their residential decisions. There remains a need for an efficient method, which can simulate spatial population dynamics by considering the interactions between employment and residential choices. This article proposes an agent-based model for simulation of spatial population dynamics by addressing the influence of labor market on individual residential decisions. Labor economics theory is incorporated into a multi-agent system in this model. The long-term equilibrium process of labor market is established to define the interactions between labor supply and labor demand. An agent-based approach is adopted to simulate the economic behaviors and residential decisions of population individuals. The residential decisions of individuals would eventually have consequences on spatial population dynamics. The proposed model has been verified by the spatial dynamics simulation (2007 to 2010) of Dongguan, an emerging and renowned manufacturing metropolis in the Pearl River Delta, China. The results indicate that the simulated population size and spatial distribution of each town in Dongguan are close to those obtained from census data. The proposed model is also applied to predict spatial population dynamics based on two economic planning scenarios in Dongguan from 2010 to2015. The predicted results provide insights into the population dynamics of this fast-growing region.

Keywords: labor economics; agent-based model; simulation; spatial population dynamics; Dongguan

1. Introduction

Since the economic reform in 1978, China has been experiencing rapid urbanization and industrialization (Song and Zhang 2002). Large concentrations of population in metropolises have become a common phenomenon in many rapidly developing manufacturing areas in China such as the Pearl River and the Yangtze River Deltas (Rain and Long

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2007). Because of the fast pace of industrialization, a large number of labors migrate to the manufacturing metropolis. This leads to an increase in demand for urban resources (e.g., urban infrastructure and residential land). Spatial population dynamics with its influence on resource planning and policy making has thus become a crucial issue in urban planning (Stevens *et al.* 2007, Rodrigues *et al.* 2011, Wu and Birkin 2012). The 30th chapter of 'Urban Planning Methods for Cities in China' (implemented on 1 April 2006) indicates that the population size of the city as well as the spatial distribution of population in each town should be predicted for urban planning (Ministry of Housing and Urban-Rural Development of the People's Republic of China 2005). Consequently, research on spatial population dynamics, which includes prediction of population size and simulation of population distribution in different districts under dynamic economy, is vital for urban planning in China, especially in rapidly developing manufacturing metropolises (Rodrigues *et al.* 2011).

In practical urban planning for cities in China, total population size is often predicted. However, the spatial distribution of population is seldom simulated (Xiao and Ding 2010). Attempts have been made to develop quantitative statistical models that can be used for spatial population distribution research, such as population density model (Clark 1951) and various geography-related models, including spectroscopic analysis model (Lo 1995, Harvey 2002), nightlight-intensity estimate model (Paul 1997, Zhuo and Chen 2005), and land-use density model (Yuan *et al.* 1997). These statistical models have few spatial details because of the strict use of mathematical equations. The limitations of these statistical models have led to the development of spatial models for simulation and prediction of population dynamics.

In the manufacturing metropolises with concentrations of immigrant labor forces, individual employment choices could have a significant effect on residential decisions, which would have consequences on spatial population dynamics. Immigrant labor forces are influenced by labor demand, as employment opportunity is the major motivation behind immigration. Hence, there remains a need for an efficient method that can simulate spatial population dynamics by considering the interactions between jobs and housing locations in such a metropolis.

Many studies have focused on employment and residential location issues (Allen and Hamnett 1991). The traditional economic model for jobs and housing is the well-known bid-rent model proposed by Alonso (Alonso 1964). In this classical model, workers optimize their residential locations by trading off commuting cost and land rent (Alonso 1964). The Mills–Muth model, an extension of the Alonso model, introduces a housing producer who makes decisions regarding the structural density of development (Mills 1967, Muth 1969). Most studies on location choices stem from the analytical framework of Alonso–Mills–Muth model (AMM) (Mok 2007). However, AMM and subsequent models assume that the city is monocentric and all employment is concentrated in the city center (Hincks and Wong 2010). Indeed, polycentrism is a reality, as shown by empirical evidence (Lemoy *et al.* 2013). Consequently, the monocentric assumption of the AMM model has been challenged by the emergence of polycentric urban systems (Giuliano and Small 1991). However, introducing polycentrism to the AMM model is difficult from the point of view of analytical tractability. There are many difficulties in extending the AMM model while retaining analytical solutions (Lemoy *et al.* 2013). Moreover, the abovementioned types of analytical models are nonspatially explicit.

Much research has been conducted to develop spatially explicit models to explore the interactions of employment and residential locations with survey data. For example, Sener *et al.* (2011) presented a generalized spatially correlated logit model and applied it to analyze residential choice based on survey data of San Francisco. Hincks and Wong (2010) empirically examined the spatial process of housing and labor market interaction via a case study of North West England. The aforementioned studies, which adopted traditional 'top-down' approaches, have limitations in reflecting and explaining the individual behaviors that lead to spatial population dynamics (Berger 2001, Li and Liu 2007, Monticino *et al*. 2007, Moreno *et al.* 2007, Crooks *et al.* 2008, Gotts and Polhill 2009). Spatial population dynamics is the outcome of the choices made by population individuals who seek jobs and select residential locations (Benenson 2004, Li and Liu 2007). Hence, spatial population dynamics involving complex individual behaviors is difficult to simulate with these types of 'top-down' models.

Studies indicate that agent-based models (ABM), which are 'bottom-up' approaches, can offer a way to simulate the complex behaviors of interacting individual agents (Benenson 1998, Ligtenberg *et al.* 2001, Macal and North 2010, Ettema 2011). These models have the advantages of modeling decision-making of individuals and their interactions and dynamically linking with social and economic processes (Parker *et al.* 2002, Matthews *et al.* 2007). Therefore, agent-based approaches have potential for use in modeling spatial dynamics that evolves from individual behaviors (Barreteau *et al.* 2001, Berger 2001, Monticino *et al*. 2007, Moreno *et al.* 2007, Crooks *et al.* 2008, Gotts and Polhill 2009, Lagabrielle *et al*. 2010, Naivinit *et al*. 2010). These approaches have been well adopted to model the spatial dynamics of complex systems such as land-use change and ecological economics (Chebeane 1999, Li and Liu 2007, Monticino *et al*. 2007, Heckbert *et al.* 2010, Macal and North 2010, Valbuena *et al*. 2010, Ettema 2011). Various ABMs have been developed to simulate the behaviors of population individual. Several models have been advanced to simulate the individual residential choices (Benenson 1998, 2004, Barros 2003, Crooks 2010, Haase *et al.* 2010). However, the purpose of these studies is to explore residential dynamics not economics.

The use of ABM to simulate the economic behaviors of individuals continues to increase because of the desire to better understand complex economic systems (Tesfatsion 2006). Several models that focus on land market were developed. Recent examples include the ABM-LM model (Parker and Filatova 2008, Polhill *et al.* 2008), ALMA model (Filatova *et al.* 2009a, Filatova *et al.* 2009b), ALMA-C model (Filatova *et al.* 2011), CHALMS model (Magliocca *et al.* 2011), and so on. These models simulate urban land patterns and land prices based on the economic interactions of land buyers and sellers in a land market. Another important issue involving complex economic behaviors is the simulation of labor market. Many economists developed the agent-based computational economic models to simulate the interactions between workers and employers (Tesfatsion 2003, Deissenberg *et al.* 2008, Martin and Neugart 2009, Dawid *et al.* 2013). However, these models mainly focus on the influence of economic policy on labor market, which is not spatially explicit.

The ABMs discussed above are used to simulate individual residential decisions and economic behaviors separately. There has been a lack of systematic research integrating residential and employment behaviors. Lemoy *et al.* (2013) recently presented an agent-based implementation of the AMM model to explore employment and housing simultaneity with theoretical data. However, the representation of the labor market is limited in this model; thus, applying the model to real-world data is difficult. As mentioned previously, immigrants in manufacturing metropolises are influenced by labor demand, which mainly results from industrial economic development. Thus, the labor market must be incorporated into location choice modeling to simulate spatial population dynamics under economic development.

This article proposes an ABM for simulation of spatial population dynamics by considering the influence of industrial economy on the employment behaviors and residential decisions of individuals. Labor economics theory is incorporated into the model, and the long-term equilibrium process of the labor market is established to define the interactions between labor supply and labor demand. An agent-based approach is used to simulate individual economic behaviors in a dynamic economic environment. The residential decisions of individuals are also simulated with the proposed approach. The presented model is applied to the population simulation of Dongguan. This city is an emerging, world-renowned manufacturing metropolis located in the Pearl River Delta, China.

2. Spatial population dynamics based on long-term dynamic equilibrium of labor market

2.1. Framework

In a manufacturing metropolis with a concentration of immigrant labor forces, employment opportunity that reflects labor demand is the main factor that encourages population to immigrate. An increasing number of labor forces would flow into the metropolis as labor demand increases. Otherwise, an outflow of labor forces would occur. Industrial and economic development determines labor demand in the labor market, whereas population determines labor supply. The equilibrium between labor demand and labor supply plays a key role in spatial population dynamics for these metropolises.

In this article, an ABM for spatial population dynamics is established based on long-term dynamic equilibrium of labor market. The purpose of this model is to simulate the influence of population employment choices on residential decisions based on the fact that employment opportunity is the primary motivation of immigrants. To model the influence of individual employment choices, a long-term dynamic equilibrium process is established to define the interaction between labor supply from individual employment decisions and labor demand from industrial economic development. An agent-based approach is used to simulate individual employment behaviors and residential decisions, which result in a specific total population size and the population distribution in different districts.

Figure 1 illustrates the framework of the proposed model. The simulation involves two types of agents: (1) labor-force individual agents (aged 15 to 65) and (2) nonlabor-force individual agents (aged 15 below and 65 above). Labor-force agents make employment choices in the labor market; firms with job vacancies opt to employ labor-force agents. The interactions between labor-force agents and firms enable the labor market to reach short-term equilibrium when labor supply is equal to labor demand. Labor-force agents make residential location decisions including entering the city, migrating within it, and leaving it. Nonlabor-force agents make residential decisions according to the behaviors of labor-force agents and the population dependency ratio. In the simulation, a city's total population size is the sum of labor-force agent number at equilibrium and nonlabor-force agent number (McConnell *et al.* 2005). The agents interact with one another and the environment. These interactions ultimately result in the equilibrium number and maximized utility of population. This determines population size prediction and spatial population simulation. Labor demand changes as the industrial economy changes, leading to disequilibrium between labor supply and labor demand. Consequently, agents make new decisions that generate new equilibrium. Long-term dynamic equilibrium is attained through interactions between labor-force individuals and firms in a dynamic economic environment. The conditions for long-term dynamic equilibrium of labor market, the population dependency ratio, and agents' behaviors are the key problems to be addressed in the succeeding sections.

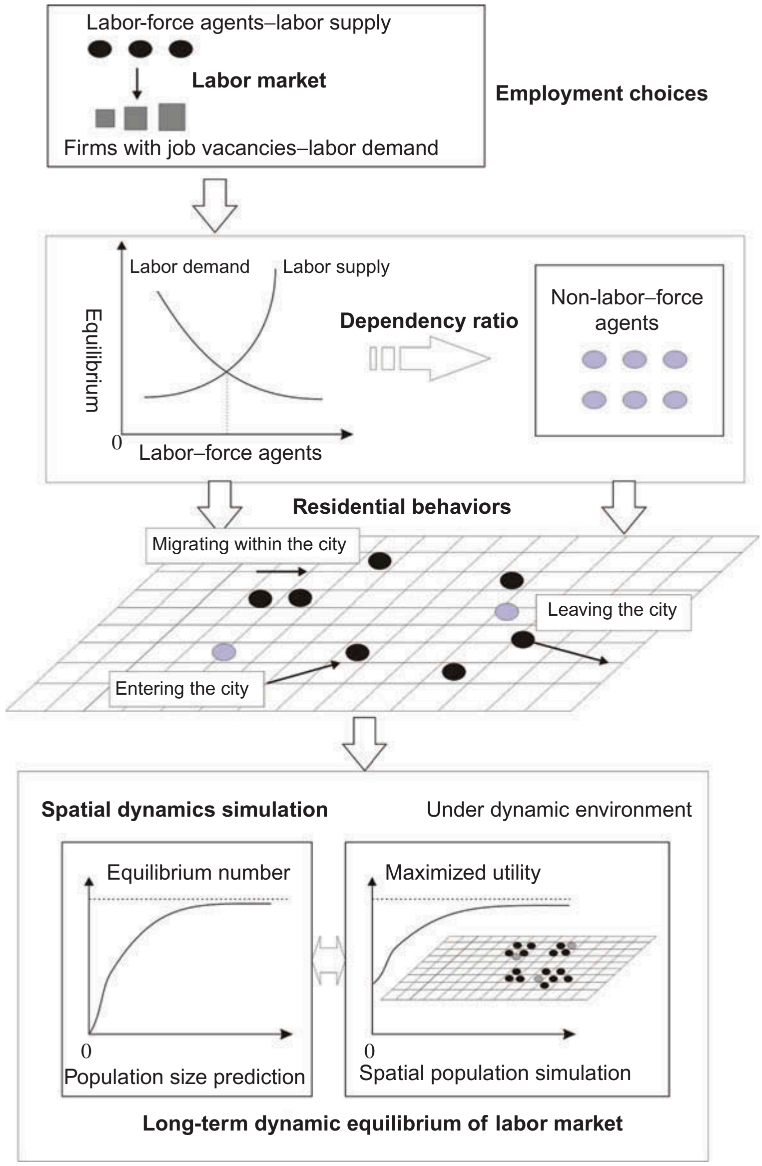

Figure 1. Framework of the proposed model.

2.2. *Conditions for long-term dynamic equilibrium of labor market*

Labor economics theory (McConnell *et al.* 2005) indicates that labor-force agents in the labor market determine labor supply, whereas firms determine labor demand. Labor-force individuals look for employment opportunities and decide whether to provide labor service in the market. Labor supply depends on the economic decisions of individuals in a particular industrial economic environment. When an individual is willing to provide labor service for a firm, then $a_i = 1$; otherwise, $a_i = 0$. The total labor supply in an economic sector at time t (L_{s_t}) is determined by the decisions of each labor-force agent a_{i_t}. The calculation is based on the following equation:

$$L_{s_t} = \sum_{1}^{n} a_{i_t}. \tag{1}$$

Firms in the labor market provide employment opportunities and need to employ a certain number of workers. It is assumed that in each economic sector, the jth firm produces output Y_j by employing a certain number of workers N_j. The output of the jth firm Y_j depends positively on the amount of employed workers N_j, which can be expressed by using the Cobbs-Douglas production function (Silveira *et al.* 2005).

$$Y_j = A(N_j)^{\alpha} \tag{2}$$

where $A > 0$ and $0 < \alpha \leq 1$ are parametric constants. We suppose that the output of firm Y_j is given in the model, which is regarded as the output with optimized profit.

Assuming that the labor market is perfectly competitive and the wage rate w in an economic sector at short-term equilibrium of labor market is fixed, given by (Espindola *et al.* 2006)

$$w = \alpha A N_j^{\alpha-1} \tag{3}$$

Y_j can therefore be expressed with wage rate w in an economic sector and the number of employment workers N_j. It can be formalized as:

$$Y_j = \frac{1}{\alpha} w^* N_j \tag{4}$$

The total labor demand of a market in an economic sector at time t (L_{d_t}) is determined by the total output of each firm (Y_{jt}) and wage rate$w$, as follows:

$$L_{d_t} = \sum_{j=1}^{m} L_{d_{jt}};\ L_{d_{jt}} = \alpha \frac{Y_{jt}}{w} \tag{5}$$

When total labor supply L_{s_t} is equal to total labor demand L_{d_t}, the labor market reaches equilibrium. The condition for the equilibrium of labor market can be expressed as follows (Bosworth *et al.* 1997, Dustmann *et al.* 2005):

$$L_t = L_{d_t} = L_{S_t}. \tag{6}$$

If total labor supply is equal to total labor demand at time t, then the labor market achieves short-term equilibrium. When the industrial economy changes at time $t+1$, labor demand also changes. The labor market is in a state of disequilibrium at this point. Subsequently, labor supply would be adjusted continuously until time $t+n$. When the condition ($L_{d_{t+n}} = L_{S_{t+n}}$) is satisfied again, the labor market reaches a new state of equilibrium. This is the long-term dynamic equilibrium process.

Two indices are established in this study, namely, average unemployment rate (u) and job vacancy rate (v), to reflect the state of equilibrium of the labor market. Average unemployment rate describes the excess of labor force, whereas job vacancy rate reflects the shortage of labor force. When a labor-force agent enters the city and obtains an employment opportunity, the agent's status changes from unemployed to employed and u

decreases. Meanwhile, the job in the firm changes from vacant to occupied and v decreases simultaneously (Pissarides 1985). When the condition for Equation (7) is satisfied, the labor force in the market is neither in excess nor in shortage.

$$u_t = v_t = 0. \tag{7}$$

Average unemployment rate at time t (u_t) can be expressed by average employment rate e_t as shown in Equation (8).

$$u_t = 1 - e_t \tag{8}$$

Consequently, the conditions for equilibrium of labor market can be expressed as follows:

$$\begin{cases} e_t = 1 \\ v_t = 0 \end{cases} \tag{9}$$

where e_t is the average of all employment probabilities of the labor-force agents at time t (Equation (15)). Job vacancy rate v_t can be expressed as follows:

$$v_t = (L_{d_t} - L_{s_t})/L_{d_t} \tag{10}$$

2.3. *Population dependency ratio and population size*

The total population size (P_t) of a city at time t is the sum of labor-force individual number L_t at equilibrium state and nonlabor-force individual number NL_t (McConnell *et al.* 2005).

$$P_t = L_t + NL_t \tag{11}$$

Nonlabor-force individual number NL_t is determined by labor-force individual number L_t and population dependency ratio dr. dr is an indicator of the dependency burden of labor-force individuals and is defined as the ratio of NL_t to L_t (Bongaarts 2001).

$$dr = NL_t/L_t. \tag{12}$$

2.4. *Agents' behaviors*

2.4.1. *Agents' utilities*

An agent-based approach is adopted in the proposed model to define the economic behaviors and residential location decisions of population individuals. Considering the influence of the industrial economy on the behaviors of individual agents, the utilities of agents are defined in the model from the point of view of economics.

The model assumes that labor-force agents search for jobs from the labor market and select residential locations that maximize their utilities. Alonso's classic location theory indicates that workers trade-off between residential and commuting costs when selecting residential location (Alonso 1964). The proposed model borrows this idea from Alonso's theory. A labor-force agent who has gained an employment opportunity is assumed to earn income from the labor market. Meanwhile, the agent has to afford economic costs, including commuting cost, residential cost, and so on. These economic costs are directly incorporated into the utility function. Hence, the utility of a labor-force agent at location i can be expressed as follows:

$$U_i = \mathrm{EI}_i - C_i = \mathrm{EI}_i - (C_{\text{commuting\_}i} + C_{\text{residential\_}i} + C_{\text{other}}) \tag{13}$$

where U_i refers to the utility of the labor-force agent at location i, EI_i is the expected economic income at location i, and C_i represents cost at location i. $C_{\text{commuting\_}i}$ is commuting cost at location i, and $C_{\text{residential\_}i}$ is residential cost at location i.

Expected economic income EI_i at location i depends on employment probability e_i and wage rate w that an agent gains from the labor market as expressed below.

$$EI_i = e_i \times w, \tag{14}$$

According to the labor economics theory (McConnell *et al.* 2005), it is assumed that the labor-force individual agents in the same economic sector have the same ability. The working time these agents provide for firms can also be regarded as the same to each other. Therefore, labor-force agents in the same sector are paid by the same wage rate w. Wage rate w (Equation (3)) can be regarded as the price of labor in the market at short-term equilibrium. To simplify the model, w is replaced by annual social labor productivity $\overline{P}_i$ in ith economic sector (Equation (4), $\alpha = 1$).

The employment probability (e_i) that an agent can obtain is determined by labor supply L_{s}^m and labor demand L_{d}^m of labor market m as follows:

$$e_i = \begin{cases} L_{\mathrm{d}}^m / L_{\mathrm{s}}^m, L_{\mathrm{d}}^m < L_{\mathrm{s}}^m \\ 1, L_{\mathrm{d}}^m \geq L_{\mathrm{s}}^m \end{cases} \tag{15}$$

Commuting cost is assumed to be a linear function of distance (Filatova *et al.* 2011). Hence, $C_{\text{commuting\_}i}$ for a labor-force agent at location i is determined by distance and the commuting cost coefficient.

$$C_{\text{commuting\_}i} = c_{\text{COMMUTING}} \times d_i \tag{16}$$

where d_i is the distance from residential location i to the firm where the agent works and $c_{\text{COMMUTING}}$ is the commuting cost per unit of distance.

Residential cost $C_{\text{residential\_}i}$ for a labor-force agent at location i is determined by the residential property price and residential cost coefficient.

$$C_{\text{residential\_}i} = C_{\text{RESIDENT}} \times p_i \tag{17}$$

where p_i refers to residential property sale price per square meter, and residential cost coefficient C_{RESIDENT} is the conversion factor for property sale price to residential cost.

Nonlabor-force agents have no direct economic income. Labor-force agents have to afford the cost of education, consumption, and health care of nonlabor-force agents (children and elders) (Bongaarts 2001). Therefore, there is a dependency cost for labor-force agents except commuting cost and residential cost. The utility of a labor-force agent at location i can then be rewritten as follows:

$$U_i = \mathrm{EI}_i - C_i = \mathrm{EI}_i - (C_{\text{commuting\_}i} + C_{\text{residential\_}i} + C_{\text{dependency\_}i}) \tag{18}$$

Dependency cost $C_{\text{dependency\_}i}$ for a labor-force agent at location i is determined by population dependency ratio dr_i of the community at location i and dependency cost coefficient $C_{\text{DEPENDENCY}}$, as shown below.

$$C_{\text{dependency\_}i} = C_{\text{DEPENDENCY}} \times dr_i \tag{19}$$

Nonlabor-force agents can obtain dependency benefits from labor-force agents. Therefore, utility U_i of a nonlabor-force agent can be expressed as follow:

$$U_i = C_{\text{DEPENDENCY}}/dr_i. \tag{20}$$

2.4.2. Agents' behaviors

The agents' behaviors include (1) entering the city, (2) migrating within the city, (3) leaving the city, and (4) staying in their current location. Figure 2 illustrates the flowchart of agents' behaviors in the simulation process. At the initialization, a certain number (N) of agents enter the city, randomly distributed in the space. The agents opt whether to migrate within

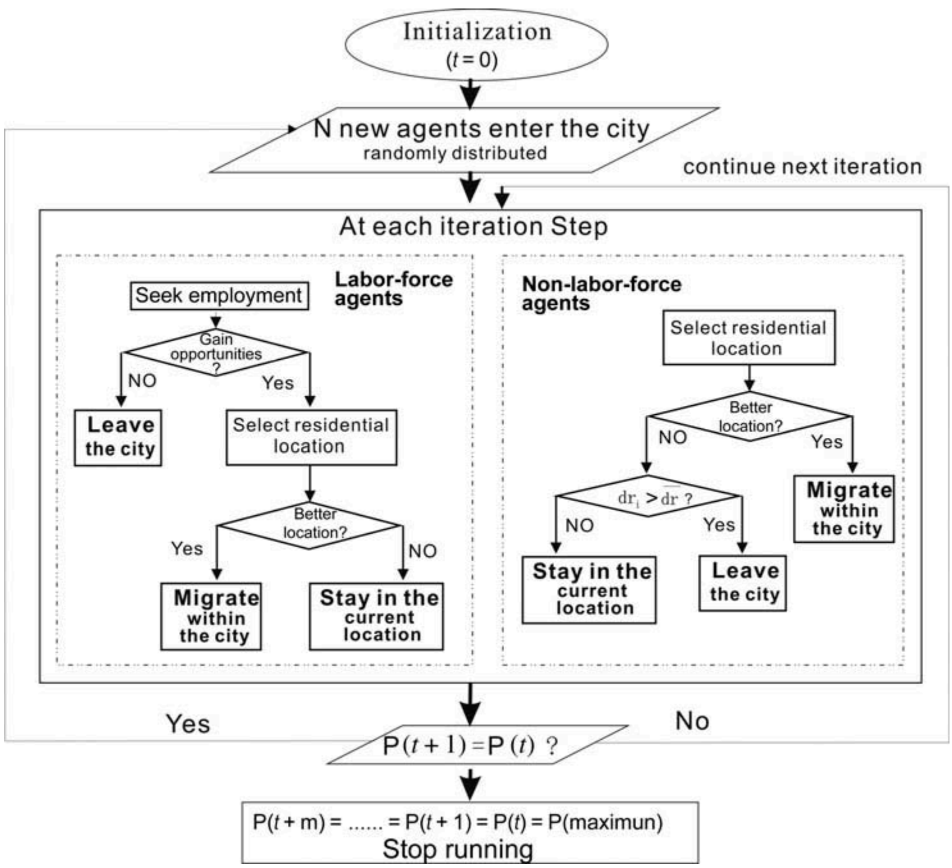

Figure 2. The flowchart of agents' behaviors.

their vision, leave the city, or stay in their current location at each iteration step. If the total number of agents remains the same in two contiguous iterations ($P(t+1) = P(\mathrm{t})$), then other new agents (the number can be also set as N) enter the city; otherwise, the existing agents continue to make location decisions in the next iteration. Agent size reaches the maximum value when all the new agents have to leave the system after entering the city ($P(t + \mathrm{m}) = \ \ldots\ldots P(t+1) = P(\mathrm{t}) = P(\mathrm{maximum})$). Thus, the boundedness of the system can be guaranteed.

Labor-force individual agents enter the city and seek employment. Agents who cannot gain employment opportunities leave the city. If an agent has gained an employment opportunity, that agent would select a residential location that maximizes utility by migrating within the vision. When the agent finds no better location, the agent stays in the current location. Nonlabor-force agents also enter the city and migrate to the locations with maximized utilities. If a nonlabor-force agent cannot find a better location and the population dependency ratio within its vision dr_i is larger than the given average population dependency ratio $\overline{dr}$, the agent would opt to leave the city; otherwise, it would stay in its current location.

Agents are assumed to have complete information of all the locations within their own vision V. We also assume that agents can make rational decisions within the vision V. The main objective of agents is to maximize their own utility as much as possible in residential location decisions. Agents select residential locations with high utilities. Thus, an agent's willingness to migrate is determined by the difference in utility before and after migration and can be expressed as follows:

$$\begin{aligned} &\mathrm{AW}_{a\to b} = U_b - U_a \\ &\mathrm{AW}_{a\to b} \begin{cases} \geq \mathrm{WT}, & \textit{be put in the candidate list} \\ < \mathrm{WT}, & \textit{not to be put in the candidate list} \end{cases} \end{aligned} \tag{21}$$

where $\mathrm{AW}_{a\to b}$ refers to the willingness of an agent to migrate, U_b denotes the utility of location b within the agent's vision V, U_a refers to the utility of the agent's current location, and WT refers to the threshold of migration.

If $\mathrm{AW}_{a\to b}$ is not less than WT, location b would be added to the candidate list. If $\mathrm{AW}_{a\to b}$ is less than WT, location b would not be added to the candidate list. A discrete choice model is utilized in this model to determine the new location that an agent selects. Following McFadden's proof (Barros 2003), the probability of selecting location b can be expressed as follows:

$$P_b = \frac{\exp(U_{(h\to b)})}{\sum \exp(U_{(h\to x)})}, \tag{22}$$

where $\sum \exp(U_{(h\to x)})$ is the sum of the exponential functions for the expected utilities at all candidate locations.

3. Model implementation and results

3.1. Model testing

Before describing a more detailed case study, we make modeling test to validate the model with simplified rules in an ideal environment. Additional ingredients can be added to the model when conducting an actual implementation. Two experiments were carried out to validate the proposed method: (1) population size estimation and spatial simulation based on short-term equilibrium of labor market; (2) spatial population dynamics simulation based on long-term dynamic equilibrium of labor market in a dynamic economic environment.

We assume that there is only one firm in the labor market located at the center of a virtual city (100 × 100 cells) (see Figure 3). The aim of this experiment is to examine the short-term equilibrium of labor market by simulating the interactions between the labor supply of agents and labor demand of firms. Moreover, the simulated spatial pattern will be validated, which results from the location decisions of labor-force agents with maximized utilities. The total output (GDP) of the firm is assumed to be 10,000 RMB yuan (1 USD = 6.23 RMB; 19 January 2013). Social labor productivity $\overline{P}$ for each agent is defined as 100 RMB yuan per year. In this test, commuting cost $C_{\text{commuting\_}i}$ representes C_i in the utility function (Equation (13)). V is set to 6 in this simulation.

The impact of parameter N (initialized agent number) on the simulation results is tested through sensitive analysis. Multiple runs ($N = 5$, $N = 10$, $N = 15$, $N = 20$, $N = 25$, $N = 30$) are performed. The results show that different initialized agent number (N) can eventually generate the same population size and spatial pattern. Figure 4 shows that a high initialized agent number N has improved the speed of convergence by comparing the runs with $N = 5$, $N = 10$, $N = 15$, and $N = 20$, whereas there is a little different in the convergence speed between runs with $N = 20$, $N = 25$, and $N = 30$. Hence, $N = 20$ is chosen for the subsequent experiments.

A total of 200 iterations are implemented for the model. At the initialization, 20 agents are randomly created in the whole virtual city. These agents search for jobs in the labor market and select residential locations within the virtual space. When an agent cannot get an employment opportunity in the labor market, the agent opts to leave the city. If the total number of agents is maintained in two contiguous iterations, then another 20 agents enter the city. Several variables are calculated in each iteration step, including average employment rate e, job vacancy rate v, and agent number. The changes in these output variables during simulation are shown in Figure 5. Initially, variable v has a high value because only a small number of agents exit in the virtual city. Variable v decreases during simulation when more labor-force agents enter the city to occupy the job vacancies. Variable e maintains a value of 1 during simulation because agents who cannot get employment opportunities

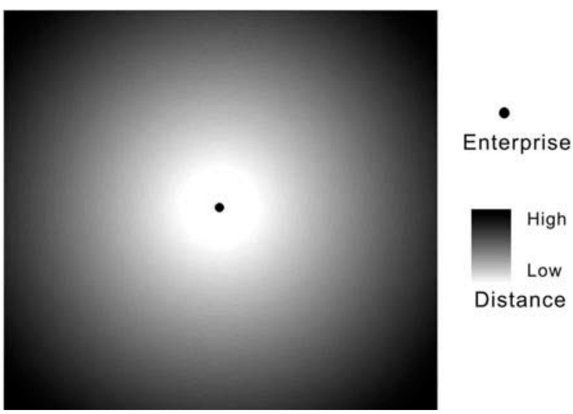

Figure 3. Data used for model testing.

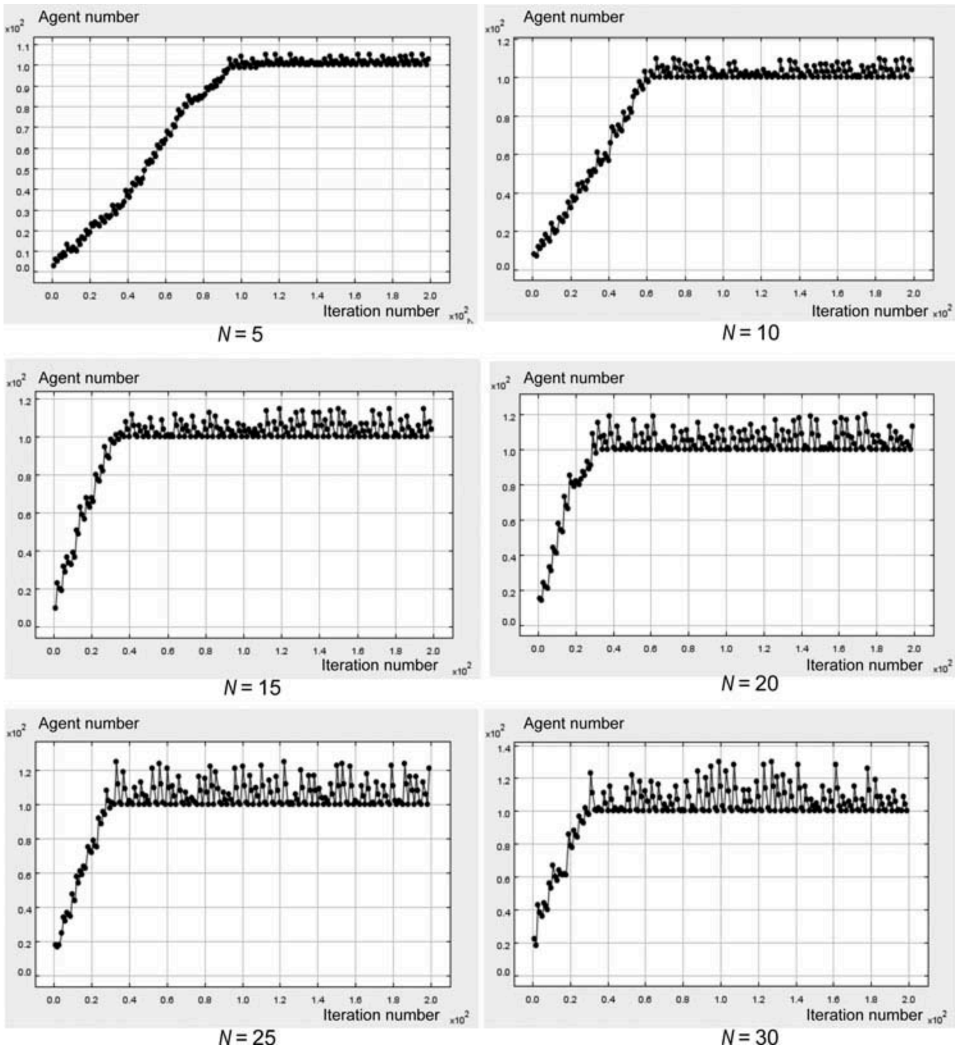

Figure 4. The simulation results of different runs with diverse initialized agent number N.

leave the virtual city. The curves of these two variables quickly become convergent in the first 40 iterations and tend to become steady afterward (Figure 5a). Average employment rate e is close to 1 at the 40th iteration, whereas job vacancy rate v is close to 0, indicating that the labor market has satisfied the equilibrium conditions (Equation (9)). The simulation results show that agent number decreases when some workers leave the system (the red circle in Figure 5b). However, when the labor market reaches equilibrium, total agent number converges to the maximum value of 100 (Figure 5b). The number of the labor-force agents is estimated to be 100 at short-term equilibrium.

Agents maximize utility as much as possible so as to select optimum residential locations. This will generate spatial macro pattern eventually. The simulated spatial distribution of agents is illustrated in Figure 6. A small number of agents enter the city initially; these agents are randomly placed in the virtual space. Then, the agents gradually move close to

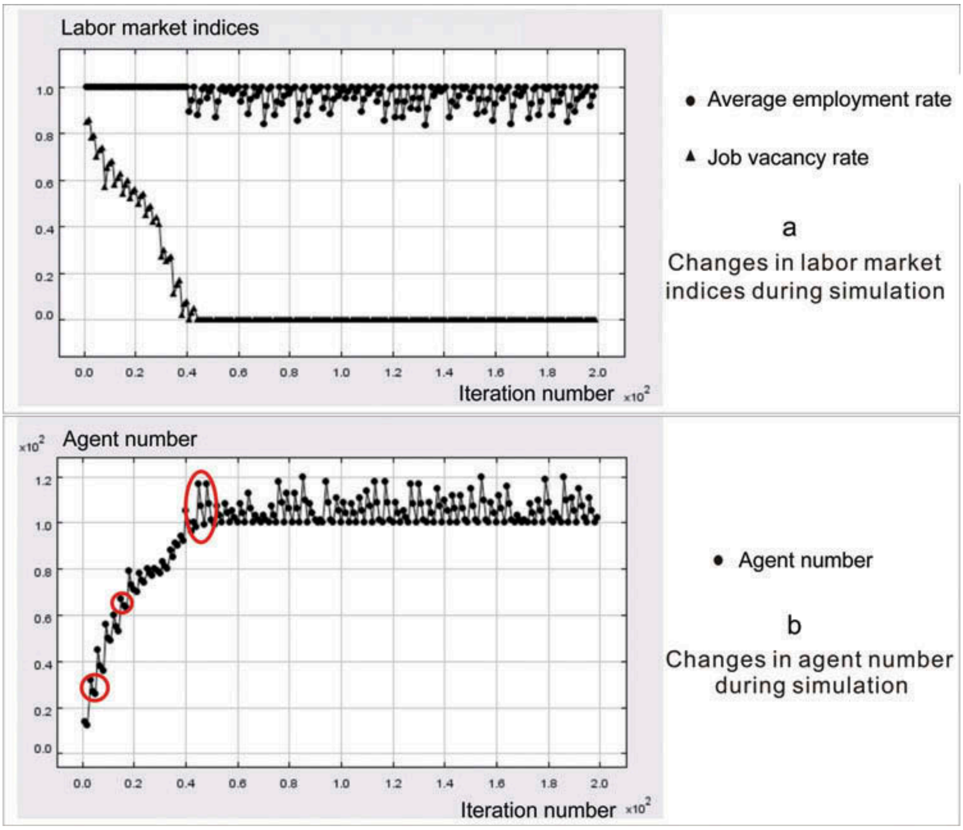

Figure 5. Changes in output variables of model testing during the simulation process.

the firm at the center of space during simulation. When $t = 40$, agent number reaches 100, the spatial distribution becomes relatively aggregate at the same time. When $t = 60$, all the agents are almost located around the firm. The spatial pattern of agents becomes steady after the threshold. Meanwhile, the average utility of all the agents converges to the maximum value when $t = 60$. The spatial distribution of the agents with maximized utilities is verified by this test.

Dynamic economic data are utilized to simulate spatial population dynamics based on long-term dynamic equilibrium of labor market. The initial GDP of the firm is assumed to be 10,000 RMB yuan and increases at a rate of 100% per year. The simulated results of spatial population dynamics are illustrated in Figure 7. The model converges to the first equilibrium situation of the labor market (equilibrium state 1) in the first year when average employment rate e is close to 1 and job vacancy rate v is close to 0 (Figure 7a). The number of agents is approximate to 100 at this equilibrium state (Figure 7b). When the firm's GDP increases to 20,000 RMB yuan in the second year, labor demand and job vacancy rate increase. This leads to disequilibrium between labor demand and labor supply. Thus, more agents enter the city to provide labor service and fill the job vacancies. When e is close to 1 and v is close to 0, the labor market reaches the equilibrium state 2 (Figure 7a). The number of agents in the virtual city is approximate to 200 at this state (Figure 7b). Similarly, as the firm's GDP increases to 30,000 RMB yuan in the third year, more agents enter the

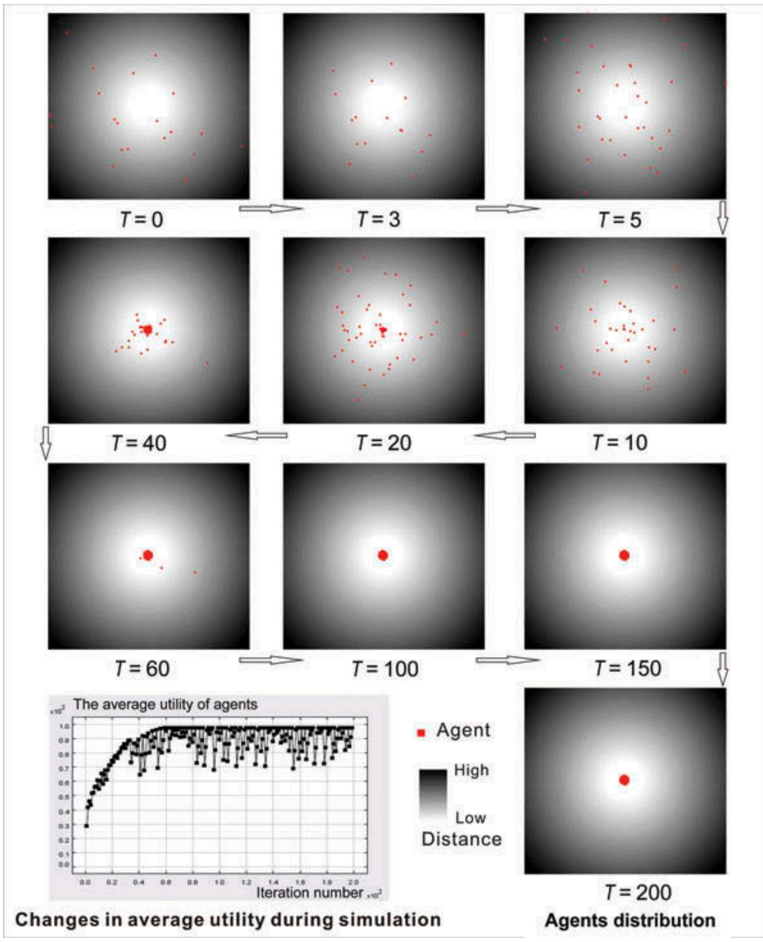

Figure 6. The simulated agent distribution of model testing during the simulation process.

virtual city to seek employment. The labor market reaches a new equilibrium state when labor supply equals labor demand (Figure 7a). At equilibrium state 3, agent number can be as high as 300 (Figure 7b). The long-term equilibrium process of labor market in a dynamic economic environment is revealed in this experiment. Agents make location decisions in the simulation to optimize utility. Population concentration around the firm is observed at each equilibrium state (Figure 7c). The spatial dynamic process of population has been simulated during the long-term equilibrium process.

3.2. Model implementation

3.2.1. Study area and data

The proposed model is applied to simulate the population of Dongguan. This city is a manufacturing metropolis located between Guangzhou and Shenzhen in the Pearl River Delta, China (see Figure 8). Dongguan has transformed from a traditional agricultural county to a modern manufacturing metropolis over the last two decades (Chun 2006). It is now

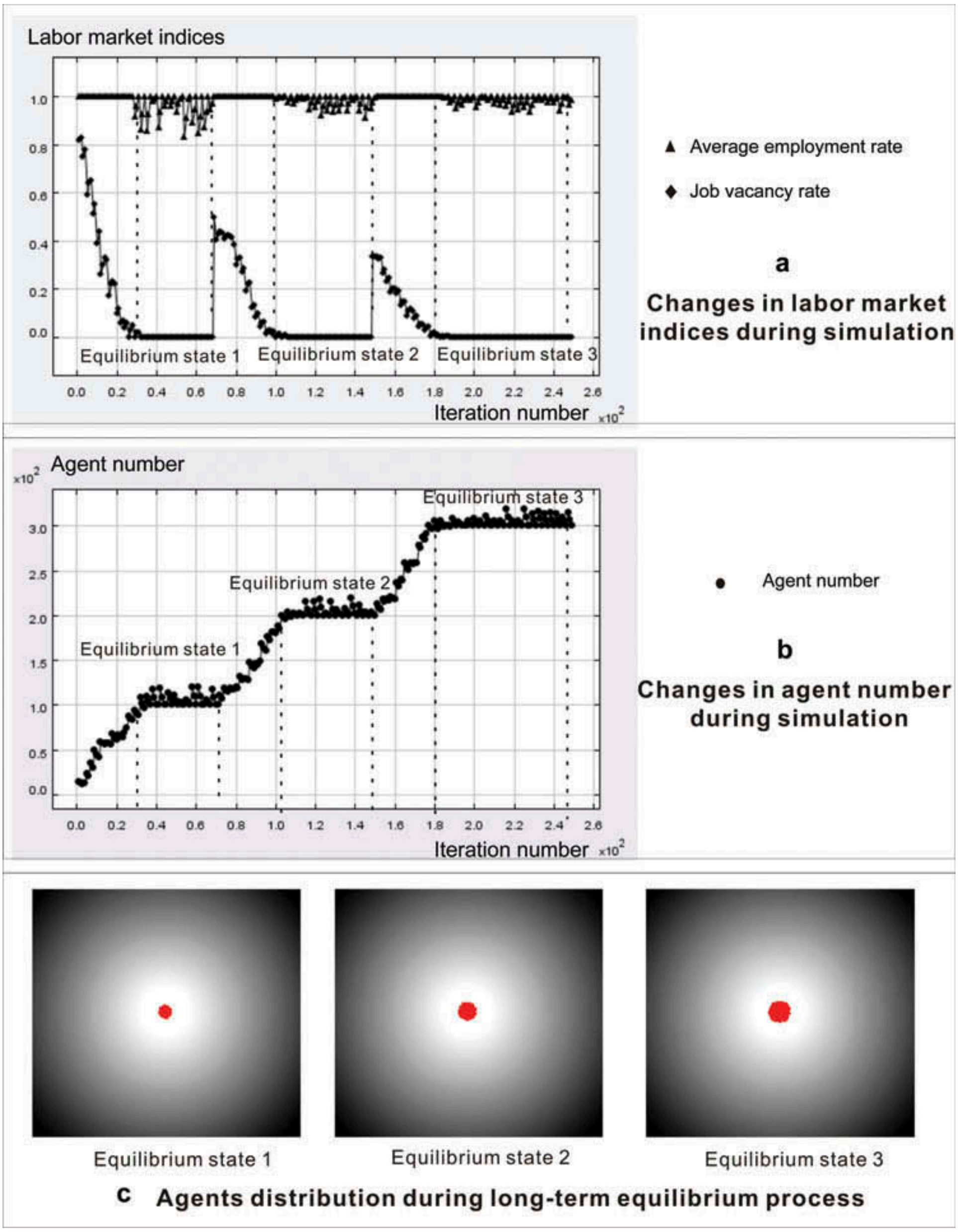

Figure 7. The simulated results of model testing based on long-term equilibrium of labor market.

one of the major destinations of immigrants from other areas in China. It has become a metropolis with high concentrations of immigrant workers because of the fast industrialization (Wright 2003). Statistical data show that immigrant workers account for 76% of the total population in Dongguan. The main motivation of population inflow is employment. Economic and industrial development, which determines employment opportunities, affects the city's spatial population dynamics. Hence, the simulation and prediction of

Figure 8. Location of the study area.

population according to the industrial economy is essential in urban resource planning for this manufacturing metropolis.

Detailed spatial data for the simulation are prepared by using remote sensing and GIS. As mentioned in the introduction, previous ABMs mainly focus on economic information that is nonspatially explicit. In the present model, we consider the spatially explicit industrial economy, which results in labor demand. In model implementation, remote sensing data and economic statistics were integrated to extract the spatial information of the industrial economy. Land-use maps were obtained by classifying the SPOT5 images in 2007. The spatial locations of firms in three economic sectors, namely, agriculture, manufacturing, and service, are identified. The sum output of each firm was calculated based on 2007 GDP statistics. Labor demand of each firm is spatially assigned according to the location of each firm and its sum output by using Equation (5). Data for the variable of commuting distance in Equation (16) was calculated with the Euclidean distance function in ARC/INFO. Two major types of land use were defined: (1) non-habitable land-use, which individuals would not choose to reside in, including water, orchards, farmland, and forest within the ecological protected areas. In China, strict mandates for the protection of important ecological land areas have been implemented in some fast-growing regions, such as Dongguan and Shenzhen (Li *et al*. 2011). Protected ecological areas are regarded as non-habitable land-use in this study because these areas cannot be converted into habitable land-use (Urban Planning Department of Dongguan 2009). (2) Habitable land-use that individuals may choose to reside in. Data for the variable of residential property price in

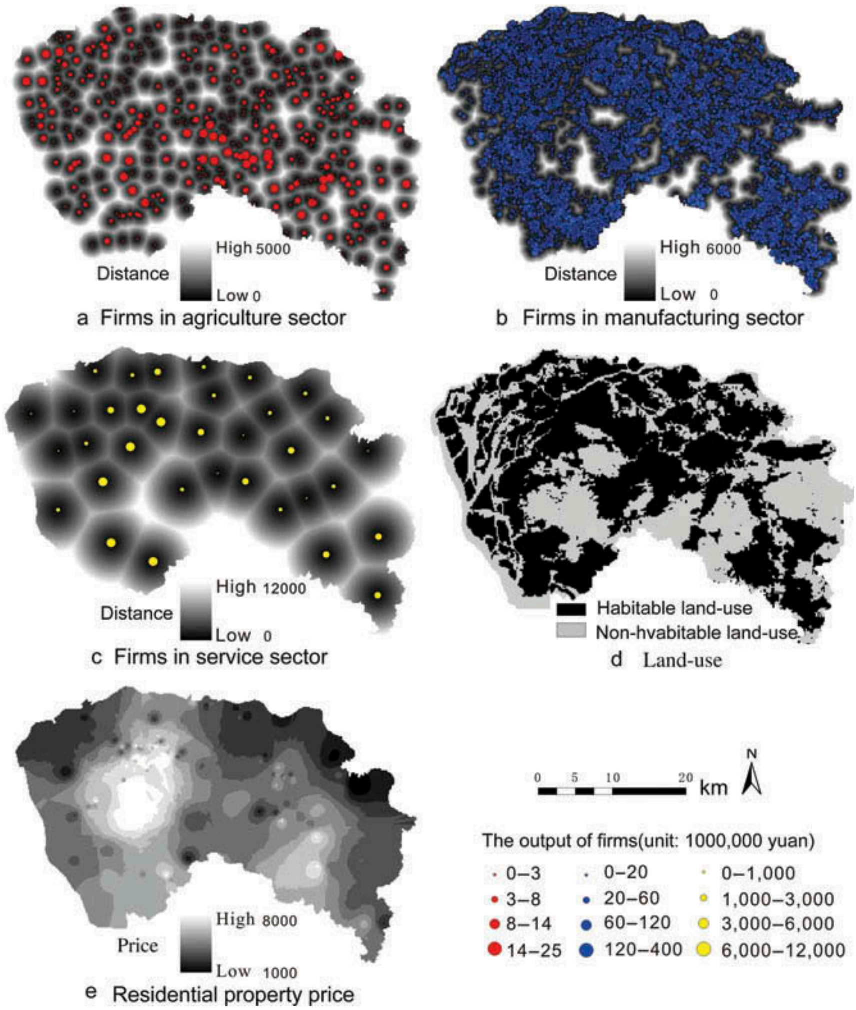

Figure 9. Data for simulation of spatial population dynamics.

Equation (17) were obtained from the known points of property sale price in 2007 by using Kriging interpolation in ARC/INFO. All the spatial data were converted into raster grids with a resolution of 200 m × 200 m to reduce the computation time for the ABM (Li and Liu 2007). The spatial data used in this study are shown in Figure 9a–e.

3.2.2. Simulation of spatial population dynamics

An economic system formed by three sectors (agriculture, manufacturing, and service) is considered in this study. Labor-force agents are classified into agriculture labor-force, manufacturing labor-force, and service labor-force agents. In model implementation, one agent represents 1000 population individuals. A grid cannot be occupied by more than one agent. $N = 400$ is chosen for model implementation with sensitive analysis for the same reason stated in Section 3.1.A total of 400 agents of each type enter the city with a random distribution during initialization. The parameters adopted in the simulation are listed in Table 1. The values of these parameters are determined according to statistical data, empirical data, or sensitivity analysis results. Average population dependency ratio $\overline{dr}$ is given as 0.12 based on the statistical data of Dongguan from 2000 to 2007. The values of parameters V (agents' vision range) and WT (migration threshold) are determined by performing sensitivity analysis with different parameter values. For instance, a high V value has improved the simulated average utility. The experiments show that $V = 8$ allows for faster simulation compared with $V = 6$. Therefore, V is set to 6 in this simulation. WT is also set to 10 through the same method. The values of the three cost coefficients are determined based on empirical data. The annual labor productivity for the three economic sectors is calculated based on GDP and actual labor force number in each sector of Dongguan in 2007. Data on industrial and economic change from 2007 to 2010 are listed in Table 2.

The proposed model is applied to simulate spatial population dynamics in Dongguan from 2007 to 2010. The simulation results are shown in Figure 10. The model converges to the first equilibrium state in the first 150 iterations. When $t = 80$, average employment rate e is close to 1, and job vacancy rate v is close to 0 (Figure 10a). This finding reveals that the labor market has reached the short-term equilibrium in 2007. Total population size reaches the maximized value (6,904,000) at this short-term state of equilibrium (Figure 10b); this value can be utilized to estimate the population size of Dongguan in 2007. This equilibrium state is broken when the economic is changed from 2007 to 2008. The increase in GDP leads to an increase in labor demand and job vacancy rate at the

Table 1. Parameters for modeling.

Parameters	Description	Default value
$\overline{dr}$	Average population dependency ratio	0.12
V	Vision range of agent	6
WT	Migration threshold value	10
$C_{\text{COMMUTING}}$	Commuting cost coefficient: the commuting cost per unit distance	0.2
C_{RESIDENT}	Residential cost coefficient: the residential cost per unit property price	0.75
$C_{\text{DEPENDENCY}}$	Dependency cot coefficient:the dependency cost per nonlabor-force individual	500
$\overline{P_1}$	Annual labor productivity in agriculture sector	8800 yuan/individual
$\overline{P_2}$	Annual labor productivity in manufacturing sector	30,000 yuan/individual
$\overline{P_3}$	Annual labor productivity in service sector	75,000 yuan/individual

Table 2. Annual increase rate of output (GDP) in each sector of Dongguan for 2007 to 2010 (drawn from Dongguan Statistical Almanac).

	Annual increase rate of output in agriculture sector	Annual increase rate of output in manufacturing sector	Annual increase rate of output in service sector
2007–2008	−3.2%	6.9%	23.8%
2008–2009	5.1%	−3.7%	15.1%
2009–2010	1.9%	16.8%	3.9%

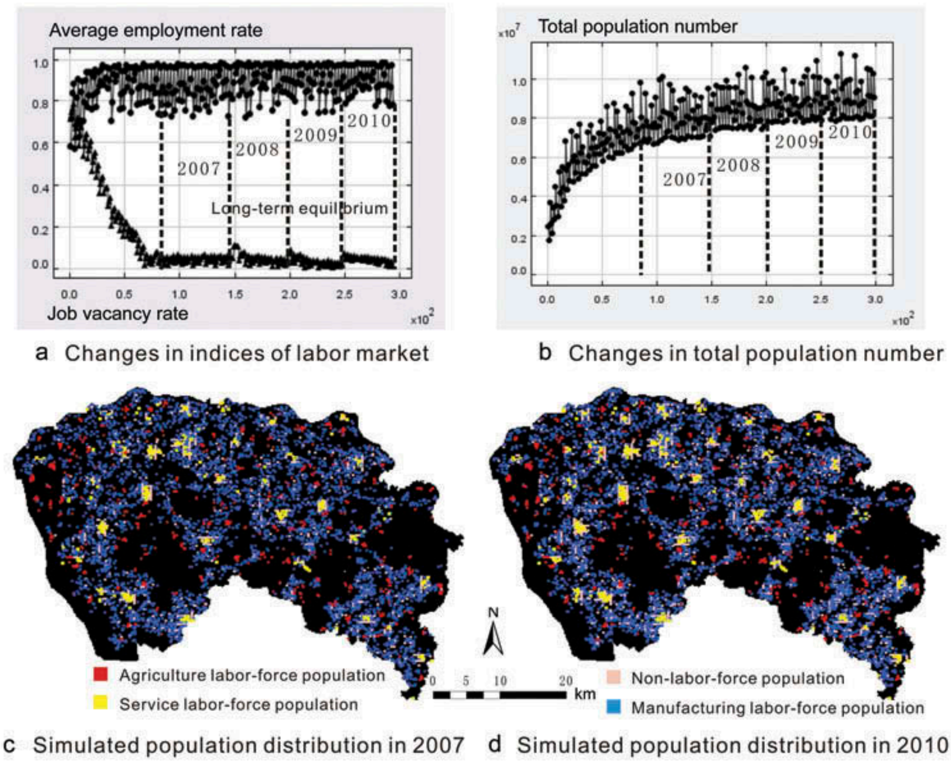

Figure 10. The simulated results of spatial population dynamics of Dongguan for 2007–2010.

150th iteration. This results in disequilibrium in labor market. More individuals enter the city and make employment choices, resulting in an increase in labor supply. The labor market reaches a new state of equilibrium in 2008 when $t = 230$ and total population is approximate to 7,382,000 (Figure 10a–b); this value can be considered the population size in 2008. The population size is approximate to 7,750,000 in the equilibrium state of 2009. The labor market reaches the equilibrium state in 2010 when $t = 280$. Population size is approximate to 7,943,000 at this state. The long-term dynamic equilibrium process of the labor market is revealed by the simulation of spatial population dynamics for the period of 2007 to 2010 (Figure 10a–b). At the beginning of the simulation, a small number of individuals enter the city, distributed randomly on habitable land. The individuals then make location decisions to maximize utility. A specific spatial distribution pattern is then generated. Individuals adjust their location decisions according to the labor market when the industrial economy changes. This will ultimately result in a new distribution pattern. The simulated population distributions in 2007 and 2010 are shown in Figure 10c–d.

Similar to other modeling approaches, the simulation results in this study may be affected by randomness. Simulations must be performed several times. The simulation is repeated 10 times in this study to test the robustness of the model. The standard deviation (Equation (23)) of population size which is used to measure the robustness of the model can be defined as follows:

$$\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(P_{\text{simulated}\_t} - \overline{P_{\text{simulated}}}\right)^2} \tag{23}$$

where σ is the standard deviation of the simulated population size at different runs, $P_{\text{simulated}\_t}$ is the simulated population size of the tth run ($T = 10$). $\overline{P_{\text{simulated}}}$ is the mean value of the simulated population size at different runs.

To further validate the proposed model, we used the relative error index r (Equation (24)) to calculate the error between the mean value of simulated population size $\overline{P_{\text{simulated}}}$ and the actual population size P_{actual}.

$$r = \left|\overline{P_{\text{simulated}}} - P_{\text{actual}}\right| / P_{\text{actual}} \tag{24}$$

The mean value of the simulated total population size in 2010 is 7,942,000, which is close to the census figure of 8,224,800. Standard deviation is 4640, revealing the robustness of the proposed model. The relative error index of total population size is 3.4%. The relative error index of population size in each town is then used to test the simulated spatial pattern. The results are presented in Figure 11. The simulated population sizes of 25 towns (out of 32) are close to the figure indicated by census data with relative error less than 20%. The average relative error for the 32 towns is 16.3%. The simulated population sizes are close to the figure indicated by census data with relative errors less than 10% for these night towns, such as Macong, Guancheng, Nancheng, Houjie, Dalingshan, Dalang, Tangxia, Shipai, and Qishi. When an accuracy standard is established with a relative error that is less than 20%, overall simulation accuracy is estimated to be 78.1%.

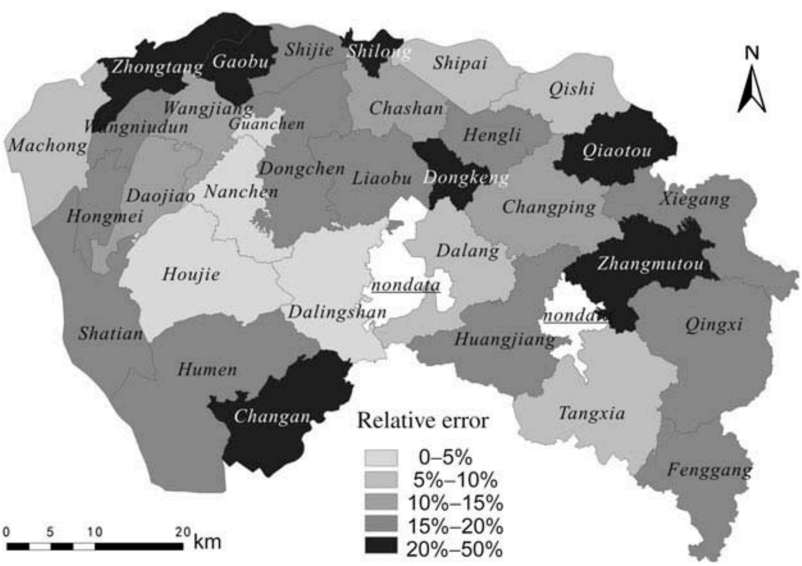

Figure 11. The relative error between simulated population size and the actual population size for each town of Dongguan in 2010.

3.2.3. *Prediction of spatial population dynamics based on planning scenarios*

The proposed model can be applied to predict spatial population dynamics based on economic planning scenarios by altering the parameters such as the increase rate of output (GDP) or labor productivity in each economic sector. Two experiments were performed to evaluate different economic policy outcomes based on the following scenarios: (1) benchmark scenario of national economic planning; (2) scenario of industrial structural transformation.

First, data on the industrial economy of Dongguan in 2010 are used to simulate the long-term equilibrium process of the labor market according to the national economic planning of Dongguan from 2010 to 2015 (see Table 3). The simulation results (Figure 12a–b) show that total population size would be approximate to 9,351,000 in 2015, with an increase of 1,133,000 people from 2010. The rapid growth of GDP in the economic sectors would cause labor demand to increase rapidly. The proportion of the labor-force population

Table 3. Annual increase rate of output (GDP) in each sector of Dongguan based on economic plan for 2010 to 2015.

Annual increase rate of GDP in agriculture sector	Annual increase rate of GDP in manufacturing sector	Annual increase rate of GDP in service sector
2%	6%	12%

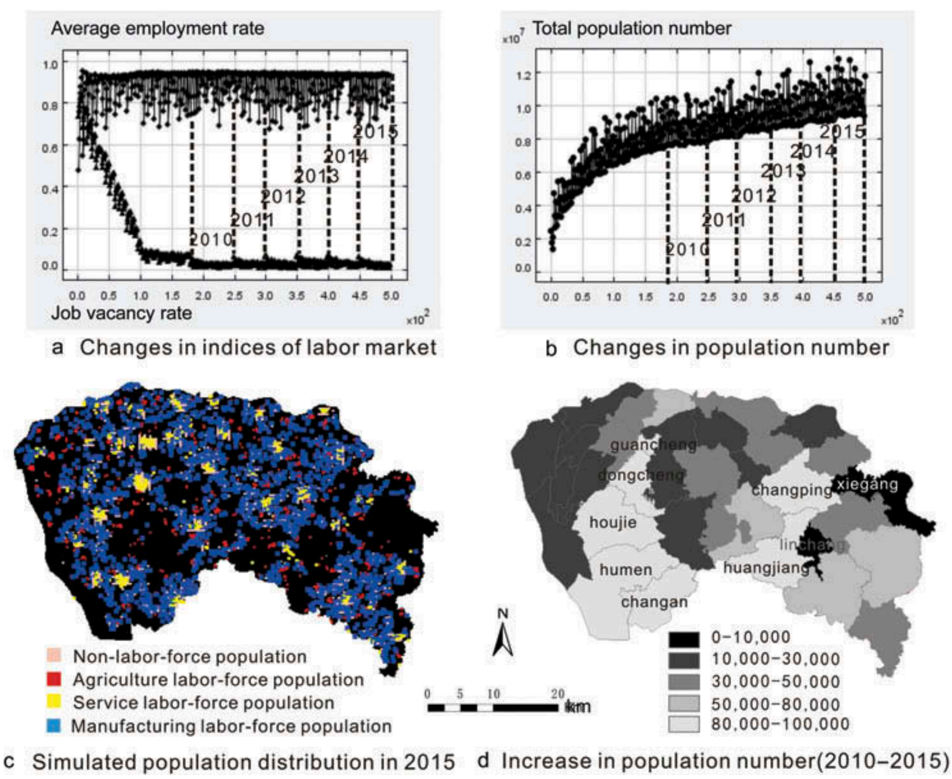

Figure 12. The predicted results of spatial population dynamics based on scenario 1.

Table 4. Annual increase rate of labor productivity in each sector of Dongguan for 2010 to 2015.

Annual increase rate of labor productivity in agriculture sector	Annual increase rate of labor productivity in manufacturing sector	Annual increase rate of labor productivity in service sector
2%	12%	12%

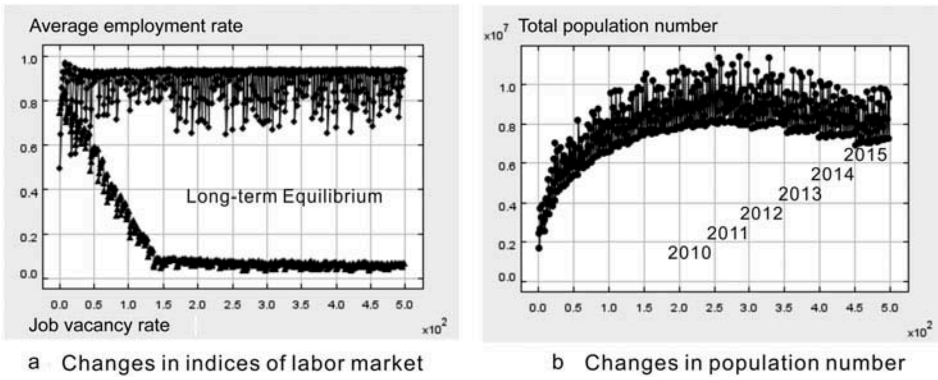

Figure 13. The predicted results of spatial population dynamics based on scenario 2.

in the three sectors would change from 2:73:25 in 2010 to 2:56:42 in 2015. According to the simulated results (Figure 12c–d), Guancheng, Nancheng, Houjie, Humen, Changan, Changping, and Huangjiang have the higher increased number of population, which is between 80,000 and 100,000, whereas Xiegang and Linchang have the lower increased number of population, which is smaller than 10,000.

Second, urban planning indicates that Dongguan would experience an industrial structural transformation. This assumption means that labor-intensive firms in the manufacturing sector would gradually evolve into technology-intensive firms. Such technological progress would result in an increase in the social labor productivity of the manufacturing sector. Consequently, the social labor productivity in each sector would experience an annual increase (Table 4). Figure 13a–b presents the predicted results of spatial population dynamics of Dongguan from 2010 to 2015. The results show that population size would be approximate to 7,144,000 in 2015. There is a decrease of 1,081,000 people compared with the population size in 2010. Industrial structural transformation would cause the labor demand in the manufacturing sector to decrease; some individuals would not be able to obtain employment opportunities in this city. These individuals have to leave the city, thereby decreasing total population size. The predicted results reveal that industrial structural transformation can seriously affect future spatial population dynamics.

4. Discussion and conclusion

ABMs can simulate the complex behaviors of interacting agents. Agent-based approaches can also model the spatial dynamics of complex systems that involve individual behaviors. Various ABMs have been developed to simulate individual residential decisions or economic behaviors. However, there has been a lack of systematic research that integrate residential and employment behaviors. Lemoy *et al.* (2013) recently studied employment and housing location simultaneity through the ABM model with theoretical data. However, the representation of the labor market was limited. In addition, the model is difficult to apply with actual data. Labor market in the manufacturing metropolises would have a significant effect on individual employment choices and residential behaviors, resulting in spatial population dynamics. Hence, there remains a need for sophisticated ABM models, which consider labor market in location choice modeling.

In this article, an ABM is developed to simulate population dynamics in a rapidly developing manufacturing metropolis by incorporating equilibrium of labor market into a multi-agent system. The model considers the influence of the industrial economy on individual economic behaviors and residential decisions. Labor economics was incorporated to address the fact that employment opportunity is the motivation of immigrants. Long-term equilibrium of labor market was established to simulate the interactions between labor supply and labor demand. An agent-based approach was utilized to simulate the economic and residential behaviors of population individuals. These individual behaviors would eventually have consequences on the outcome of spatial population dynamics.

The proposed model was applied to simulate the spatial population dynamics in Dongguan from 2007 to 2010. The simulated total population size in 2010 is approximate to 7,942,000, which is close to its census record (8,224,800). The average relative error of the simulated results for the 32 towns is 16.3%. The overall simulated accuracy is estimated to be 78.1%. These simulated results have demonstrated that the proposed model is effective for the prediction of spatial population dynamics in rapidly developing manufacturing metropolises.

The proposed model was also utilized to predict spatial population dynamics with regard to two economic planning scenarios. The simulation results show a significant increase in total population and a remarkable change in population proportion in the three sectors from 2010 to 2015 based on national economic planning for Dongguan. The simulation results also show a decrease in total population from 2010 to 2015 based on the assumption that Dongguan will experience an industrial structural transformation. It is argued that the use of the proposed model could allow us to test the effect of different economic policies on spatial population dynamics. Predicting spatial population dynamics can provide important guidance to urban planners as they deal with urban resource allocation.

The exogenous forces of global or national economies would have a significant impact on the labor market, especially for rapidly developing manufacturing metropolises. For example, the global economic crisis would result in the mass loss of migrant jobs, which leads to the disequilibrium in the labor market and outflow of migrant workers (Cai and Chan 2009). A research perspective is to extend the proposed model to simulate the influences of such exogenous economic changes on unemployment and population dynamics in manufacturing metropolises. Another perspective can be considered to calibrate the proposed ABM model with swarm intelligence algorithms. In this study, the values of the model parameters were chosen based on empirical data or sensitivity analysis results. Hence, there is limitation in model calibrating. Future work will incorporate swarm intelligence algorithms to automatically derive model parameters.

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