INTEGRATION OF GENETIC AGENTS AND CELLULAR AUTOMATA FOR DYNAMIC URBAN GROWTH MODELLING: PILOT STUDEIS

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ABSTRACT

Urban land change phenomena include spatial and a-spatial dynamics. As Holland (1995) suggests "a city's coherence is somehow imposed on a perpetual flux of people and structure". However, it seems most of the traditional economic and geographic studies tried to separate the two entities associated with land use change, human decision-making and environmental consequences, into two separate models (Sethuram et al., 2008). CA model explores only the spatial dynamics of the urban system, although the transition rules often are representations of human decision making, this representations are not explicit. In order to explore the two fluxes (the spatial and a-spatial dynamics), we need to take human adaptation and learning into account, in which actors can act in complex and realistic ways. Agent based model opens up an avenue for analysis of a-spatial dynamic processes that links spatial development with social issues, whereas, agent based model is insufficient to deal with spatial dynamics. The integration of agent based model and cellular automata model, it comes to meet the understanding that human decision making in spatial context and the dynamic spatial changes under social-economic interactions. So we defend that the inclusion of CA for spatial dynamics and ABMs for a-spatial dynamics is a better solution for urban modelling.

In this paper, we present an integrated model that incorporates ABM, CA and genetic algorithm (GA) to include both spatial and a-spatial dynamics in an urban system in order to supply a new solution for urban studies. In our model, the social economic behaviours of heterogeneous agents (resident, property developer and government) will be regulated by GA and Theory of Planning Behaviour (TpB). The macro level of emergence (e.g., land pattern change) which is produced by the interactions at the micro level (the heterogeneous behaviours and interactions between agents, and the discrete spatial dynamics represented by CA) will also be analyzed. Besides, the heterogeneous interactions between agents and the influence of these interactions on decision making will be captured with a social network

in our research, both social neighbours and physical neighbours of residents are considered to make the simulation more realistic.

Keywords: Urban model, agent based modelling, cellular automata, integrated model, theory of planned behaviour

1. INTRODUCTION

The complexity and dynamics of urban systems make the applicable practice of urban modelling very difficult. This is one of the reasons why Lee (1973) made an attempt to bury urban modelling by enumerating the "Seven sins" of large scale models in planning in his "Requiem for large-scale models". Several decades of changes in society, science and technology, especially in computer science and information technology are going to forgive (or have already forgiven) Lee's sins (Rabino 2007). As Harris (1994) defended, it is time to put this behind us and find ways to strengthen both planning and modelling through collaboration in investigating the real issues. The Nitty-Gritty of model building and pragmatic opinions about urban modelling have been stated by many researchers (Batty 1994, Wegner 1994, Silva 2004, Wu and Silava 2009a) with their disagreements to Lee's commentary. Various increasingly sophisticated urban models from literature (Wu and Silva 2009 b,c, Verburg 2004 , Agarwal 2002) have demonstrated the great return of large scale urban models, as Rabino (2007) described this as a sure revival and a possible "renaissance" new era by taking into account more explicitly in model building.

Admittedly, Lee's "Requiem" had extensive adverse effects on modelling, partly on modelling but largely on planning (Harris 1994). It also evoked our critical thinking on where the future of urban modelling lies and how to enrich model-building in order to make them more applicable. The past several decades have witnessed the great improvements of computing speed, data availability and solutions on complex and non-linear analysis. The improvements might continue, as they have, and permit much more attention on details and realism of urban modelling. Nowadays, the third phase of urban modelling (Silva 2004) and the fifth generation modelling systems (Chau et al 2006, Chau and Chen 2001, Abbott 1989) are acknowledged to have the features of integrating AI technology and computational hybrid-dynamics into a single system to furnish assistance for non-experienced users. Cellular automata (CA) based models and agent based models (ABM) are flourishing in this generation. The increasing use of AI approaches has led to a new generation of urban growth models, in which dynamic models based on fine-scale cells and individual behaviours involving agents (Batty 2005) has begun to find favor to enhance the existing interaction and synchronization between different scales over the model and capture the emergent

It is also a fact that the increasing interactions between scientific fields (i.e., social sciences and natural and physical sciences) are important needs to overcome today's barriers for a seamless integration of methodologies. These needs are particularly felt in behavioural studies of land use change which are based on social economics and social psychology. These scientific studies would have a lot to win if more integration with spatial explicit methodologies were to be included. For example, the integration of Genetic algorithm (GA) and CA, the complementarities of CA (on spatial explicit representation) and GA (on individual agents' behaviours optimization) have been mentioned by Silva (2008a). So with the integrations, we can overcome the modelling divide of spatial versus a-spatial dynamics in urban land use change.

In this paper, we present a genetic agents and cellular automata based model that incorporates agent based modelling, CA and GA, with both spatial and a-spatial dynamics included in an urban system in order to supply a new solution for urban growth phenomena studies. Urban land use dynamics are the direct consequence of the actions of individuals, public and private corporations acting simultaneously in time over the urban space. In our model, the social economic behaviours of different agents (resident, property developer and government) in urban system are regulated by GA and the theory of planned behaviour (TpB). The macro level of emergence (e.g., land pattern change) which is resulted from the micro level interactions (e.g., the heterogeneous behaviours, the interactions between agents, and the discrete spatial environment represented by CA) are also analyzed. Besides, the heterogeneous interactions between agents and the influence of these interactions exerted on decision making are influenced by a social network in our model, so both social neighbours (the agents in an extended Moore neighbourhood) and physical neighbours (location cells in Moore neighbourhood) of residents are considered to make the simulation more realistic.

The paper proceeds as follows: Firstly, we briefly review the related literature, and discuss the "renaissance" of urban models. Next, we introduce the theoretical basis of the integrated model. We then present the conceptual model, the framework of the integrated model, the modelling environment, the heterogeneous agents and their decision behaviours. Following this, the integration and synchronization processes are introduced. We then present a pilot study of the integrated model to analyze the applicable practice of the model. Finally, we conclude with a discussion of a potential path for transferring the model to an empirical context.

2. LOCATION BEHAVOR, SPATIAL PATTERNS AND ECONOMIC AGENTS

Understanding the urban growth is a prerequisite for urban modelling that involves various actors with different patterns of behaviours. We argue that scientific understanding must be based on the elaborated complexity theory and multidisciplinary research areas.

2.1 Inclusion of spatial and a-spatial dynamics in urban modelling

It is of high demand of understanding the residential expansion with human behaviours in micro scale including: what types of stakeholders take actions in residential expansion process, what are the interrelationships between their behaviours, and what are the effects of their a-spatial actions on the spatial-temporal complex processes of residential expansion.

Therefore, it's necessary to explore the possibility of interacting spatial and a-spatial dynamics, improving the existent modelling approaches.

Complexity analysis came into the field of spatial analysis later in time, during the 1970s (Silva 2004). Since then, many urban studies based on the complex theory have been presented in publications, particularly with techniques such as cellular automata, agent based modelling and GIS. However, it seems that most of the traditional economic and geographic studies tried to separate the two entities associated with land use change, human decision-making and environmental consequences, into two separate models (Sethuram 2008). As a result, two research streams can be detected, the one with CA to be decisive to the understanding of complexity at spatial scale, and the other focusing on behavioural and social systems complexity (Silva 2004).

Both the spatial dynamics of an urban system such as the biophysical variables (e.g., slope, soil type, and hill-shade) and a-spatial dynamics such as the social economic variables (e.g., demography, social network and economic utilities) are essential to urban modelling. So we defend that the inclusion of CA for spatial dynamics and ABMs for a-spatial dynamics is a better solution for urban modelling. CA has evolved greatly from its initial concepts, many functions have been improved (e.g., action at a distance, calibration and definition of transition rules) to make CA more flexible and efficient approach for urban studies. However, poor a-spatial representation in a CA still limits its ability to reflect the feedback of system and social economic influence on decision making. So one of the major failure associated with current environment management is the failure of non-inclusion of human-decision making in natural resource management (Sethuram 2008). This can be improved by incorporating agent based models (ABM) for their ability to represent the impacts of autonomous, heterogeneous, and decentralized human decision making on the landscape. ABM makes the modelling of urban and land systems more comprehensive in an entirely nonlinear way, which offers a way of incorporating the influences of human decision making on urban land dynamics and the ability to analyze the response of a system to exogenous influences such as urban-rural dynamics, policy and planning changes. Thus, it seems that, the hybrid model, which is composed of CA and ABM, is a more appropriate method for urban modelling since it possesses the advantages of both CA and ABM (Nara and Torrens, 2005). In this context, urban and land dynamic models include two important components: a cellular model that is used to describe spatial dynamics and an agent based model that provides complementarities to spatial model by incorporating social interactions.

2.2 Theory of planned behaviour and decision making mechanism of location choice

Urban economics provide theoretical basis for urban modelling. Location theory, for example, is essential to urban growth, and it relates the planning behaviour to a spatial context. The model of Von Thünen (1826) formalizes the relationship between transportation costs for agricultural goods to the central business district (CBD) and land rents, demonstrating the location of agricultural activity. Alonso (1960) developed a model based on Von Thünen model that can be regarded as the foundation for household location choice. The basic principle of the model is that rents decrease outward from the city centre. Most of urban models are based on the basic theory background, so the location theories of Von Thünen and Alonso are not sufficient to explain the real world complex spatial structures that we encounter (Otter 2000).

Classic economic theory treated land as a factor of production, and the residents and developer as customers based on market forces. The urban land change partly emerges from the micro interaction of residents' and developers' location behaviours and discrete choices. However, most of the traditional economic studies model human actors only as utility maximizing functions (Ormerod 1994). This is against the norm of most human psychological studies that argue that most humans make decisions based on cognitive limitations and bounded rationality (Simon 1957). Individual user decision on choosing an innovative product is not only a function of the benefit and cost of the product, as described in economic theories, but also, and in some cases perhaps more so, a function of the factors from the user's psychology and the social networks in which the users participate (Zhang and Nuttall 2008).

The theory of planned behaviour (TpB) (Ajzen 1985) is a theory about the link between attitudes and behaviour. According to TpB, human action is guided by three kinds of considerations: beliefs about the likely outcomes of the behaviour and the evaluations of these outcomes (behavioural beliefs), beliefs about the normative expectations of others and motivation to comply with these expectations (normative beliefs), and beliefs about the presence of factors that may facilitate or impede performance of the behaviour and the perceived power of these factors (control beliefs). The social network influence on residents' decision and the heterogeneous agents with multiple social behaviours can be modelled by TpB. As bounded rational agents, rather than trying to find an optimal solution that fully anticipate the future states of the system of which they are part, they make inductive, discrete, and evolving choices that move them towards achieving goals or levels of aspiration (Simon, 1957; Rabin 1998).

2.3 The behaviour regulation of agents with genetic algorithm

Agent based models have presented their ability to model individual decision making entities and the interactions between agents, especially when the interactions are complex, nonlinear, discontinuous, and discrete, or when there are multiple heterogeneous agents acting independently, or when the agents represents complex behaviour such as adaptation and learning (Bonabeau 2002). The behaviours and strategic choices of agents have been the central topic in this research area, so there is an increasing number of researchers who are exploring the appropriate way to model the strategic choices of agents in agent based complex models.

The use of artificial adaptive agents (Holland and Miller, 1991) allows the relatively easy analysis of such complex learning behaviours. In adaptive agents based models, GAs provides a highly efficient mechanism for effectively searching optimized solutions in both enormous search spaces and objective functions with nonlinearities, discontinuities, high dimensionality, and noise (Miller 1996). Further more, their underlying structure indicates that they may be an appropriate model of certain types of adaptive learning behaviour (Miller, 1986). With GA, the agents' complex decision making processes are modelled as adaptive agents that respond to socioeconomic diving forces such as profit maximization, social network interactions and feedbacks. As GA models can represent decisions making processes that lead to specific spatial actions, so it is important for its behavioural roles are very apt to model individual agents and their behaviour (Silva 2008a), so the incorporation of GA into agents as genetic agents might provide a better solution for regulating the behaviour of agents. In this context GA works as a high level pattern of 'human behaviour', which produces solutions for the behaviours choices of 'human' (agents) in a social-economic environment.

The local interactions and the dynamic behaviours of heterogeneous agents in urban systems play significant roles in explaining many macroscopic dynamics such as urban growth, sprawl and segregation. In our model, the adaptive agents in urban modelling include agents that represent entities (residents, developers, governments) and the behaviour regulations (e.g., optimization on transport cost function of agents) that GA exerts on them. The solution samples of adaptive agents' behaviours are set randomly in GA at initialization. Each solution can be seen as a chromosome, which is defined by a sequence of decision variables known as genes. The evolution processes of GAs such as selection, crossover and mutation, they yield the next optimized generation of solution samples. The strategies of agents such as the location choice of resident agents are encoded to the series of 1 or 0 with the variables of designed utility formulation.

3. THE MODEL DESCRIPTION

3.1 The conceptual framework

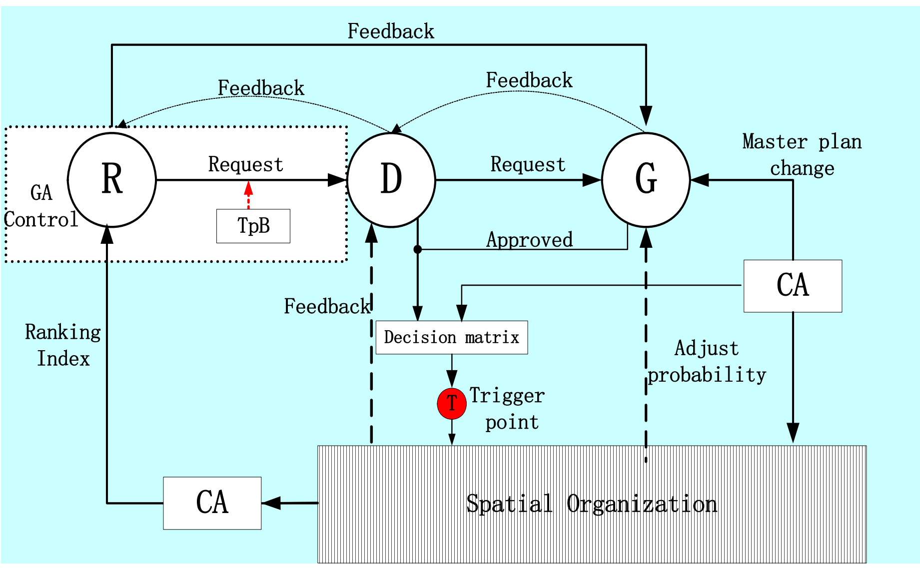


Figure 1 – Concept framework of model

The framework of the model mainly includes three components: (1) the heterogeneous agents (Resident agent -R, Developer agent -D and Government agent -G), (2) cellular automata model (based on SLEUTH), (3) a GA (Roulette wheel selection) that is used to control the behaviours of resident agents to perform the optimization of decision rules. The interactions between the components and their social/spatial environments yield to either direct or indirect influences on the urban land use change processes.

As is shown in Fig 1, the decision processes mainly based on the interactions of different actors as well as the interactions between actors and environment. There are mainly four decision tables which reflect the four important processes in the system and they trigger different actor behaviours: (1) Resident agents' utility table, which is controlled by TpB model and GA, represents the request of residents to developers about their demands on locations. (2) The developer agents' development application table, which represents the response of developers to residents' requests, and the development applications to government after evaluation. (3) The government's approving table, which reflect the government agent's response to developer agents' development applications, all the approved applications in the table will be read by developer agents in order to execute development. (4) Synchronized decision table, which represents the synchronized decision matrix between agents based model and SLEUTH model on urban land use change.

3.2 Model environment

3.2.1 Spatial Environment

The spatial environment in this model is mainly provided by raster data (raster gray scale images) supplied by GIS, which includes a grid of cells that change state as the model iterates, with a neighbourhood of eight cells, two cell states{urban/non-urban} and a number of spatial attributes.

Land use attributes: The collection object *S* (*slope, land use, excluded, urban, transportation, hillshade*) is the main spatial characteristics of the spatial layer. It provides the spatial environment that CA model works on and represents the geographic attributes which determine the suitability of land parcels for residential development. For example, the excluded areas (water and hill areas) and the areas with specific slope (for example, in SLEUTH model the land with slope above 21% cannot be urbanized) and hillshade situation cannot be used for urban development.

Land price distribution: land price (p) is a crucial factor to the residents' expansion, and it also represents one of the competitive advantages of the property developers and an important influence factor for developers' market strategies. The differentiation of real estate market is the response to the various demands of residents with different house prices, which is mainly determined by land price. Therefore, we consider the land price layer which demonstrates the land price distribution in our pilot study as one of spatial attributes.

Surrounding environment: In our model, we defined a number of factors that are commonly considered by residents for location choice. Generally, surrounding environment for residential development includes factors like environment quality, public facilities, and traffic accessibility. The sites with good surrounding environment will attract more residents' interests.

Traffic accessibility evaluates a site primarily in terms of proximity to roads (D_{road}), expressways and ($D_{highway}$) urban centers ($D_{citycenter}$). We use Euclidian distance and Logistic model to formulate the utility of traffic accessibility ($E_{traffic}$) of one site as follows:

$$E_{traffic} = w^t_1 \cdot A \cdot e^{-B_1 \cdot D_{road}} + w^t_2 \cdot A \cdot e^{-B_2 \cdot D_{highway}} + w^t_3 \cdot A \cdot e^{-B_3 \cdot D_{citycenter}} \quad (1)$$

Where, w^t_1, w^t_2 and w^t_3 are the weights for the three kinds of distance utilities and $w^t_1 + w^t_2 + w^t_3 = 1$. A is the limiting value of the logistic model. B_1, B_2, B_3 are the decay coefficients for these variables.

Public facilities are another important factor that affects the residents' decision on location choice. It represents a location characteristic that have closer distance to facilities such as school, hospital entertainment center, supermarket and so on. The utility of living convenience ($E_{convenience}$) can be formulated as follows:

$$E_{convenience} = w^c_1 \cdot A \cdot e^{-B_1 \cdot D_{hospital}} + w^c_2 \cdot A \cdot e^{-B_2 \cdot D_{school}} + w^c_3 \cdot A \cdot e^{-B_3 \cdot D_{supermarket}} \quad (2)$$

Where, w^t_1, w^t_2 and w^t_3 are the weights for the three kinds of living conveniences respectively and $w^t_1 + w^t_2 + w^t_3 = 1$. We use the same limiting value with Eq.(1) in order to restrict the values ($E_{traffic}$ and $E_{convenience}$) in the same range. Moreover, considering that both of the utilities in Eq. (1) and Eq. (2) are mainly related to road distance, we use the same coefficients and initial constants which can be used for utility calculation based on maximization utility theory.

Environment quality factor in this model mainly includes two spatial indicators: the percentages of green land and water areas surrounded, as the sites with good landscape will be more attractive to residents. To calculate the percentage of green land around site *L(x,y)*, we define an environment influence zone with a radius R, the percentage of green land cells (P_{green}) and the percentage of water cells (P_{water}) to all the cells in the zone will be used to calculate the utility of environment quality ($E_{environment}$), and both of the spatial indicators will be weighted by the preference of residents to water (w^e_1) or green land (w^e_2) :

$$E_{environment} = w^e_1 \cdot P_{green} + w^e_2 \cdot P_{water} \quad (3)$$

Therefore, based on the descriptions above, the cells in the spatial environment can be described by *BasicCell* objects as:

$$BasicCell = \{s, i, j, f, p\} \quad (4)$$

Where *s* is the land use attributes of the land ($s \in S$), *i*, a geometric position identifier of the *BasicCell* in the environment, *j* the number of residents interested in the site, *p*: land price, and *f*: the status of the cell (occupied by resident or not). All *BasicCell*s are combined into a collection object. The collection object is equipped with approaches to spatially reference the

*BasicCell*s, the collections of *BasicCell* objects constitute the spatial organization (and the immobile layer) of model environment.

3.2.2 Social economic environment

The social environment in this model mainly consists of the land market, the social backgrounds that cultivate the social attributes of the heterogeneous agents, economic and policy issues, and the social network in which the agents interact with their neighbours.

Real estate market: In our model, we consider the residential expansion as the major drive of urban land use change, so the real estate market is crucial to the modelling environment. We assume that the virtual land market is of limited access, there are a fixed number of bounded rational residents and developers in the market. And only the lands with enough interests from residents and developers can be allowed to circulate in the development market. Besides, all agents' decision making will be influenced by its social neighbours. Considering the difficulty of getting real trade data for the virtual market we defined a number of personal satisfactory utilities, and the optimization behaviours of developer agents in the market are aiming to satisfy their personal utilities instead of profit or pure economic utility maximization. The virtual market is also divided into three different levels (low-end, mid-range, and high-end) according to firm clusters (which are determined by developers' brand personal traits and their competitive advantages) and residents clusters (which are determined by residents' social attributes).

Social network is very important to social entities such as residents. The social neighbours mean the people who have close relationship in society and benefit from being close to each other (e.g., our friends, colleagues, classmates and neighbours). Resident agents are attracted to each other for different reasons, such as social contacts, the quality of the neighbourhood or team work. This will emerge the agglomeration effects and these effects are translated into agent's decision behaviours. The agglomeration of agents in social environment will emerge segregation of urban residents in spatial environment.

Initially, the resident agents are populated in the social environment (the cells in Repast modelling environment) according to the census. We define the social neighbours of an agent with extended Moore neighbourhood in the environment (Fig.2.b). For each agent, its social neighbours are all the other resident agents within a specified area which is defined by a radius in Repast environment. As is shown in Fig 2.b, the value of the radius depends on the social ability of the agent, i.e., the stronger of the social ability, the bigger the radius is. This reflects the diversity of people's social network. The resident-agents' personal traits determine the degree to which they are influenced by other agents.

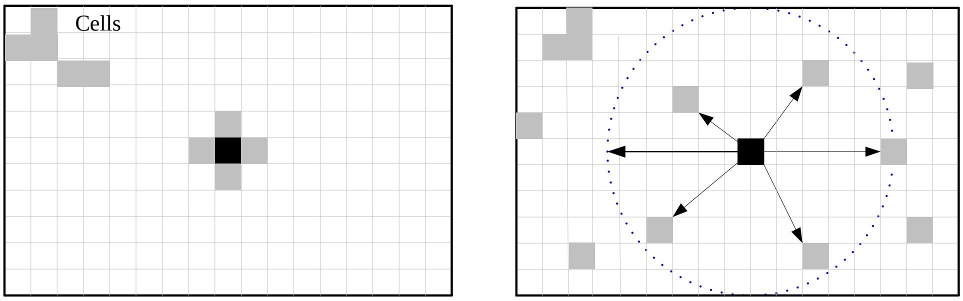


Figure 2– a. spatial neighbourhood in CA 2–b. social neighbourhood in agent based model

Government policies: The policies issued by the government will influence the behaviours of the residents and the developers. One of the most important aspects related to government policies is the master plan, which will have significant influence on urban growth, developers' market strategies and residents' buying behaviours. For example, the policy that encourages economically affordable housing development will influence low-income residents' buying behaviours. Other policies such as the welfare policies for increasing incomes of low-income households and narrowing down the incomes gap between the rich and the poor, might in turn change the residents' preferences towards land price when choosing residential locations. We can construct different scenarios which include different weights and parameters in the residents' behaviour formulation to reflect the policy influence.

Casualty factors: The casual factors will influence the property development market and the strategies choice behaviours of property developers, as a result producing indirect influence to urban land use. We set a random event to represent the social and economic casualty. When the event is captured by agents, we think there are policy changes, new legislations, market turbulence or other unexpected events happening which can influence urban land use change. As a result the influence will be exerted to the stable growth that represented by CA model with calibrated history growth data. Therefore, the weights in decision matrix which synchronize the change decision of agent based model and CA will be changed accordingly.

3.3 Heterogeneous agents

We defined three types of agents which create a virtual replica of the real world's residents, developers and governments. With the behavioural micro-simulation, the analysis is able to test policies and gain greater insight into the systems functioning, as well as to study their social, economic and environmental impacts to urban changes.

3.3.1 Resident agents

The residents in our model refer to the candidate residents that are interested in those newly development residential lands. There are two kinds of residents: new residents moving in from outside and existing residents relocating new places to live. Residents will affect the investment strategies of the property developers which results in residential expansion. As for residential expansion, it means the increased residential lands towards urban fringes.

Table 1 – Properties of resident agents

Resident Agent	Properties	Values
Personal traits (social attributes)	House price sensitivity *(PS)* Transportation cost sensitivity *(TCS)* House environment sensitivity*(ES)* Commuting status*(C)*	*(0 - 1)* *(0 - 1)* *(0 - 1)* *Cost of transportation*
Demographic attributes	Financial ability (income level) *(I)* Occupation *(O)* Family structure *(F)* Age *(A)* Education degree *(E)*	*Low/ middle/high* *Cultural properties* *With/without children* *(0 -100)* *Low/middle/high*

With the defined properties above, a given resident *R* is presented as:

$$R_i(PS_i, TCS_i, ES_i, C_i, I_i, O_i, F_i, E_i) \qquad \forall \mathrm{i} \in \{1,2,...,\mathrm{m}\} \tag{5}$$

The residents agents can be further divided into several clusters as is shown in the following table 2, the clusters manifest the residents' aggregation in social network, it is one of the reasons for urban segregation.

Table 2 – Resident agent cluster matrix

Family structure	**Without Children**			**With Children**		
Income	Low	Middle	High	Low	Middle	High
Proportion	*A%*	*B%*	*C%*	*D%*	*E%*	*F%*

3.3.2 Property developer agent

Brand personal trait and their market attributes are critical issues in the property developer industry. The brand personal trait decides in which part of the business they are going to have the competitive advantage. For example, developers supply different types of houses for specific customer classes (with income level: low, middle, high). Apart from that, the brand utility and history trade records of the developers will influence the preference of residents. The property developer agents' properties are as follows:

Table3 – Properties of property developer agents

Developer Agent	Properties	Values
Brand personal traits	Market location orientation Customer orientation House price range	Property location area Low/middle/high Presented by Land price range
Market attributes	Market share Credit record	Market Influence power successful applications rate

3.3.3 Government agent

Planning authorities decide if a land development application from developers is successful or not according to a number of factors.

Table 4– Properties of government developer agents

Government Agent	Consider factors	Influence Values
Master plan	Excluded area Infrastructure plan	*Excluded areas* *Road growth*

	Developers attribute	*trust probability*
	Residents' interests	*adjust probability*

The marketing mix may be differentiated with the variety of the brand personality trait of developers. In a sense, most residents as buyers have their own set of factors adopted in their evaluation of a location. Based on the clusters of resident agents and the marketing mix of developers, we can assume that the basic relationship emerging from the interactions between residents, developers and land prices is shown in Fig 3: the low income class residents prefer to choose economically affordable housing (low price) that are developed by corresponding low end market oriented developers. Resident with high incomes can afford to buy good-quality homes in locations with high land prices which are developed by high end oriented developers. All types of lands developments should be approved by the government.

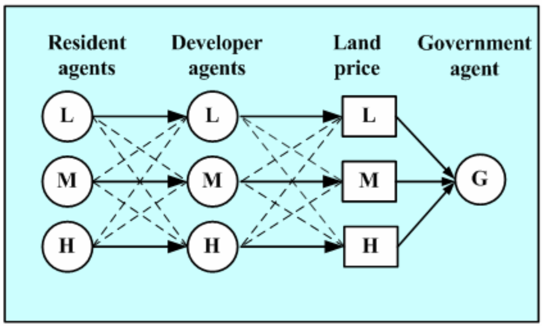


Figure 3 – the relationship between agent clusters in market

3.4 The behaviours of agents

3.4.1 Behaviours of resident agents

With the growth of population, the residents' housing demands drive the growth of urbanization, so the residents' decision behaviours on housing are crucial on urban growth phenomena. In our model, we introduce TpB and utility maximization theory to capture the behaviours of resident agents, and use GA to optimize agents' decision making process.

The behaviours of resident agents are mainly determined by two aspects of influences: the first influence is the intention of the agents which reflect agents' psychological readiness to reside in one selected location. This aspect is usually decided by the agents' personal social status and it relates closely to their social attributes (for example, the agents' attitude, the influence from other resident agents, and their subjective norm to the location). The second influence is the location attraction, which reflects the quality of the location which is decided by some attributes of location site, for example, the surrounding environment (the green land, riverside), the continence (distance to shopping centre, or CBC) and the traffic condition (distance to road network and cost of commuting). So the decisions of resident agents can be formulated as follows: The agents' decision (*D*) is determined by the two determinants: *I*, the influence of agents' intention and *EI*, the environment influence towards the attraction to residents.

$$D = f(I, EI) \qquad (6)$$

Residents' decision on location choice is a kind of consumer buying behaviour, so according to TpB (as is shown in Figure 4), the characteristics features of resident agents' intention can be formulized as follow: (i) agents' *attitude toward behaviour* is the degree to which performance of the behaviour is positively or negatively valued. It is determined by the total set of accessible behavioural beliefs linking the behaviour to various outcomes and other attributes. (ii) *Subjective norm* is an agent's perception of social normative pressures, or relevant others' beliefs that the agent should (not) perform such behaviour. It is determined by normative belief, an individual's perception about the particular behaviour, which is influenced by the judgment of significant others (e.g., agents' social neighbours). (iii) *Perceived behavioural control* is an individual's perceived ease or difficulty of performing the particular behaviour. It is assumed that perceived behavioural control is determined by the total set of accessible control beliefs. (iv) Intention is an indication of a person's readiness to perform a given behaviour (e.g., to choose a location site), and it is considered to be the immediate antecedent of behaviour. The intention is based on the attitude toward the behaviour, subjective norm, and perceived behavioural control, with each predictor weighted for its importance in relation to the behaviour and population of interest.

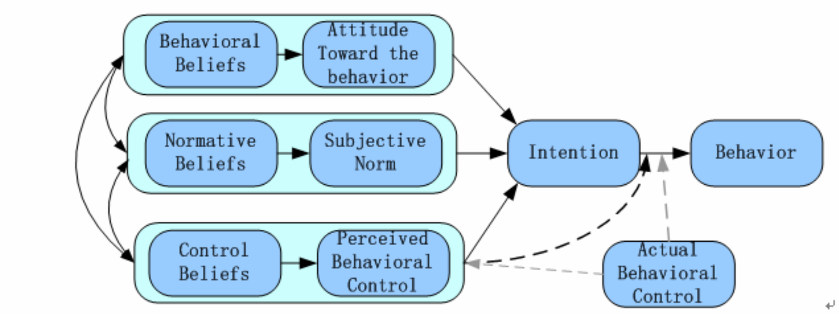


Figure 4 –TpB model (Icek Ajzen 2006)

Firstly, in this model, we assume the attitude of resident agent ***i*** towards choosing developer ***d*** is determined by two behaviour beliefs: the house price and cost of transportation (commuting). Based on the interaction of resident agent ***i*** with property developer agent ***d***, the information about house price such as the acceptability of price (A_p) will influence agent ***i***'s attitude toward choosing it's option *a*. The lower the housing price supplied by developer ***d***, the higher resident ***i*** is willing to accept it. Therefore, there is a negative relationship between the house price and the residents' attitude toward it. Similarly, the acceptability of cost of transportation at time ***t*** (A_{ct}) is another factor that influences the attitude. Both of the influence factors (behaviour beliefs) are weighted by the evaluation of the attributes, price sensitivity and travel cost sensitivity.

$$A_i^a = Ap_d^a \cdot W_p^i + A_{ct} \cdot W_{Ct}^i \qquad (7)$$

Where: A_i^a = resident agent i's attitude toward choosing option a

W_p^i = resident agent i's personality trait "price sensitivity" to price p

W_{Ct}^i = resident agent i's personality trait "Transportation cost sensitivity" to cost c at time t

Secondly, individuals tend to agree most with those whom they like the best and tend to like best those with whom they agree the most. There is a strong correlation between shared attitudes and attractiveness (Brown, 1977; Byrne et al., 1986). The social effects of resident agents can be explained by subjective norm of TpB. The interactions between resident agents produce influence to each agent's normative belief about its location behaviour. A persuasive message or personal influence about option *a* (for example, the recommendation or negative information about one developer) from an important referent resident agent *j*, will influence resident agent *i*'s subjective norm towards choosing option *a*. Therefore, resident agent *i*'s subjective norm from its social neighbour *j* (1≤*j*≤n) towards choosing option *a* can be formulated as follows:

$$SN_i^a = \sum_{j=1}^{n} (M_{ij} \cdot Inf_{ji}^a) / N^i{}_{neighbor} \quad (8)$$

Where: SN_i^l = resident agent *i*'s subjective norm toward choosing property developer *d.*

Inf_{ji}^a = influence from resident agent *j* to resident *i* on option *a*

M_{ij} = resident agent *i*'s motivation to comply with resident agent *j*

$N^i{}_{neighbor}$ = the number of resident *i*'s neighbour agents

The definition of resident agent's social neighbours has been described in part 3.2.2, here we assume that the radius of social neighbourhood is dynamic, i.e., the bigger the radius is the more cost that the agent will spend in exploring their neighbourhood. The resident agent *i*'s motivation to comply with resident agent *j* is defined as the distance between them d_{ij} , so $M_{ij}=d_{ij}$. The influence of resident agent *j* to resident agent *i* is mainly based on resident agent *j*'s intention towards option *a* and the influence is calibrated by the distance (d_{ij}) between them and the intention is calculated by a the limiting value *W*:

$$Inf_{ji}^a = W \cdot I_{intention\ j}^a \quad (9)$$

Thirdly, confronting to a number of behaviours, resident agent *i*'s demographic attributes or social factors such as *i*'s income, education level, age and family structure may facilitate or impede his/her performance (Perceived behavioural control) of housing location choice. Therefore, these factors can be regarded as control beliefs in TpB. This is coherent with the reality that the residents with high social position have much more choices on choosing developers (whether the property is economically affordable or luxury oriented) as they have stronger ability to perform these choices. And the resident with low social position must abandon some good locations as these choices are beyond their ability. So based on TpB, the resident agent *i*'s perceived behaviour control *PBC* towards choosing developer *d* can be formulated as follows:

$$PBC_i^a = \sum_{k=1}^{m} Cb_{ik}^a \cdot P_{ki}^a \quad (10)$$

Where:

Cb_{ik}^a = resident agent *i*'s (k_{th}) control belief towards choosing option *a*

P_{ki}^a = agent *i*'s perceived power of the k_{th} control belief towards choosing option *a*

m = the number of control beliefs

So, based on the analysis above and combining the resident agent *i*'s attitude, subjective norm and perceived behavioural control, the resident agent *i*'s Intention (I^d) towards choosing developer *d* can be summarized as follows:

$$I^a = (P_D^a \cdot W_p^i + Ct \cdot W_{Ct}^i) + \sum_{j=1}^{n} (M_{ij} \cdot Inf_{ji}^a) / N^i{}_{neighbor} + \sum_{k=1}^{m} Cb_{ik}^a \cdot P_{ki}^a \quad (11)$$

Fourthly, the environment influence of the location (*EI*, for example, the environment, traffic condition and the continence to access living facilities) and the quality of the house developed by developer *d* will also exert important influence on resident agent *i*'s decision of location choice. These influence factors actually can be explained as actual behavioural control (*AbC*) in TpB model, which refers to prerequisites needed to perform a given behaviour. For example, although there are many beautiful places that are very suitable for living such as public gardens, lake areas and forests, but these sites are not allowed to be developed for residential location by developers. Instead, developers are more likely to develop the sites which are surrounded by a large number of already developed sites, as these sites have more well developed infrastructures. In this model, we assume the traffic accessibility ($E_{traffic}$), environment quality ($E_{environment}$) and the continence to public facilities ($E_{convenience}$) as the main environment influence factors to resident agent's choice on option *a*. So EI^a can be formulated as follows:

$$EI^a = a \cdot E_{traffic} + b \cdot E_{environment} + c \cdot E_{convenience} + \varepsilon_{tij} \quad (12)$$

Where the three environment factors are weighted by the preferences of different cluster of resident agents, and *a* + *b* + *c*=1. ε_{tij} is the stochastic factor in the formulation.

As described above, $E_{traffic}$, $E_{environment}$ and $E_{convenience}$ can be regarded as actual behavioural control in TpB model, namely, *EI*=*AbC*. So based on TpB model, the behaviour of resident agents are determined by their intentions (*I*) and actual behavioural control (*AbC*). Therefore, resident agents' behaviour (*Be*) can be formulated as follows:

$$Be = W_1 \cdot I + W_2 \cdot AbC = W_1 \cdot I + W_2 \cdot EI \quad (13)$$

Finally, resident agents prefer to choose the developer and the location to which they have greatest intention utility. So the Be in equation (13) reflect not only which developer the resident agent prefer to choose but also which location to which the resident have the most interest. Therefore, the resident agents' decision can be formulated as follows:

$$D = \max\{Be^1, Be^2, Be^3 .... Be^n\} \quad (14)$$

3.4.2 Behaviours of property developer agent

In our model, two kinds of interactions can influence the developer agent's behaviours. One kind is the interactions between the developer agents and the resident agents, where developer agents consider resident agents' interests for specific location sites and respond to the demands for site development. The other kind is the interaction between the developer agents and the government agents, where the government agents approve the developer agents' applications for sites development. So we construct property developer agents' behaviours based on the two interactions.

Firstly, in this virtual environment, the major behaviours of developer agents are the interactions with resident agents for getting the housing demands of specific location sites, and execute such sites development when the developers' application are approved by government agent. Generally, the objective of developers is to achieve a certain amount of profit, they are interested in developing the sites where an estimated profit utility is in maximum. For example, the utility can be formulated as follows:

$$Utility \propto \sum (H_{price} - L_{price} - D_{cost}) \qquad (15)$$

Where: $H_{priceis}$ is the price of house, L_{pirce} is the price of land and D_{cost} the cost of construction.

However, it is very difficult to get the relevant realistic data for the utility simulation, so in our virtual environment we consider the response of developer agents to resident agents' demands based on their competitive strategy. Market report (Porter 1989) suggests that currently the competitive advantage between property developers comes in two flavours: low cost and differentiation. Fah and Cheok (2008) suggest that the developers' marketing strategies are not price differentiation but more in terms of differentiation of the marketing mix which may be differentiated by using the brand personality trait. Therefore, in our model land price (cost) and brand personality traits (e.g., house type, influence) are the two main determinants to developer agents' behaviours.

The interactions between developer agents to resident agents can be summarized as follows:
(i) disseminating its price information and brand personality trait to resident agents.
(ii) evaluating the probability of the locations being developed. In the virtual property development market, we set limited market access mechanism for lands, and only the lands (locations) which have high land attractions value (*LAV*, the number of residents who interested in the land) to resident agents are allowed to be traded in the property development market (Namely the circulating lands in land market), and then the lands will be competed by some property developer agents. For the lands which are circulating in the property developer market (the number of residents who interested in the land > *LAV*), the developer agents will consider the number of their potential customers (resident agents) in order to decide if the location should be their land candidates for future development. Only when the number of developer agent *d*'s potential customers in land location *L*(*x,y*) is more than an acceptable resident number (*ARN*), the land will be considered as one development candidate. This can be formulated as follows:

$$P^t{}_d(x,y) = P\{(NR^t{}_d \geq lav_d) \cap (NR^t \geq \overline{arn})\}_{x=X,y=Y} \qquad (16)$$

Where: $NR^t{}_d$ = the number of resident agents who are interested in location *L*(*x,y*) and prefer developer agent *d*
NR^t = the number of resident agents who are interested in location *L*(*x,y*) at time *t*
lav_d = developer agent *d*'s individual development threshold
$\overline{arn}$ = developer agents' average acceptable resident threshold

(iii) Select the best candidate site to be submitted to the government agent for approving. For all the land candidates in different locations, the one which has the biggest development probability at time *t* will be submitted for development to the government agent by developer agent *d*.

$$D^d(t) = \max(P^t{}_d(x_1, y_1), P^t{}_d(x_2, y_2), P^t{}_d(x_3, y_3)........P^t{}_d(x_n, y_n) \big/ _{t=t}) \qquad (17)$$

Secondly, after deciding the land candidates for future development, the developer agents will submit their applications to government agents for approving. This will involve the interaction between property developer agents and government agents. The main behaviours of the developer agents in the interactions are described as follows: (i) to submit their land development applications to government agents; (ii) if the applications are approved by government agents, then to interact with CA to apply the land change; (iii) if their applications are not approved by the government agents, the developer agent will choose the second ranking candidate and submit it again; (iv) if all the development applications are rejected by the government agent, the developer agent will finish its application process in round *t*.

3.4.3 Behaviour of government agent

The government agent evaluates the development applications from developer agents, and calculates the approving probability. We assume the evaluation criteria are mainly based on the master plan (particularly the infrastructure plan, for example, traffic network and green land) and the development ability of the developers (the brand personality trait, market credit and history records). Apart from that, the adjust probability (the influences from residents' reactions and the surrounded sites' conditions) will also be considered by the government agent. So we formulated the behaviours of government agent as follows:

(i) Urban master planning making is the most fundamental and powerful action that government takes when intervening in the residential expansion process. In this model, in terms of land development application in location *L*(*x,y*), the government agent evaluates if the land development is conflict with the traffic road growth in $\triangle t$ period ($P_{traffic}^{t+\triangle t}$) and if the land development is in excluded areas ($P^t_{excluded}$). Therefore the development probability based on the consistency of the master plan (P^t_{mpc}) can be formulated as follows:

$$P^t_{mpc}(x, y) = P^{t+\Delta t}_{traffic}(x, y) \cdot P^t_{excluded}(x, y) \qquad (18)$$

Where: $$\begin{cases} P^{t+\Delta t}_{traffic}(x, y) = 0 \text{ if the applicaton is conflict with traffic road growth} \\ P^{t+\Delta t}_{traffic}(x, y) = 1 \text{ others} \end{cases}$$

$$\begin{cases} P^t_{excluded}(x, y) = 0 \text{ if locatoin } L(x,y) \text{ is in excluded areas in time t} \\ P^t_{excluded}(x, y) = 1 \text{ others} \end{cases}$$

(ii) In the property developer market, credit mechanism plays an important role for customer choice therefore it is an important reference for authorities' decision regarding developers' applications. In our model, government agent uses criteria to evaluate the developers' credit, namely a trust barometer (P_{trust}) which represents the development ability of different developers and their credit in market. We assume two factors determine developers' trust barometer: the brand personality trait (*BPT*) and the history trade records. $P_{initial}$ is the initial probability set by the government agent (with standard normal distribution) to developers, which is determined by the developers' *BPT*. Besides, the developers' trade records (for example, the number of successful or rejected applications) have either positive or negative influence on their application. Based on our assumption, P_{trust} is formulated as follows:

$$P^{t}_{initial}(d) \propto BPT \sim N(0,1) \tag{19}$$

$$P^{t}_{trust}(d) = P^{t}_{initial}(d) + z_1 \cdot Inf_n + z_2 \cdot Inf_p \tag{20}$$

Where: z_1: the number of successful applications of developer *d*; z_2: the number of unsuccessful applications of developer *d*. Inf_n: the negative influence to P_{trust}; Inf_p: the positive influence to P_{trust}.

(iii) Although the initial approval probability is decided by the government agents, it is subject to adjustment according to the influence from residents and other factors such as the surrounded neighbourhoods. For example, the probability will increase if a location has been applied for development many times. Another similar situation is that there are many mature neighbourhoods surrounding the location site. This means the infrastructure and living facilities have been constructed, so the land is more suitable for residential location. The adjusted probability (P^{t}_{adjust}) can be formulated as:

$$P^{t}_{adjust} = s \cdot \Delta p_1 + l \cdot \Delta p_2 \tag{21}$$

Where *s* is the total number of the residents interested in the location, $\triangle p_1$ is the probability increase related to residents which reflect the influence of residents to authorities. *l* represents the built-up sites number approved by the government agent within the Moore neighbourhood of location *L(x,y)*. $\triangle p_2$ is the probability increase related to neighbourhood.
Therefore, the probability that the application is accepted by the government can be summarized as:

$$P^{t}_{accept}(d,x,y) = P^{t}_{mpc}(x,y) \cdot \left[P^{t}_{trust}(d) + P^{t}_{adjust}(x,y) \right] \tag{22}$$

Based on equation (19), (20) and (21), equation (17) can be expressed as:

$$P^{t}_{accept}(d,x,y) = P^{t+\Delta t}_{traffic}(x,y) \cdot P^{t}_{excluded}(x,y) \cdot \left[(P^{t}_{initial}(d) + z_1 \cdot Inf_n + z_2 \cdot Inf_p) + s \cdot \Delta p_1 + l \cdot \Delta p_2 \right]$$

(x∈[1,n], y∈[1,m]) (23)

4 INTEGRATION OF CA MODEL AND AGENT BASED MODEL

One of the key challenges integrating CA and agent based model in the context of dynamic urban simulation is to understand the interaction and synchronization of spatial/temporal processes, as the urban land dynamic process is self-organizing, stochastic, catastrophic and chaotic, in our model an extended SLEUTH model is used as the CA model to capture the spatial dynamics in urban system and integrate with agents in order to make the simulation more realistic.

4.1 SLEUTH model

SLEUTH model is one of the most popularly used CA models in urban studies. According to Dietzel and Clarke (2006), SLEUTH is the evolutionary product of the Clarke Urban Growth Model that uses cellular automata, terrain mapping and land cover deltatron modelling to address urban growth. The main characteristics of SLEUTH are shown in table 5. The name comes from the acronym for the input layers that the model uses in girded map form: Slope, Land Use, Exclusion, Urban Extent, Transportation and Hillshade. The implementation of SLEUTH mainly includes three phases: (i) the calibration phase to set coefficient values, where the five growth coefficients (dispersion, breed, spread, slope, road gravity, the five coefficients may be seen as the DNA of regions Silva 2001) are trained by comparing simulated land cover change to a study area's historical data in order to replicate historic development trends and patterns; (ii) the prediction phase, where, the future trend is presented with the calibrated data and a set of growth rules; and (iii) the self modification phase: in response to rapid or depressed growth rates, the coefficients may be increased or decreased to further encourage system wide growth rate trends.

Table 5 – Analysis of SLEUTH model

SLEUTH	
Objective	*Projects urban growth and examines how new urban areas consume surrounding land and impact the natural environment*
Types of growth	*SLEUTH models four types of urban growth: spontaneous, diffusive, road-influenced, organic*
Classifications	*Spatial, urban growth, CA model, non-linear, dynamic model*
Key parameters	*Slope, Land Cover, Exclusions, Urban Areas, Transportation, Hydrologic*
Spatial	*CA based simulation, cell size: User defined (50 m -1 km)*
Temporal	*Yearly*
Data format	*Same extent, same projection, same resolution, Gif format*
Input	*Five growth coefficients: Dispersion, Breed, Spread, Road Gravity, Slope; Excluded layer: Areas resistant or excluded to change(water, shoreline-buffers, parks)*
Output	*Snapshot of a particular year(GIF), Cumulative image that results from multiple runs and show a probability of urbanization for a given year(GIF)*
Metrics	*Lee-Sallee metric, Compare, Population, Edges, Cluster, Slope X-Mean,Y-Mean, Rad, F-Match, % Urban, Cluster Size, error matrix analysis, kappa statistics, Product*
Calibrate Methods	*Brute force, GA*
Strengths	*1.Concurrently simulates four types of growth (spontaneous, diffusive, organic, and road influenced)* *2.Provides both graphical and statistical outputs* *3.Incorporates momentum of booms and busts using threshold multiplier with subsequent temporal decay* *4. Allows for relatively simple alternative scenario projection*
limitations	*The model does not explicitly deal with population, policies and economic impacts on land use change, except in terms of growth around roads.*
	Utility for identifying Infill development (smart growth) is limited
	SLEUTH does not have an adequate mechanism to simulate the potential impacts of incentive policies
Applications sites	*Areas covered more than 35 sites, vary from small town to multi-city urban region.*
	including UK, United sates, Netherlands, Portugal, China ,South America, Africa, and Australia

The spatial dynamics in SLEUTH are mainly expressed by four growth rules: spontaneous growth (the occurrence of random urbanization of land), new spreading centre growth (the dynamics of new spreading centres), edge growth (the part of the growth that stems from existing spreading centres) and road influenced growth (the tendency of new settlements to appear close to transportation lines and encourages urbanized cells to develop along the transportation network). Besides, a second level of growth rules in SLEUTH, namely self modification growth, allows individual levels to reflect feedbacks to global changes in land change system by enabling and disabling boom and boost.

4.2 The interactions of actors

The intentional actions of actors (agents and CA) invoke a number of interactions between the environment and the actors. Mainly there are three kinds of interactions in our model which are summarised as follows: (i) the interactions between agents in a-spatial layers, (ii) the interactions between CAs in spatial layer, and (iii) the interactions between CA and agents. As is shown in Fig 5, in a-spatial layers, the heterogeneous agents (developer agents, resident agents and government agent) interact with each other representing a-spatial dynamics. In spatial layer, each cell in CA model interacts with its neighbour cells and the spatial environment representing spatial dynamics. Besides, the interactions between CA and agents produce synchronized decisions which exert spatial changes on land use in the GIS layer.

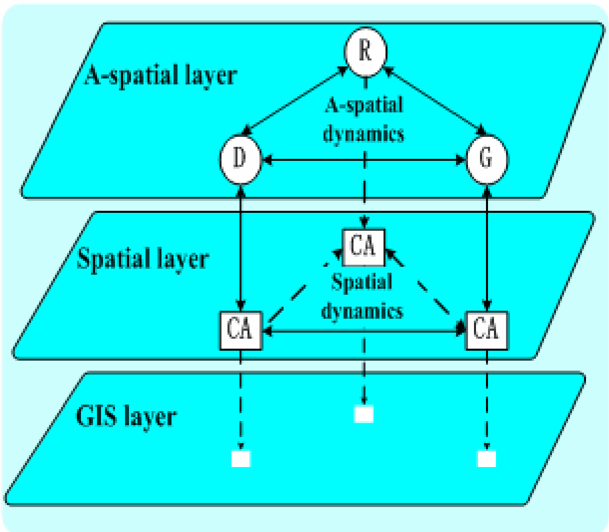


Figure 5 – The interactions between actors

(i) The interactions between cells in SLEUTH can be mainly expressed by three growth rules. *New spreading centre growth*, where if cell *(i,j)* is allowed to become a spreading centre, its two nearest neighbours adjacent to the new spreading centre cell *(i,j)* also have to be urbanized. *Edge growth*, where if a non-urban cell has at least three urbanized neighbouring cells, the cell has a certain global probability to become urbanized also. *Road influence growth*, where if a road is found within a given maximal radius of the selected cell, with a temporary urban cell, the neighbouring cell and adjacent cells to the selected cell will be urbanized. The three growth rules are the main reflections of the interactions between cells, their neighbours and spatial environment (for example, neighbourhood and transportation infrastructure) with the calibrated coefficients based on historical growth data.

(ii) The interactions between developer agents (D), resident agents (R) and government agent (G) and their behaviours have been described in part 3. Here in this part we summarize the interactions of agents in table 6.

Table 6 – The interactions between agents

Actors	Interaction behaviours
R-R	*The social network influence to resident agents' subjective norm*
R-D	*Preference to developer choice*
R-G	*Master plan adjustment, publication involvement*
D-R	*Location sites selection， evaluation on land development threshold*
D-G	*Development applications submission*
G-R	*Influence of government's policies on housing on the preference of residents*
G-D	*Approval of residential land development proposal submitted by developers*

(iii) The interactions between CA and agents are based on the loose coupling of the integrated (CA and Agents) model in our simulation.

Although agents (a-spatial actors) mainly focus on economic and social aspects in our model, their behaviours are inevitably influenced by the spatial data (provided by CA). The resident's location behaviours also have effects on residential environment after the household has been occupied: bring about changes to neighbourhood environment, which in turn might affect residential location choices of other households. This is a typical research of environment psychology (Lawrence,2002) that has focused on the relationship between people and their residential environment on different levels.

As is shown in Fig.5, a-spatial layer can be seen as the high level architecture based on spatial layer, some spatial parameters and coefficients in CA are formulated into agents' behaviour regulations to represent the spatial influences on agents' decision making. For example, in the resident agents' behaviours, the environment influence factors of location EI ($E_{traffic}$, $E_{environment}$ and $E_{convinence}$) are calculated based on CA. The neighbourhood of a location in the CA model are also counted into the consideration of the developers' behaviours on deciding which locations are the development candidates. The neighbourhood of CA is also an important determaint for governments' adjust probability. Bedsides, when a location is decided as the most suitable development candidate and approved by government agent, the developer agents' decision will be synchronized with CA's prediction behaviour to produce the final decision on urban land use change. In term of government agent's behaviours, CA can represent the road network development plan in the master plan, which will be considered as one of the government agent's decisions on whether to approve the development applications submitted by the development agents.

5.4.3 Synchronization

Spatial and temporal processes refer to the sequence of changes in space and time. It should be noted that spatial and temporal processes cannot be separated as all geographical phenomena are bound to have a spatial and a temporal dimension (Silva 2008a). In this model, two important aspects need be synchronized: the spatial/temporal synchronization and decision making synchronization.

Agents and CA have different discrete time steps in the model, so the synchronization in temporal scale is very necessary for the two kinds of actors. Agents usually runs based on months and days, CA runs based on a longer time scale, for example, years. So in our hybrid model, the synchronization mechanism watches the different measure scales cells and human agents in temporal and spatial processes, and synchronize the time schedule of them in spatial context. Fig 6 depicts the temporal synchronization process, the agents' schedule takes CA's discrete time step as baseline, and every N time steps in agent schedule there is one synchronization process happens between CA and agent, and put forward to a synchronized time step in the simulation. After one prediction period's running, the agents' decision on land use change and CA's transition decision will be synchronized in spatial context.

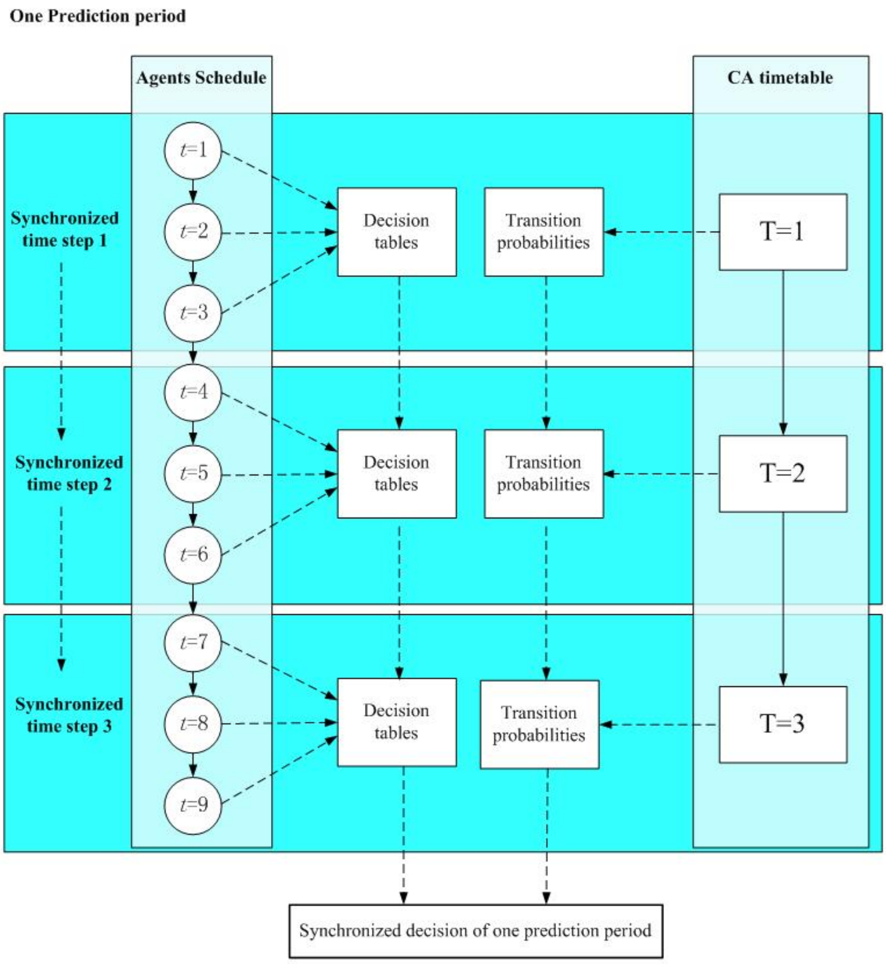


Figure 6 – Temporal synchronization in the model

The spatial synchronization not only happens in the end of a period of simulation, we consider the traffic roads growth predicted by SLEUTH as a master plan control factor to the evaluation of development applications. As is shown in Fig 7, the predicted road status by SLEUTH in period 3 will give a feed back to the decisions of agents in period 1. Without this synchronization, we don't know if a location can be urbanized or not, because the location probably will be in the road lines after a period time. In that case, it should be in consideration of government's master in advance, so the government will reject the development application on this location.

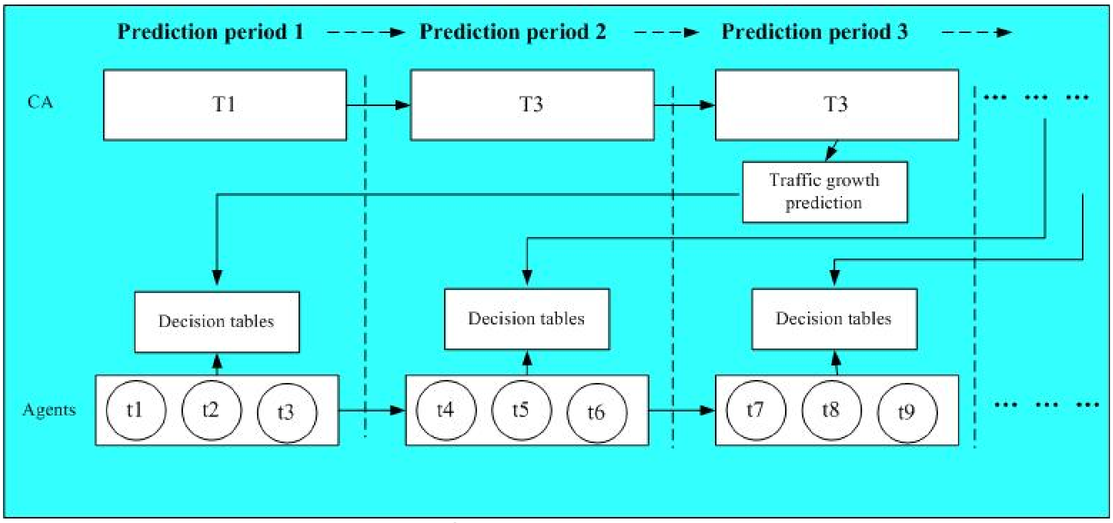


Figure7 – Spatial synchronization in the model

In the simulation process, agents and CA will have their decision matrix to the cells respectively, so there will be conflicts on when decide that if a cell should be urbanized or not. In order to synchronize decisions, we set a random event in the model, if agent based model captured the random event we assume the social-economic has more significant influence to urban land change in the prediction period. Besides, in order to avoid there are too many isolated urban cells in the simulation, we need consider the neighbourhood influence on conflict cells. Based on the mechanism, if in the period if agents can capture the random event and the conflict cells are not isolated cell in agents' decision table we will execute land use change based on agents' decision table. Otherwise, the urban land use change happens based on CA's transition matrix.

5 THE PILOT SIMULATION

The model requires several basic spatial data layers exported from a geographic database (grayscale GIF image format). It requires input of seven types of greyscale gif image files: Land Pride, Slope, Land use, Excluded, Urban, Transporatation, Hilllshade. Theses spatial layer images provide the basic spatial attributes for the simulation. All the images are read into the model via a scenario file in SLEUTH, after loading the images into the model the a-spatial data will be configured to each agent. With different a-spatial environment, a number of resident and developer agents are scattered in the model space based on the population density. Each agent is randomly set a number of properties (for example, income, education background, family structure), based on them the residents are clustered into four clusters. The personal traits of residents and developers will be decided by their properties and the clusters they are in. Normally, the distribution of residents and the personal traits of agents are supposed to reflect the real investigation data before the simulation. As is shown in Fig.9 and Table 7, in the pilot simulation there are a number of parameters in the control panel, which represents the global control parameters to the simulation.

Table 7– the initial parameters of the model

Parameters	**Values**	**Comments**
AdjustProbability_neighbourhood	0.8	The increase of adjust probability to government for every urbanized cell in an neighbourhood
AdjustProbability_ resident	0.6	The increase of adjust probability to government for every resident who interested in the site
Decay_coefficient_ Environment	100.0	The decay coefficients to make the values of environment attributes' calculation result in a standard range
Decay_coefficient_ Traffic	100.0	The decay coefficients to make the values of traffic attributes' calculation result in a standard range
Decay_coefficient_ Convenience	100.0	The decay coefficients to make the values of convenience attributes' calculation result in a standard range
DevTrust_negative_Inf	-0.01	The influence of every rejected application to developers
DevTrust_positive_Inf	0.2	The influence of every successful application to developers
Gov_approved_rate	0.2	In which probability the government should approve the developers' applications
LandDevelopment_ Threshold	0.005	The threshold for land considered as development candidates for developers
LandEnterMarket_ Threshold	0.8	The threshold for land circulating in land market
PopulationGrowthRate	0.15	Residents' population growth rate in each year
Population_Density	0.0025	The residents' population density in the raster data in order to get the number of resident agents in the simulation

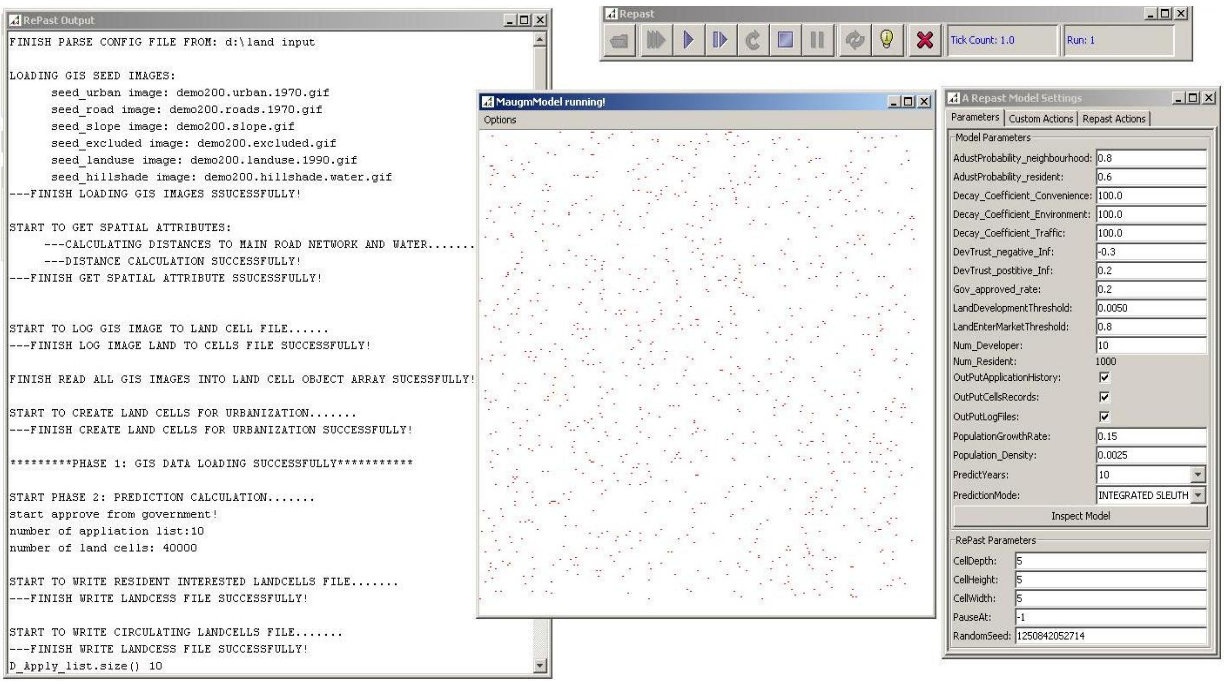
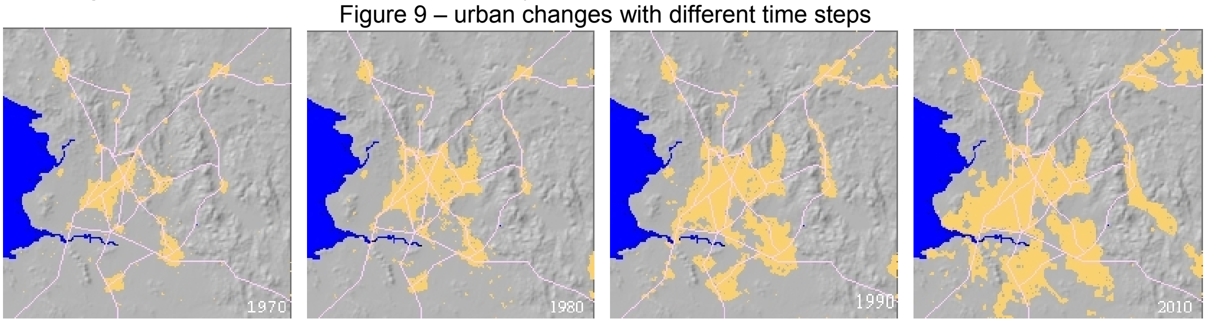


Figure 8 – modelling running and model's control panel

6 SIMULATION RESULT

The results of the simulation for the pilot study have demonstrated that the integrated model can provide reasonable representations of the future evolution of cities, even when, as in this study, the amount of supporting data is limited, and the simulated period is quite long (1970-2020). In this simulation, one time step represents one year's evolution of urban growth, so through the simulations through time steps (as is shown in figure 9) we can clearly see the urban growth processes in the pilot study.

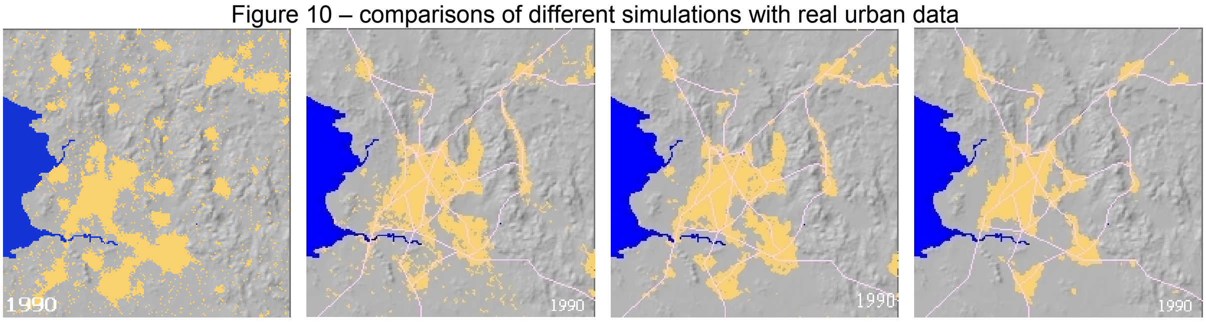
Figure 9 – urban changes with different time steps



Time step 10 Time step 20 Time step 40 Time step 80

By comparing the different simulation results with historical data (as is shown in figure 10), it's also clearly that the inclusion of both spatial dynamics and a-spatial dynamics in this integrated model yields a more realistic modelling period than running SLEUTH and the genetic agents sub-model standby respectively. The differences between (a) and (b) obviously show that the influences of social economics factors to urban growth processes are very important. Despite some constraints (In this pilot study, we set an virtual city with it's historical urban growth data in order to calibrate the model parameters, so without real investigation some parameters in this simulation are set randomly), the capacity of the integrated model to reproduce the actual urban form through large-scale patterns maintaining the resolution of the spatial data included in the model is presented. It also shows the casualty factors in this simulation can work very well to help reduce isolated urbanized cells, because when CA and Agents have conflicts on urbanization decisions to some isolated cells (for example, agents think cell x should be urbanized, but cell x is not in the process of CA's urbanization), the model will set an random event as casualty factor, either agents or CA can capture this random event in this simulation, for example, when CA captured the random event, the isolated cell will follow CA's decision, which means the cell x will not be urbanized. So this random event reduces one isolated urbanized cell. This can be demonstrated by the comparison of picture (b) and (c).

Figure 10 – comparisons of different simulations with real urban data

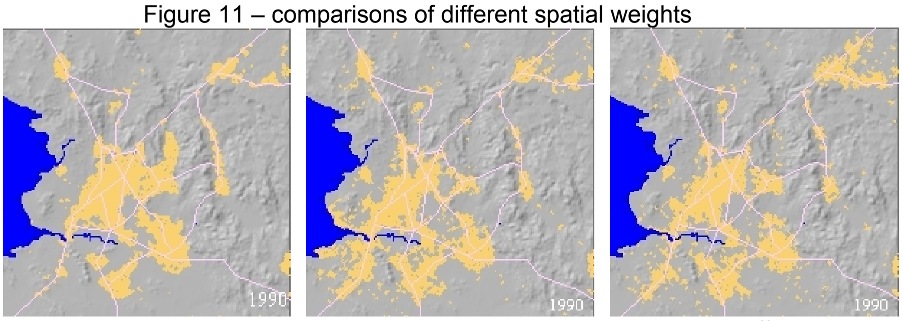


(a) run CA standby (b) run agents standby (c) run integrated model (d) real urban data

Different spatial weights and residents' spatial preference will emerge different urban growth pattern. For example, Fig.11 shows the simulation result with different decay coefficients and spatial preferences to convenience, environment and traffic.

The figure 11(a) shows that there will be more residents choose locations near city center when increase the convenience decay coefficient, because this will increase the TpB utilities of the cells that around city centre to all residents. So when calculate their utilities, residents tender to choose cells with bigger utilities firstly. In figure 11(b), there are much more locations near water are urbanized than figure (a) and (c), this is because when set a high value to environment decay coefficient, the cells near water and green land will have bigger utilities to other cells. The figure (c) shows there will be more residents interested in the areas near transportation network (for example, locations along with roads) when increase traffic decay coefficients (80% residents with high traffic preference).

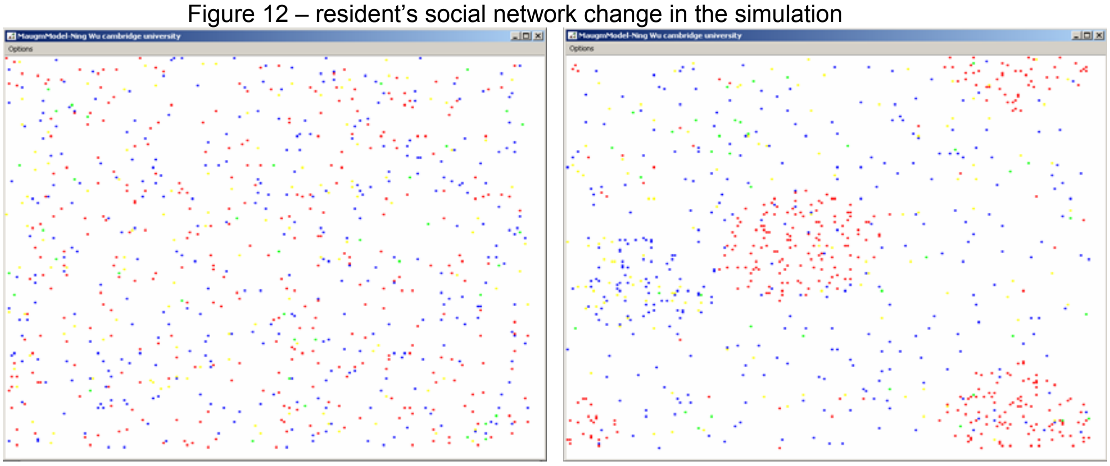
Figure 11 – comparisons of different spatial weights



(a)high convenience weight (b)high environment weight (c) high traffic weight

As is shown in Figure 12, the resident segregation phenomena are reproduced in this model. Because in this simulation, different residents in the same cluster have similar preferences to location choices, so they would like to choose the locations with similar spatial attributes. As feedbacks, when they settled down in the locations, their social network will be influenced by their spatial neighbours, there will be more residents in the same cluster coming into their social networks and the residents who have much personal traits difference with them will leave their social network.

Figure 12 – resident's social network change in the simulation



Time step 20 Time step120

7 CONCLUSIONS

In this paper we introduced an integrated model for urban land use change. The model makes the inclusion of both spatial and a-spatial dynamics in urban modelling approach one important step forward from theoretical development to practical application. A methodological contribution of this model is that it successfully incorporates CA, agent based model and GA into an integrated model, and introduce human psycho-behavioural theory into resident utility simulation. With a pilot study the model presented its capacity of providing reasonable representations of the future evolution of cities, the interactions between social-economic factors and spatial factors can be demonstrated with the simulation result. By cell-cell comparison from simulation result to the virtual history data, we can find the model properly made a prediction to urban use change.

As extended research in the future, a real case study will be done in order to investigate the possibility of applying the model to practical research work. With the further empirical data collection, a calibration process will be taken to get the more realistic agents' properties and behaviours. And the influence of social-economics and policy issues on urban growth will be investigated based on the pilot study more in depth. In terms of model improvement, there are several considerations to achieve more realistic urban simulation. One of the key issues is that it is necessary to gain more social-economics behaviour data for applying simulation in the context of real urban dynamics as well as for model validation and calibration. The lack of accurate micro-scale data may introduce validation deficiencies. In order to prevent such deficiencies results, sufficient social-economic behaviours data is necessary, which may be obtained through market survey, questionnaires investigation or using a more sophisticated synthetic population method to estimate realistic data. Moreover, the acquisition of historical data would be useful to calibrate simulation process and validate a simulation result, and also to determine appropriate simulation time phase and scale. In this study, some of the model assumptions also constrain the simulation's ability to represent real urban dynamics, which is due to data limitations and model simplification. This could be improved by adding additional agents' behaviours and rules to represent complex behaviours in the model.

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