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A planning support system for supporting the achievement of a low carbon form in cities: the framework and a virtual study

Yongping Zhang

Nijmegen School of Management, Radboud University Nijmegen, the Netherlands

School of Planning and Geography, Cardiff University, the UK

Email: zhangyongping2112@gmail.com

Ying Long

Beijing Institute of City Planning, Beijing, China

Email: longying1980@gmail.com

Abstract: Climate change, as a serious environmental problem contemporary society faces, has led to an international debate over what should be done to reduce energy consumption and corresponding negative environmental impact. Extensive research has found that a dominant share of urban energy consumption belongs to transport sector (e.g. commuting, shopping travel, and school travel etc.), which has a strong relationship with urban form. However, little attention has been paid to the relationship between urban form, transport energy consumption, and its environmental impact in the inner-city level. This paper aims to propose the LCF-PSS: an integrated planning support system for supporting the achievement of the low carbon form in cities. After proposing the whole framework, we tested it in a simplified virtual space to demonstrate its workability. In this test: 1) three land use types (R Residential, C Commercial, and O Others) were considered; 2) Planner Agents (PAs) established four urban forms (including land use allocation and urban density distribution); 3) 2000 agents, with various socio-economic attributes, found a R parcel to live, and a C parcel to work; 4) each agent chose a travel mode to commute be-tween living and working parcels; 5) we calculated the amount of energy consumption and environmental impact for the commuting of each agent using provided indicators for each travel mode; 6) finally, we found a low carbon form (LCF) by comparing the total amounts of energy consumption for four established forms. Results show the framework has the potential to support the achievement of low carbon forms in cities.

Keywords: Low carbon form; Energy consumption; Environmental impact

1. Introduction

Climate change, as a serious environmental problem contemporary society faces, has led to an international debate over what should be done to reduce emissions of greenhouse gases (GHGs). The proportion of GHG emissions resulting from cities is between 40 and 70%, and urban areas are now regarded as a vital part of the global response to climate change (UN-Habitat, 2011). Against this background, many actions have to take place in cities to mitigate the phenomenon of climate change.

Urban form, or land use pattern, is defined herein as spatial distributions of different land use types and development densities for parcels or blocks. A low carbon form (LCF) here means an urban form that creates less energy consumption and negative environmental impact compared with other urban forms. Many studies have proved that achieving a LCF of urban areas is crucial to the reduction of GHG emissions and the development of a low carbon city. For example, Williams, Burton, et al. (2000) presented a systematic research, which defined elements of sustainable urban form from macro to micro scale and provided case studies around the world, to illustrate how to achieve sustainable urban form. Holden and Norland (2005) conducted a survey in eight residential areas in the Greater Oslo Region, and the results supported the hypothesis that there is a connection between land use characteristics and household consumption of energy and transport. Hamin and Gurran (2009) identified five key factors that can assist in reducing vehicle miles travelled (VMT); they are higher development *density*, *diversity* (greater mix of land uses), *design* (e.g. smaller block size), *destination accessibility* (e.g. more jobs or other attractions reachable within a reasonable travel time), and *distance to transit* (shorter distance from home or work to nearest rail station or bus stop). Although consensus is lacking about the exact nature of the relationship between the shape, size, density and uses of a city and its sustainability (e.g. Echeniquea, Hargreaves, et al., 2012), its existence has been now widely accepted (Williams, Burton, et al., 2000).

Among existing LCF-related studies, a large portion is focused on the quantitative analysis of the relationship between urban form and energy consumption or CO_2 emission. Energy consumption in cities are mainly from transport, household, and industrial sectors. Among various sectors, transport and household ones have been most widely studied. For example, Ewing and Rong (2008) presented a conceptual framework linking urban form to residential energy use via electric transmission and distribution losses, energy requirements of different housing stocks, and space heating and cooling requirements associated with urban heat islands; Hatzopoulou, Hao, et al. (2011) proposed a activity-based model, which can provide agent-based output that allows vehicle emissions to be tracked back to individuals and households who are producing them; Liu and Sweeney (2012) investigated the relationship between household space heating energy use and urban form (land use characteristics) for the Greater Dublin Region; Marique, Dujardin, et al. (2013) analyzed the energy consumption, travel distances and mode choices for school commuting based on two decennial surveys in Belgium. However, most of these studies usually use aggregate data, and treat the city as a whole sample, while not too much attention has been paid to the analysis of city parts. The application at a fine scale (e.g. a parcel level in the city) is greatly limited to the availability of individual or household data. Some have considered a fine scale analysis, but the consideration is limited to some extent. For example, the planning support system (PSS) called FEE-MAS (Long, Mao, et al., 2013) are not aimed to the application of urban planning or to establishing a LCF in real cities; only a conditional disaggregation process was applied to the residential cells in the model proposed by Schindler and Caruso (2014).

There is some literature aims to find out what kind of urban form scenarios are low carbon. They can support the achievement of LCF, and make a good reference to decision-makers and urban planners. Gomi, Shimada, et al. (2010) developed a local (city-scale) low-carbon scenario creation method; an estimation model was developed to show a quantitative and consistent future snapshot, and applied to Tokyo City to identify countermeasures to achieve the low-carbon target. Phdungsilp (2010) used long-range energy alternatives planning (LEAP) system model to simulate arrange of policy interventions, and to show how energy usage might develop in Bangkok from 2000 to 2025. Keirstead and Shah (2011) presented a tool for calculating absolute minimum urban energy benchmarks, which can be used early in the planning process to complement more behaviorally realistic land use transport models. However, the number of these studies is limited, and a disaggregated way is still ignored among them. Additionally, although they can provide good reference to decision-making and planning processes, all of them didn’t integrate the establishment process of urban forms, by considering the role and function of urban planners, into their models or methods, and identify which alternative can be regarded as a LCF by comparing different urban scenarios.

In this paper, an integrated framework of planning support system (called LCF-PSS) is proposed for achieving a low carbon form in cities. After this, a virtual space test will be conducted. In detailed process, several urban forms should be established at first, followed by the generation of residential agents. After the choice of residential and workplace locations, the energy consumption and environmental impact (EC-EI) will be calculated for the commuting of each agent, then for each urban form by summing the amount of all agents. After the comparison among different urban forms, the most low carbon one (or low environmental impact) can be identified as the LCF. In Section 2, the framework will be provide, followed by the virtual space test in Section 3. Finally, a concise conclusion will be given in Section 4.

2. The LCF-PSS framework

2.1 General description

Travel energy consumption and environmental impact (EC-EI) depends on travel demands, which include travel type (e.g., job, study and entertainment), frequency (e.g., 5 times a week), distance, and mode (e.g., bike and car). Travel demands can be influenced by socioeconomic attributes of residents (e.g. age and income), and the urban form (land use types and development density). For example, travel type and frequency are related to socioeconomic characteristics of travelers, travel distance is related to the urban form, and travel mode is related to all of them. According to these, a series of steps are introduced to identify the relationship between the travel EC-EI and the urban form, and support the calculation of travel EC-EI for each established urban form (See *Figure 1*). Each main step corresponds to a model or a module, and there are six models (modules) in total in the proposed LCF-PSS framework. Six models (modules) are as follows:

1) an urban growth model for simulating future urban development from non-urban built-up land to urban built-up land; 2) an urban allocation model, called Planner Agents for allocating land use types and development intensity; 3) a population synthesis model, called Agenter for disaggregating heterogeneous agent attributes; 4) a location choice model for simulating the residential and work location choices of each agent; 5) a travel mode choice model; and 6) a EC-EI calculation module.

Firstly, an urban growth model is used to simulate future urban development from non-urban built-up land to urban built-up land at the parcel level. The model adopts a vector-based CA method, and a process of automatic subdivision of land parcels can be integrated into it. Secondly, Planner Agents is used to establish the urban from, including land use allocation and urban density distribution. The allocation of floor area ratio (FAR), defined as the ratio of a building's total floor area to the size of the piece of land upon which it is built, is used to represent the development density distribution in this paper. Thirdly, a certain number of residents with socioeconomic information will be generated using Agenter using aggregate data, small-scale surveys, and empirical studies. Generated agents have socioeconomic attributes, such as age and income etc. Fourthly, a location choice model is used to simulate the residential and work location choices of each agent. Residential parcels are selected as residents' home places, and commercial or industrial parcels are selected as agents' work places. The location choice should obey the constraint of each parcel's FAR value. For example, no more than three residents can reside in a parcel with the FAR as 3. Fifthly, agent commutes between home and work places via bus, car or walk etc., which is determined by a travel mode choice model. And finally, the EC-EI of each agent can be calculated based on the normal amount of EC-EI for various travel modes. The EC-EI of the urban form can be calculated by summing up the amount of all agents. The LCF can be identified by comparing the EC-EIs of different urban forms.

The detailed description for each model is in the following subsections. Figure 1 shows the flow diagram of the LCF-PSS framework.

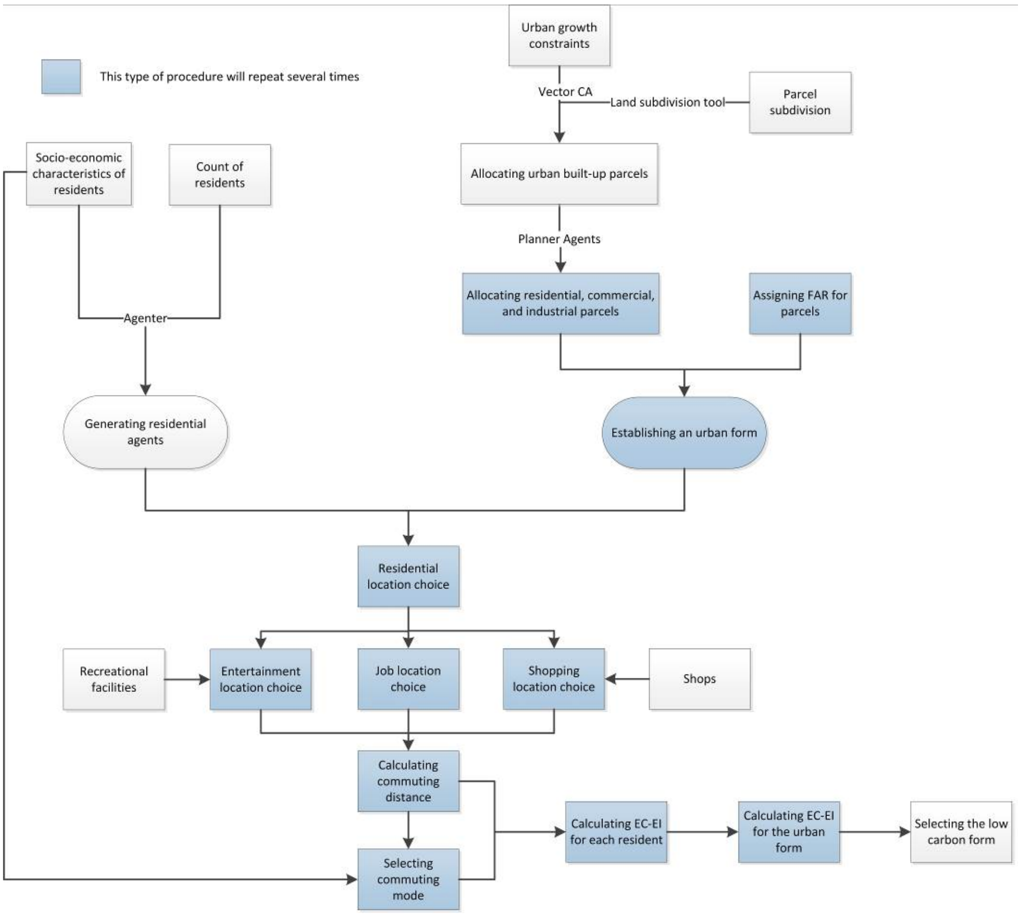


Figure 1. The flow diagram of the LCF-PSS framework

2.2 The urban growth model

Over last two decades, Cellular Automata (CA) has been widely applied in generating realistic urban growth scenarios for its ability to simulate the dynamic spatial process from a bottom-up perspective (Landis, 1995; Guan, Wang, et al., 2005; Moghadam and Helbich, 2013). For most existing CA models, the geographic space is typically represented as a regular raster grid and the neighborhood is defined as an assembly of adjacent cells. However, recent studies have demonstrated that the simulation results of such raster-based CA models are sensitive to the cell size and the neighborhood configuration (Moreno, Wang, et al., 2009). Additionally, when the resolution is increased, spatial entities in real world, such as blocks, census tract boundaries, and even individual parcels, can be identified. The use of a grid of regular cells creates areas of assumed homogeneous land use that may contain variability in reality, thereby cannot precisely represent real entities with irregular sizes and shapes (Stevens and Dragicevic, 2007).

The adoption of a vector-based, or irregular-based, CA method is one way to avoid the questions mentioned above. V-BUDEM, proposed by Zhang and Long (2015), is a vector-based CA urban growth model. It’s a constrained CA model, which has considered various constraints during the urban growth process. The conceptual model is shown as Equation 1.

$$V_i^{t+1} = f\left\{V_i^t, A_{status}, A_{loc}, A_{gov}, A_{nei}\right\} \quad (1)$$

Where V_i^t is the status at cell i of iteration t; f is the transition rules of the constrained CA. In the V-BUDEM model, the parcel, with various shape and size, is treated as the cell, and the cell status represents 0 for undeveloped or 1 for developed from non-urban built-up parcel to urban built-up parcel. The neighborhood is defined as all parcels surrounding the cell within a certain distance. Constrained conditions in the urban growth process consist of four aspects, including self-status constraints A_{status}, location constraints A_{loc}, government (or institutional) constraints A_{gov}, and neighborhood constraint A_{nei}. Locational and institutional constraints are assumed to remain static during the future urban growth process, and they do not change across simulation iterations. Self-status (e.g. whether the parcel is agricultural land) constraints can also be treated as keeping static, because the parcel will be excluded in the simulation process if its self-status has changed in previous iteration. The neighborhood effect, however, continues to change with simulation iterations of the constrained CA. The detailed information can be found in Zhang and Long (2015).

2.3 Planner Agents

In this framework, Planner Agents are divided into three types: Non-spatial Planner Agent (NPA), Spatial Planner Agent (SPA) and Chief Planner Agent (CPA). The NPA is responsible for formulating special plans such as for transport, municipal public facilities and nature reserves, which correspond to data like road network, public facilities and nature reserve zones. Special plans formulated by NPAs are as parts of an urban master plan. The SPA is responsible for establishing land use patterns. The SPA considers constraints of local development conditions, and communicates and coordinates with the NPAs to confirm formulated special plans that can support implementation of the established land use pattern. The CPA is responsible for negotiating with the GA, ensuring the rationality of comprehensive constraints, establishing the final land use pattern based on an evaluation of established scenarios by several SPAs, then determining it after the public participation process involving Resident Agent (RA). When the CPA negotiates with the GA and RA, it's on behalf of the planning institution, not a planning bureau. Decision makers in the planning bureau, with extensive research on their behavior and preference, are not accounted in this paper that focuses on planners.

Planning rules (PRs) are defined as the criterias or guidelines of planner thinking and action during the establishment process. The main content of PRs consists of the planning impact factors (PIFs) considered by planner and their weights. There are many PIFs for land use patterns, such as roads, rivers, parks and traffic noise. Different planners with varying demands and inclinations will consider different sets of PIFs, for which weights are usually different. The planner's PRs reflect his or her requirements and preferences. For example, whether to consider the river and the determination of its weight for a residential parcel pattern reflects the demands and inclinations of a riverfront development strategy. To identify the PRs is crucial for the application of Planner Agents. Theoretically, the PR identification can be realized through existing plan drawings, questionnaire surveys, real models, or virtual reality tests. The flow of LUPSA using Planner Agents is shown in *Figure 2*.

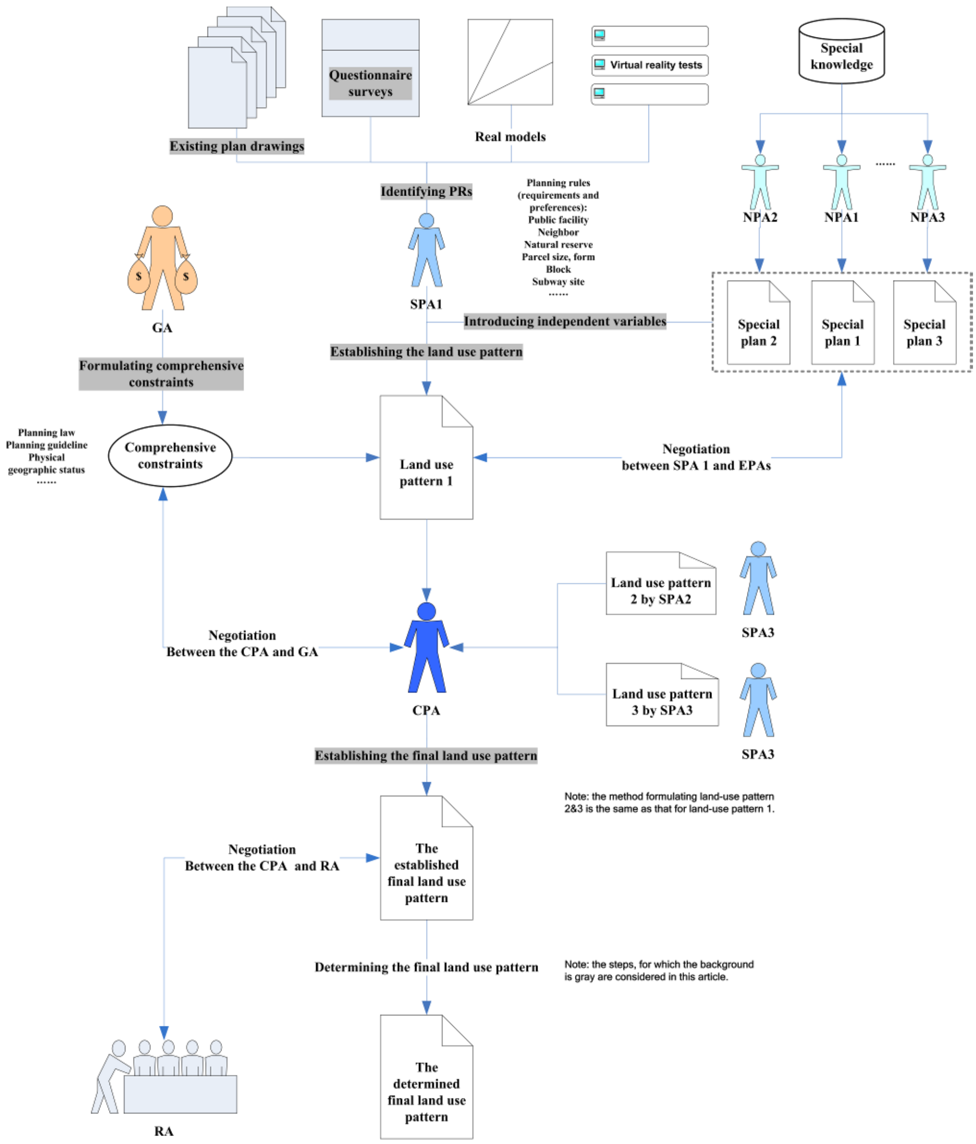


Figure 2. The flow diagram of LUPSA using Planner Agents

2.4 Agenter

Micro-models using individual-level data, such as agent-based models (ABMs) and micro-simulation models, have been discussed increasingly in the context of regional, urban, and population studies as supplements to traditional macro-models (Wu, Birkin, et al., 2008). However, the use of micro-models has been hindered by the poor availability of individual data due to privacy and cost constraints. To rectify this hindrance, Long and Shen (2013) proposed Agenter to disaggregate heterogeneous agent attributes and locations.

The probability distribution of an attribute (distribution) and the dependent relationship among attributes (relationship) can be inferred from existing data sources, including aggregate data, small-scale surveys and empirical studies. When it comes to non-spatial attributes disaggregation, which we are focused on in this paper, there are mainly two situations: known distribution information and known relationship information. The first example is about known distribution information: if the categories of the attribute marriage are married, unmarried, and divorced, and the corresponding frequencies are 45, 20, and 35, then 45 agents are married, 20 are unmarried, and 35 are divorced among every 100 individuals. The second example is about known relationship information: For every 100 persons, the attribute *age* has two intervals, 18-30 years old (40%) and 31-60 years old (60%). Its conditional probability with the attribute *marriage* is known: out of all individuals 18-30 years old, 60% are married and 40% unmarried. This means there will be 40%*60%*100 = 24 married persons within the age range of 18-30 and 40%*40%*100 = 16 unmarried persons are in 18-30. Detailed explanation of Agenter can be found in Long and Shen (2013).

2.5 The location choice model

There are two processes for the location choice of each agent. Firstly, agent chooses a residential parcel as his or her home place; then, agent chooses a commercial or industrial parcel as his or her work place.

The most common residential location choice model used in practice is the multinomial logit model (MNL). The basic logic of the MNL model is that households are evaluated based on their own attributes, such as income and household members. The sampling of available, vacant housing units and their characteristics, such as price, density, and accessibility to service facilities were considered. The relative attractiveness of these alternatives was measured by their utility. The model then computed the probability that a given household would select a given location from the available alternatives, defined as vacant housing units, given the preferences and budget constraints of the households seeking housing. This idea was borrowed and used to allocate agents into spaces while considering each agent as a resident and each geographical space as a housing market for residents to select. The agent location then depends on both its non-spatial attributes and related spatial layers in its environmental context. For example, a residential agent's socio-economic attributes can influence its preference for each type of spatial layer, such as the accessibility, amenities, and landscape. Parcels have distinguished spatial attributes, and residential agents with different preferences for spatial layers will select the parcel with the greatest preference as their place of residence. This solution is expressed as follows:

$$P_{ij} = \sum_k W_{ik} * F_{kj} + r_{ij} \quad (2)$$

Where, P_{ij} is the preference of agent i for parcel j, F_{kj} is the value of the spatial layer k at parcel j, which can be calculated by overlaying the parcel with the spatial layer in GIS; W_{ik} is the preference coefficient of agent i for spatial layer k, and r_{ij} is the random item of agent i for parcel j. P_{ij} is standardized to range from 0 to 1.

An updated form of choice, the constrained choice solution allocates agents using a residential location choice theory that obeys the statistical information of agent spatial distribution. It differs from choice in that the number of agents with the highest preference selected by a parcel is constrained by the statistical information. For example, if the aggregate data indicate there are six agents in parcel B, then parcel B can be used to select the top six agents with the highest preference for this parcel, after evaluating preferences for all parcels by all agents.

2.6 The travel mode choice model

The choice of travel mode is not only determined by the socioeconomic characteristics of a resident but also by his or her commuting distance. The latter can be elaborated as:

$$M_j = f(A_j, Dist_j) \quad (3)$$

where M_j is the commuting mode of resident j, A_j are the socioeconomic attributes of resident j, $Dist_j$ is the commuting distance of resident j, and f is the commuting mode choice function, which is used to determine the resident j's commuting mode based on his or her socioeconomic attributes A_j and commuting distance $Dist_j$.

2.7 The EC-EI calculation module

The commuting distance can be calculated from the results of residential location choice and job location choice. Regarding the confirmed commuting mode of each resident, the EC-EI can be calculated using indicators for various commuting modes. The EC-EI on the whole city can be then calculated by summing up all residents.

3. Virtual space test

3.1 Hypothesis

In this virtual space test, we tested a simplified version of our LCF-PSS framework. Main hypothesis is as follows:

1. The hypothetical space as a closed system has no transport link with outside regions. Parcels in the city are square and identical in size. The road networks are grids with no subway system. More specifically, there are 10×10 parcels in the virtual space, and the length of each parcel is 1 km; the transport network (*Figure 3*) is of a homogeneous grid shape (corresponds to the parcel boundary).

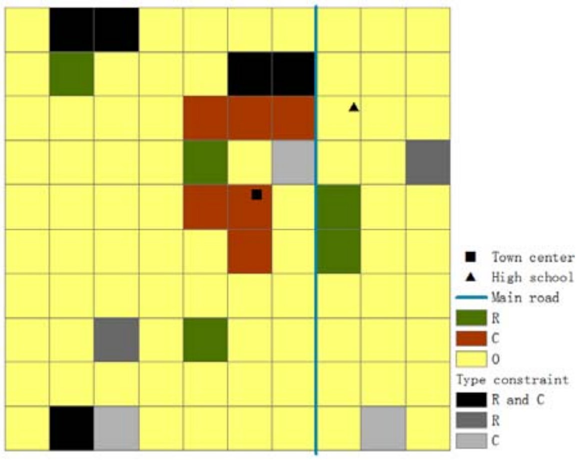


Figure 3. The virtual space

2. There are three land use types (R: residential, C: commercial, and O: other types). The numbers of existing R and C parcels are 5 and 6, respectively. 25 R parcels and 15 C parcels are developed, namely there will be 30 R and 21 C parcels after the establishment process of urban forms by planners.
3. The urban growth process is not considered at this stage;
4. Each urban form is established using Planner Agents, and the establishment process contains land use allocation and urban density (FAR) distribution. The Existing PRs are known (*Table 1*). Land use type constraints consist of R (land use type is constrained to be R), C, R&C, and no constraint. Existing R and C parcels remain unchanged. For density distribution, no constraint has been considered. The school plan, road plan and central business district (CBD) location, which correspond to PIFs, are special plans formulated by NPAs.

Table 1. Planning rules

weight factor	The PRs for land use allocation (LUA_PRs)						The PRs for urban density distribution (UDD_PRs)			
	LUA_PR1			LUA_PR2			UDD_PR1		UDD_PR2	
	R	C	O	R	C	O	R	C	R	C
High school	0.5	0.3	0.2	0.5	0.4	0.1	0.5	0.5	0.6	0.4
Town center	0.3	0.4	0.3	0.3	0.5	0.2	0.6	0.4	0.3	0.7
Main road	0.5	0.4	0.1	0.4	0.5	0.1	0.2	0.8	0.5	0.5

5. Agent data is directly from the generation of Agenter, which has been done by Long and Shen (2013). The agents exclude those don't commute (such as children and the seniors older than 65).
6. A R or C parcel with a floor-area ratio (FAR) of 1 corresponds to one resident living or working in the parcel.
7. Every resident works and commutes.
8. Only job-housing commuting EC-EI is counted for residents; household, entertainment, shopping, and other types of energy consumed are excluded.
9. Residents choose the residential parcel randomly; residents choose the closest working parcel to work; both are not related to their socioeconomic attributes.
10. Three types of commuting modes are considered: car, bus, and biking/walking. To simplify the agent's mode choice process, we adopted a decision tree. Supposing the

commuting mode M is related to the resident's monthly I (unit: CNY) and commuting distance $Dist$ (unit: km), the decision tree is expressed as follows:

$if\ \ I \geq 5000$ and $Dist \geq 4$:

$\quad M = Car$

$elif\ \ Dist \geq 3$:

$\quad M = Bus$

$else$:

$\quad M = Biking\ or\ Walking$

This decision tree rule is generated from the household travel surveys of Beijing conducted in 2005.The transport EC-EI indicators are shown in *Table 2*.

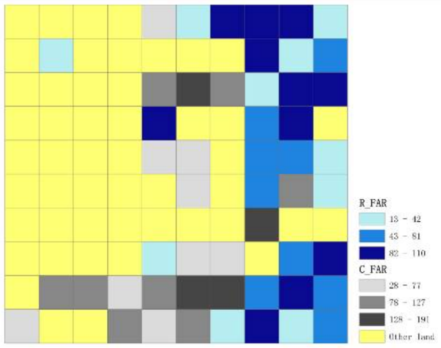
Table 2. Transport EC-EI indicators for various modes

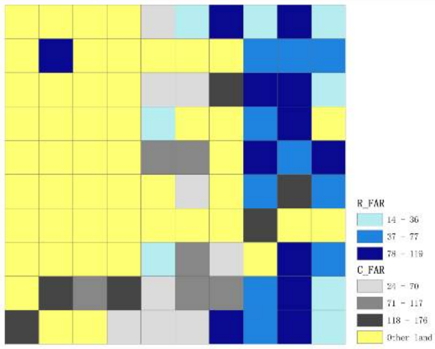
ID	Travel mode	Consumed energy per kilometer per capita	Environmental impact per kilometer per capita
1	Car	10	10
2	Bus	2	1
3	Bike or walk	0	0

3.2 Results

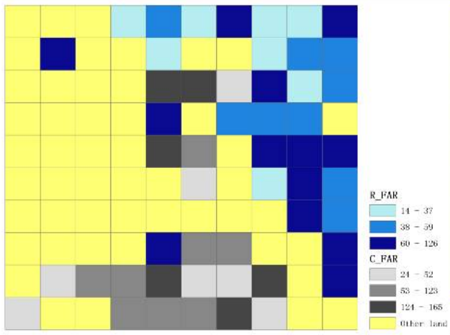
This LCF-PSS framework can be developed using Python language and ArcGIS software.

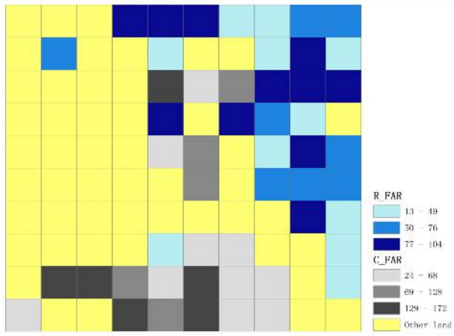
Firstly, we established four urban forms using two LUA_PRs and two UDD_PRs based on existing special plans, land increase demand and land use type constraints. The established scenarios are shown in *Figure 4*. Scenario 1 and 2 were formulated using LUA_PR1 and UDD_PR1 & UDD_PR2, while Scenario 3 and 4 were established using LUA_PR2 and UDD_PR1 & UDD_PR2. Therefore, the land use distribution of Scenario 1 and 2 (or Scenario 3 and 4) are the same, and the FAR distribution of Scenario 1 and 3 (or Scenario 2 and 4) are the same. Taking Scenario 1 and 4 as examples, the residential center (where the R FAR is relatively high) is located in northeastern corner of Scenario 1, and in northeastern corner of Scenario 4 (distributed more dispersedly); the working center (where the C FAR is relatively high) is mainly located in the middle part of Scenario 1, and in the middle and southern part of Scenario 4.





Scenario 1 Scenario 2





Scenario 3 Scenario 4

Figure 4. Established four urban forms

Secondly, we got 2000 agents randomly from the generated database from Long and Shen (2013). Their data contains 13.819 million agents in the Beijing Metropolitan Area, and synthesized by using the Fifth Population Census Report of the BMA conducted in 2000 and the Household Travel Survey of Beijing conducted in 2005. To get 2000 agents who work and commute, we narrowed the original database using the age constraint (aging from 20 to 65). The sample information of these agents are shown in *Table 3*.

Table 3. Socio-economic information of five sample agents

Agent ID	Age	Sex	Marriage	Education	Job	Income	Family number
193392	36	male	married	junior high/middle school	production, transport equipment operator, and related	2385	three persons
19831	41	female	married	high school	production, transport equipment operator, and related	5966	three persons
37094	61	male	married	high school	professional technology employee	4744	three persons
49808	21	male	unmarried	junior high/middle school	business and service employees	2684	five persons
165014	27	male	unmarried	high school	business and service employees	5559	five persons

Thirdly, each parcel found a certain number of agents to live, and then each agent found a closest parcel to work. Both of these two process were constrained by the parcel's FAR value.

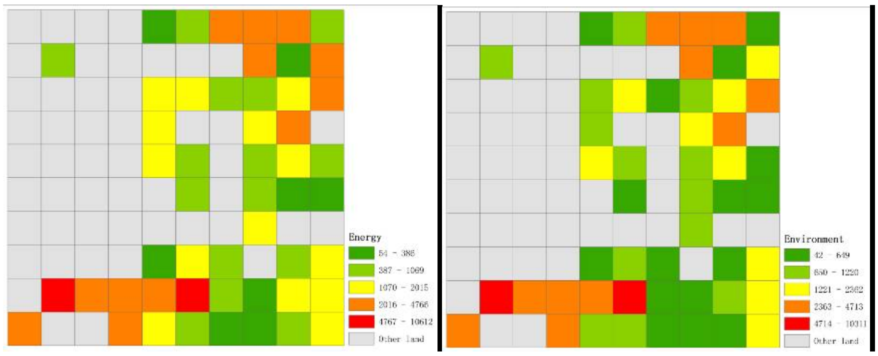
Finally, each agent chose a travel mode based on the decision tree shown in Section 3.1. Based on the choice, the corresponding EC-IC of this agent can be calculated by the indicators in *Table 2*. The final statistical results of EC-IC are shown in *Table 4*, in which the total distance is the total commuting distance for the whole scenario. According to *Table 4*, the LCF is definitely Scenario 1 for it has the shortest total commuting distance, the least energy consumption and environmental impact. Simultaneously, the Scenario 4 is the one having the most energy-consuming, environment-negative, and causing the longest commuting distance.

Table 4. The EC-EI calculation results for four scenarios

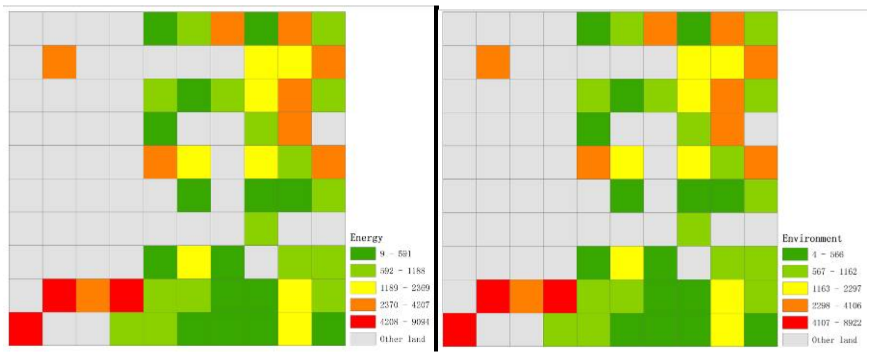
Scenarios Aspects	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Total distance	10915	11217	12368	14326
Energy consumption	82848	85228	98776	117746
Environmental impact	80579	82999	96213	115023

To illustrate the calculation results more clearly, *Figure 5* shows the spatial distribution of average energy consumption and environmental impact of urban form scenario 1 and 2. In Scenario 1, the highest amount of energy consumption is 10612, while the lowest is 54. In Scenario 2 the highest amount of energy consumption is 9094, while the lowest is 9. The highest amount of environmental impact is 10311, and the lowest is 42 in Scenario 1, while the highest amount of energy consumption is 8922, and the lowest is 4 in Scenario 2.

The facts show that although Scenario 1 is regarded as a LCF, the variance of the energy consumption and environmental impact in Scenario 2 is less than that in Scenario 1. Additionally, comparing the spatial distributions of energy consumption and environmental impact, we found that there are relatively similar, which implies the more energy consumed in a parcel, the more environmental impact created at the same time.



Scenario 1



Scenario 2
Figure 5. Simulation results of EC-EI for Scenario 1 and 2.

4. Conclusion

The paper proposed a LCF-PSS framework for supporting the achieving a low carbon form in cities by quantitatively calculating transport energy consumption and the corresponding environmental impact (EC-EI). There are several advantages or highlights for this simulation framework. Firstly, it identifies the quantitative relationship between urban form and EC-EI in a manner of inner-city analysis using synthesized individual person as the agent and the urban parcel as the basic spatial unit; this kind of analysis is not possible for conventional researches focusing on the level of cities as a whole. Secondly, several dominant bottom-up methods, such as Cellular Automata (CA), and Multi-agent system (MAS), are included and make the framework more comprehensive. Thirdly, it can be used to evaluate planning alternatives, and provide a positive reference for urban planners to achieve or establish low carbon urban forms. And finally, it's also meaningful for policy makers to make relevant urban policies to support the creation of the LCF in cities.

In the preliminary study, we tested a simplified framework to calculate EC-EI in a virtual space. In this test, we considered three land use types (R, C, and O) and constraints condition in the establishment process of land use allocation. There were 2000 agents adopted; each agent has various socio-economic attributes. Agents randomly chose a R parcel to live, and chose a closest C parcel to work; both choices were constrained to parcel's FAR value. Additionally, the travel mode was decided according to socio-economic attributes of agents and commuting distance. After all of these, the EC-EI was calculated for each agent based on the travel model adopted, determined EC-EI indicator for the travel model, and travel distance, and the EC-EI of an urban form was calculated by summing EC-EI of all agent. Finally a LCF was found by comparing the EC-EI of all urban forms. Results shown the feasibility of LCF-PSS for finding out the low carbon urban form.

In next step, the research of the LCF-PSS framework may be improved in the following aspects. Firstly, we can test it in a real situation. We already have generated the whole population in Beijing in 2000, and done the application of urban growth simulation using V-BUDEM model and urban form establishment using Planner Agents framework; the next stage is to apply this framework to calculate commuting EC-EI in the whole Beijing. Secondly, school, entertainment travels can be included in the calculation process. Thirdly, the choice of living and working places can be based on constrained multinomial logit choice model, which will consider the impact of agents' socio-economic attributes in the process. And finally, we can calculate the amount of CO_2 emission based on the real values, which can be found in relevant literature (Ma, Heppenstall, et al., 2014).

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