Modelling shopping transport energy performance to explore low carbon potentials

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Abstract

Using shopping activity as an example, this paper presents a probabilistic model that can be used to estimate shopping transport energy consumption in the absence of empirical data and analyse the potentials of reducing shopping trips by car. Based on the combination of Huff model and Gravity model, some new metrics were developed to quantify the shopping activities. The property of shopping facilities, spatial distribution, travel distance, travel patterns are the key part of model to determine how much transport energy is consumed. With the assistance of GIS system, an international comparison between the two cities in New Zealand and China was conducted using this model to investigate the differences and relevant factors that can affect transport energy use. The results showed that the residential density plays a critical role in reducing shopping transport energy use, the majority of residence living in both cities are adaptable to non-motorized trips in terms of essential shopping activities.

1.Introduction

The reliance on energy in transport and rapidly growing transport CO_2 emissions are a global problem. In New Zealand, transport is the third largest sector of CO_2 equivalent (CO_2-e) greenhouse gas (GHG) emissions, contributing to 18.1% of total emissions in 2012. According to the Ministry for the Environment (2014), a provisional post-2020 target of 30 percent below NZ's 2005 greenhouse gas emissions (GHG) level by 2030 should be met. To mitigate the impacts of Climate Change, it is estimated a 72%-42% reduction in CO_2 emissions is required by 2050. Almost 87% population of New Zealand live in cities, which are the main focus area for transport energy consumption. Accordingly reductions in transport energy consumption can contribute to this mitigation target, projected energy efficiency and vehicle performance improvements could reduce final demand by 40% and transport CO2 emissions by 15%-40% below baseline (IPCC, 2014). It is widely acknowledged that new energy vehicles, mixed land use, transit-oriented transport system and compact urban form can lead to more active mode trips and reduce the heavy dependence on fossil fuel. Although the considerable emphasis on sustainability with more renewable energy and green technologies has been integrated into development plans in many countries, it is believed that the majority of countries are still far from achieving fully sustainable energy systems (The World Energy Council, 2012). Moreover, owing to the peak oil risks and unstable price of petroleum, the need to keep the balance of energy supply-demand becomes more urgent than before. Also China, as a growing economy without sufficient resources, has attached much importance to sustainable development in consideration of energy saving and environmental protection. There is not enough space for transport infrastructure to accommodate a large vehicle fleet. The negative impacts of massive motorization in China such as traffic congestion and air pollution will be even more serious if the dependence on motor vehicle is not effectively controlled (Kenworthy& Hu,2002). In fact, human beings have adaptive capacity to cope with changes in their living environment.

Within an interactive urban transport system, people could adjust their travel behaviour to meet their trip purposes and participate economic activities when land use, transport network or socioeconomic condition is changed. For a car driver, if he or she could access as many as places by alternative travel modes without wasting too much time, he or she would have high adaptive capacity under the condition of energy constraints. For a city or city area, if the majority of activities could be accomplished efficiently without using private cars, its potential in low carbon travel is likely to increase. Living in this area, people's living and trips would not be severely affected given policies such as restrictions on car driving to reduce CO_2 emissions. Based on Huff shopping model(Huff,1963), this paper introduces new measures to quantify shopping activities and develops a comprehensive analytical methodology that simulates urban shopping trips to calculate shopping transport energy use and explore urban adaptive potentials for low carbon shopping trips(i.e. walking and cycling). In this paper, only the spatial factors and travel patterns are considered, the socioeconomic factors are neglected due to the lack of data. All the trips are home based excluding the return-to-home trip legs.

2. Terms and definitions

2.1 Essentiality classification for shopping

It is revealed by surveys of travel behaviour that people rate as 'unnecessary' or 'discretionary' as many as 30% of their trips(Gordon et al.1988;Cevero and RADISCH,1996; Banister et al.,1997). Susan and Shannon(2010) quantified the relative importance of each trip for choosing which trips to take and which activities are preferable. Based on the essentiality theory from Susan, the shopping activity is further refined and divided into three classes:

Essential goods (Dietary needs such as foods and drink): the importance and frequency is highest to human life, which could be accessible in such facilities as grocery store, market, supermarket, department store.

Necessary goods (Clothes, appliance, communication): the importance and frequency is moderate to human life, which could be accessible in supermarket, department store, exclusive store.

Optional goods (upmarket consumption or leisure expense such as flower, pet, antique, jewel): the importance and frequency is relatively low to the majority of people, which could be accessible in department store, shopping mall, exclusive store.

2.2 Huff model

The Huff model(Huff,1963) is a spatial interaction model that calculates gravity-based probabilities of consumers at each origin accessing each shopping facility in the study area. As a gravity model, the Huff model is heavily dependent on impedance such as trip distance or travel time. The definition of the attractiveness of a shopping facility is not generalized, and owing to the lack of available data, only few parameters are used to measure the possibility of consumers patronizing each facility as below:

Scale: The size of shopping facility, ***A.***

For grocery store: the value is set at 20-100 m^2.

For supermarket and market: the value is set at 100-5000 m^2.

For department store and shopping mall: the value is greater than 10000 m^2

Attractor: The frequency to this facility based on essentiality categories, At. For example, the attractor of a grocery store or supermarket or department-store is set as 3, the clothing store is set with 2, the antique store is with 1.

Trip momentum: The trip potential from origin *i* to destination *j*. Based on the gravity model in combination with Huff model, the calculation of trip potential is calculated from the following equation:

$$W_{ij}=(A \times At)/d_{ij}^2 \tag{1}$$

Where d_{ij} is the minimum distance between origin *i* and destination *j*.

Trip probability: The probability from origin *i* to facility *j*, which is normalised as below:

$$P_{ij} = W_{ij}/\sum W_{ij} \tag{2}$$

2.3 Shopping value

The measurement to evaluate the level of shopping prosperity in an area is usually divided into a number of dimensions including diversity, quantity, Scale etc. To simplify the calculation, the conception of shopping value is created to represent the average shopping prosperity in certain area, which is illustrated as below:

$$(SV)_i = \sum_{j=1}^{n} \left(A_j \boldsymbol{At}_j\right) \tag{3}$$

Where $(SV)_i$ is the overall shopping value in a study area *i*, A_j is the area of facility *j*, $\boldsymbol{At}_i$ is the essentiality of facility *j*.

2.4 Local weighted shopping activity value

The term of shopping value is a quantitative measure to describe the level of shopping service in each cell. Nevertheless, for each origin *i*, the overall shopping activities it can access within a city is distinctive depending on its location, distance to each shopping facility and the attractiveness of each shopping facility accessible. It is obvious that the shopping activities for people living in the city centre are different from those living in suburb areas. Accordingly the term of 'local weighted shopping activity value' is defined as the function of shopping frequency, shopping value in destination *j* and probability to this destination (see Equation (4)).

$$LSV_i = \sum_{j=1}^{n} \left(f_{shopping} \times SV_j \times p_{ij}\right) \tag{4}$$

Where LSV_i is the overall accessible shopping value in origin *i*, $f_{shopping}$ is the annual shopping frequency in origin *i*, which can be obtained from the travel survey. SV_j is the shopping value in destination *j*, p_{ij} is the probability from origin *i* to destination *j*.

3.Methodology

3.1Spatial analysis for shopping facilities

3.1.1 Mesh grid simplification for study area

To simplify the analysis and reduce the workload, the study area is divided into a fishnet of rectangular cells using GIS tools. Each cell size is set as a 1km×1km square with a centroid (see Fig.1).The centroid is an agent representing the characteristics of origin or destination. For the people living in a cell, it is assumed that they have similar socioeconomic situation. The difference in age, income, personal travel preference are neglected due to the lack of data. All the houses in a cell were abstracted as a point (i.e. the centroid) when running GIS analysis.

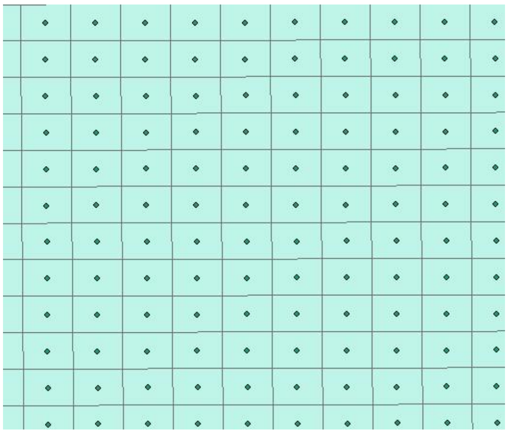

Figure 1. An example of urban grid

3.1.2 Classification and quantification for shopping facilities

All the shopping facilities are classified into different categories and assigned with distinctive values according to the rule of essentiality, then the shopping value in each cell is calculated as the function of number, scale and essentiality of shopping facilities. An example of shopping value distribution in Beijing is presented in figure 2. For a study cell with massive shopping facilities or large scale shopping malls, the shopping value in this cell is assigned with high value(see the red cells in Figure 2). A screenshot of one origin's shopping trips matrix to each shopping destination is illustrated in table 1. As shown in table1, the coefficient 'Value_shop' describes the level of shopping activities in destination j, 'prob_orig' means the possibility from origin to this destination, 'dist_orig' means the minimum travel distance from origin to this destination.

3.2 Transport energy calculation on shopping activities

Given the travel survey data and VKT data in a study area, the local area transport energy consumption could be calculated. However the detailed survey data on shopping activities are difficult to obtain and the individual shopping destinations are extremely random, hence in this paper, it is assumed that for an origin i, all the shopping destinations are accessible with certain possibilities. The trip from origin cell i to each destination cell j is iterated throughout all the study area, then a weighted shopping trip matrix of origin i is generated as the shopping trip base data to analyse current shopping transport energy use.

3.2.1 Transport patterns assignment

The detailed travel mode share data based on distance bins is required to do adaptive capability analysis. By doing so, the travel patterns in different distance bins are explicit to explore the possibility of travel mode shift. On the basis of literature view and travel survey data(Guo,2010; MOT,2015), an example of travel mode share matrix of Beijing and Christchurch is listed in tables 2 and 3 respectively.

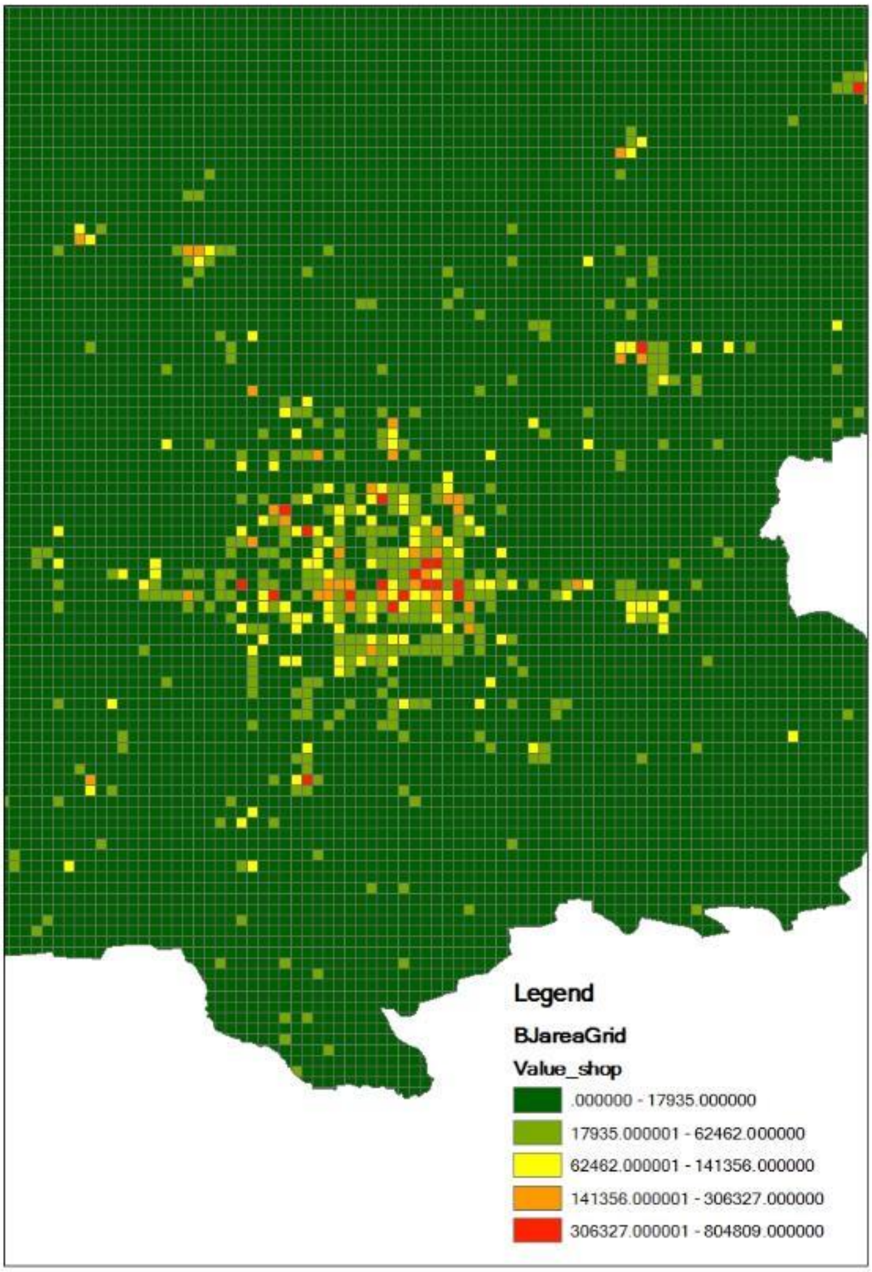

Figure 2. An example of shopping value distribution in Beijing

Table

shopping_centrid

FID	Shape *	Value_shop	prob_orig	dist_orig
0	Point	60	.000020	28062.23935
1	Point	1430	.000494	27519.224042
2	Point	1601	.000573	27030.921267
3	Point	135	.000058	24660.698857
4	Point	41014	.015670	26172.67254
5	Point	461	.000185	25510.661277
6	Point	226	.000103	24019.344488
7	Point	267	.000116	24527.650848
8	Point	240	.000098	25379.957048
9	Point	132	.000050	26329.052992
10	Point	624	.000259	25127.914816
11	Point	235	.000106	24076.829734
12	Point	1555	.000733	23566.918862
13	Point	1286	.000683	22206.235948
14	Point	861	.000485	21560.816478
15	Point	1811	.000944	22405.485116
16	Point	267	.000129	23294.831926
17	Point	727	.000260	27036.85188
18	Point	384	.000145	26367.035187
19	Point	1914	.000735	26109.477626

1 (0 out of 162 Selected)

Table 1. A screenshot of one origin's shopping trip matrix

Trip Mode Split for Shopping (%)	**Distance Bins**(km)					
	*d*1(0-1)	*d*2(1-2)	*d*3(2-3)	*d*4(3-5)	*d*5(5-10)	*d*6(>10)
Walk	90	40	10	0	0	0
Cycle	5	18	20	16	3	0
Bus	3	5	10	10	15	15
Car	2	47	60	74	82	85
Subway	0	0	0	0	0	0

Table 2. Distance-based trip mode split in Christchurch, New Zealand

Trip Mode Split for Shopping (%)	**Distance Bins**(km)					
	*d*1(0-1)	*d*2(1-2)	*d*3(2-3)	*d*4(3-5)	*d*5(5-10)	*d*6(>10)
Walk	89	40	4	0	0	0
Cycle	10	26	30	20	10	0
Bus	0.4	10	30	35	32	35
Car	0.6	10	20	25	35	40
Subway	0	14	16	20	23	25

Table 3. Distance-based trip mode split in Beijing, China

From above tables, it can be seen that the active mode share in Beijing has the same descending trend as Christchurch when the trip distance increases. The car tip share in Christchurch however is relatively higher than that in Beijing mainly because the car ownership ratio is different in these two countries.

3.2.2 Shopping activities simulation

Using GIS tools and python programming, an activity-based transportation model is developed to simulate people's shopping activities in a year.

Study area input

1. Demographic data: the population of residence living in a cell (persons/km^2).
2. Origins: the centroid of each cell is seen as the representative of local dwelling distribution.
3. Destination: the centroid of each cell is seen as the representative of local shopping facilities distribution with distinctive shopping values.
4. Transport networks: the travel cost is defined by travel distance. The distance of 3km and 5km is defined as comfort and maximum threshold for cycling travel respectively. Congestion and trip chains are neglected.

Constant input

5. Modal energy intensity, $\boldsymbol{em_{mode}}$
   {'walk': 0; 'bicycle':0; 'bus': 0.37MJ/(person×km); 'subway':0.26MJ/(person×km), 'car':3.64MJ/(person×km)}
6. Shopping trip frequency $\boldsymbol{f_{shopping}}$**.** The average annual shopping frequency at the city level can be derived from travel survey data.
7. Distance-based travel mode share data, $\boldsymbol{T_d}$.

3.2.3 Transport Energy calculation

For an origin *i*, the transport energy consumption for shopping by travel mode is calculated from the following equation:

$$E_i^m = \sum_{j=1}^{n} \left(d_{ij}^m \times em_{mode} \times f_{shopping} \times T_d \times p_{ij}\right) \tag{5}$$

$$E = \sum_{i=1}^{n} (E_i^m) \text{ /population} \tag{6}$$

Where *E* is the average transport energy use per person in origin *i*, d_{ij}^m is the distance from origin *i* to destination *j*, em_{mode} is the energy intensity of travel mode, $f_{shopping}$ is the shopping frequency per year, T_d is the distance-based travel mode share.

3.2.4 Adaptive capacity analysis

In this paper, it is assumed that for a short distance trip (less than 3km for walking or 5km for cycling), the fossil fuel transport mode is not necessarily required and could be replaced with non-motorized travel modes like walking and cycling. If the majority of shopping activities could be accomplished by active modes, the low carbon potential in this area would be the highest. In view of the limitation on space, only the adaptive capacity in walking and cycling was considered in this paper. The analysis on public transport adaptive capacity will be presented in the future.

The adaptive capacity for shopping is defined as the local weighted shopping value within walking distance (0-1km) and cycling distance (0-5km). The higher the local shopping value, the more adaptable to non-motorized trips.

Step 1. Shift all car trips within 1km into walk trips.

Step 2. Shift all car trips between 1km and 5km into cycling trips.

Step 3. Keep the car mode share beyond 5km constant.

Step 4. Recalculate the local weighted shopping activity value of each cell assuming all the car trips within 5km are replaced with walk mode(<=1km) and cycling mode(<=3km or 5km) to see how much shopping value could be realized with 0 transport energy use.

It is not clear that how many shopping facilities would be critical to meet individual commercial requirement, also the question on how much adapted shopping value is satisfactory for consumers is difficult to define. In this paper, the 25 percentile of original local shopping value is used as the evaluation criteria to assess the impact of mode shift on **essential** shopping activities, the 75 percentile of original local shopping value is used as the evaluation criteria to assess the impact of mode shift on **necessary** shopping activities. The ratio of population that can access essential and necessary shopping activities within non-motorized trip distance bins (0-1km,0-3km,0-5km) will be compared between the two cities.

4. Case studies

The method was applied into two cities in China and New Zealand to compare the shopping transport energy consumption and results of mode shifting. Beijing and Christchurch are completely different in terms of urban form, demography, transport systems. One is a megacity with highly mixed land use, high-rise buildings and dense population, the other one is a medium-sized city in a way of dispersal, low-density and separation. The urban area of Beijing is around 1368.32km^2 with 18,590,000 population, the Christchurch urban area is 607.73km^2 with 381,800 residents (Fig.3 and Fig.5). In the aspect of shopping activities, the geographic shopping value in each cell is calculated using Eq.(3) and mapped using GIS(see Fig.4 and Fig.6). From these maps, it can be seen that the average shopping value in Beijing is much higher than Christchurch, the city centre is the important concentration area with extensive shopping activities no matter in Beijing or Christchurch. The hot spot for shopping in Christchurch is more evenly distributed than that in Beijing. Nevertheless there are number of small shopping districts outside the urban area of Beijing city

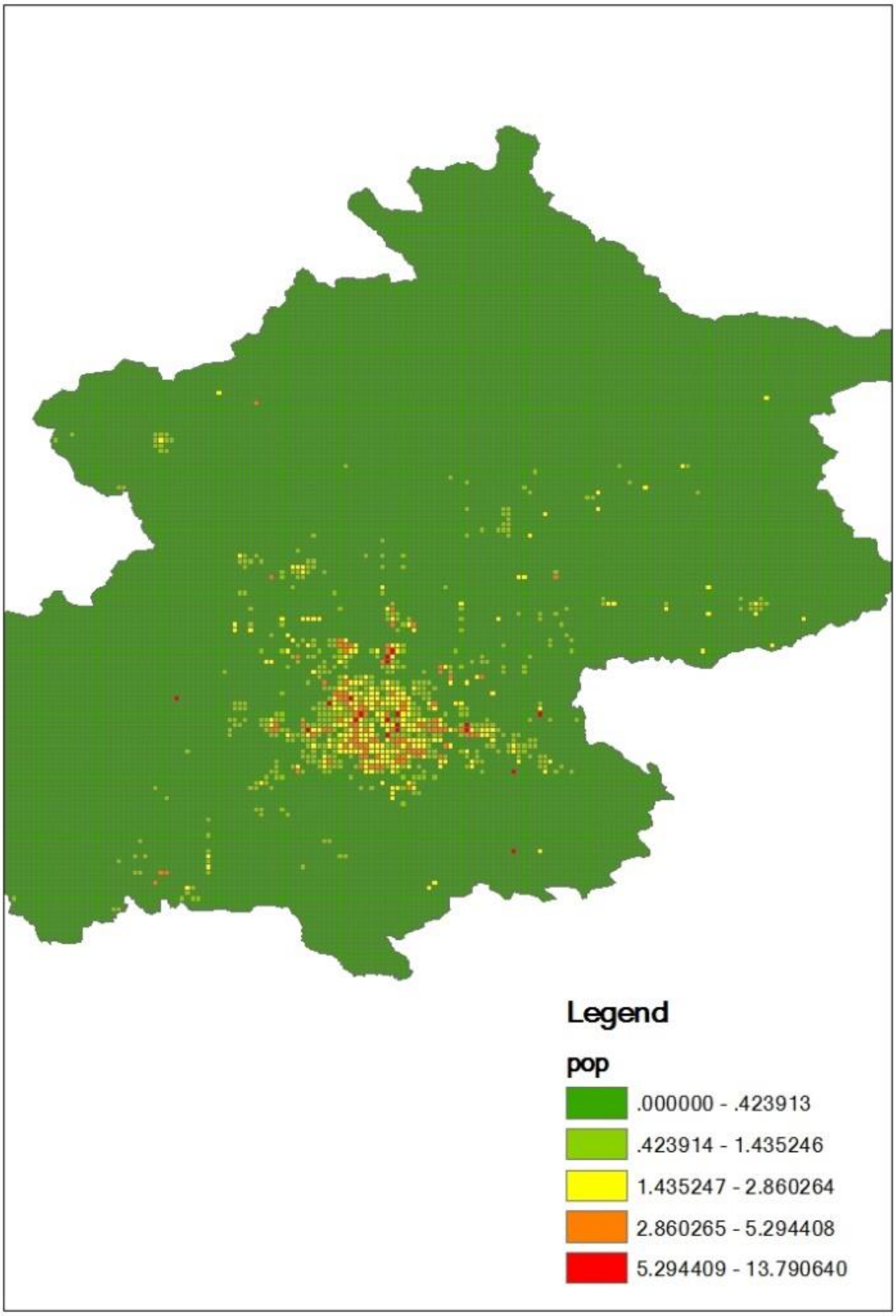

Figure 3. Population density distribution in Beijing

(Unit: 10,000person/km²)

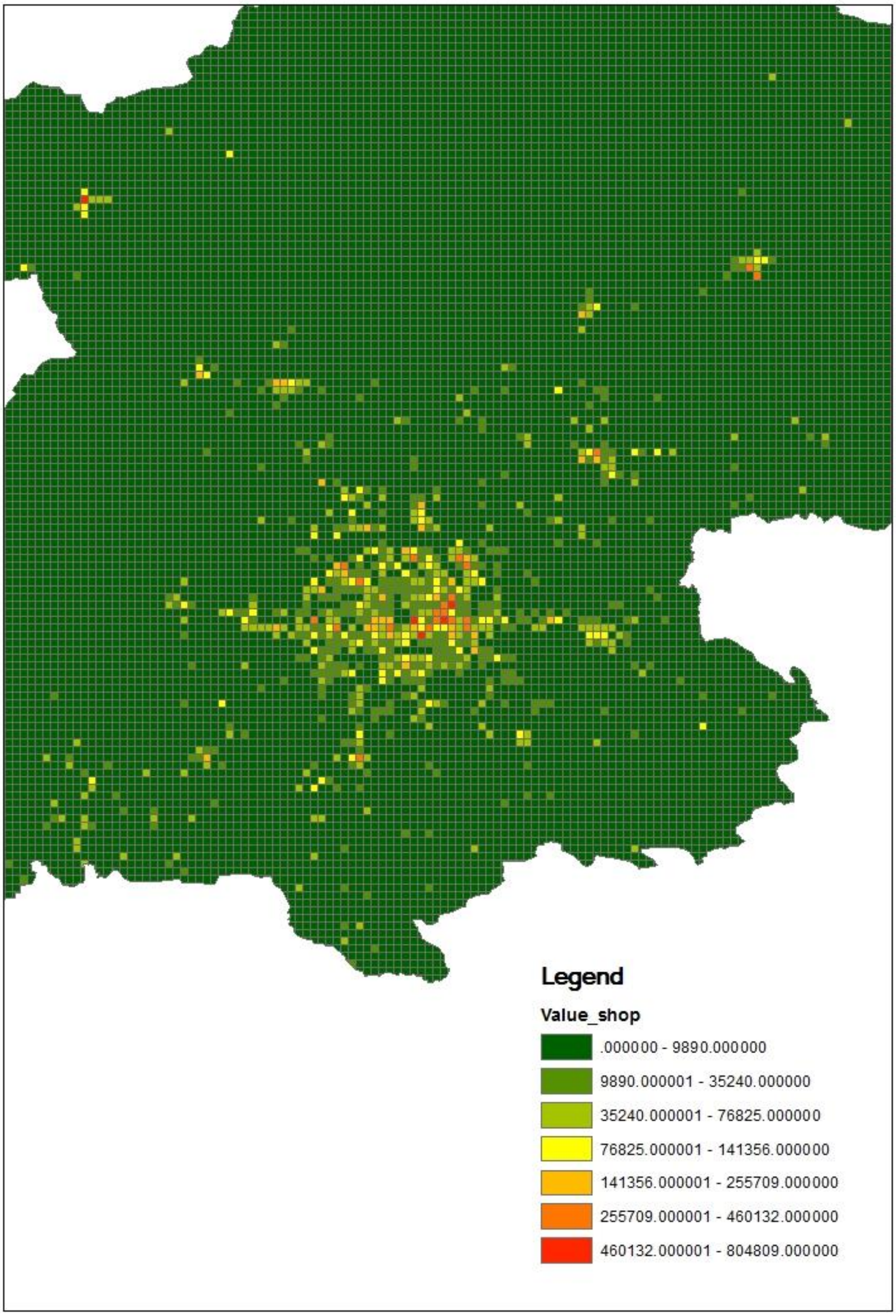

Figure 4. Shopping value distribution in Beijing

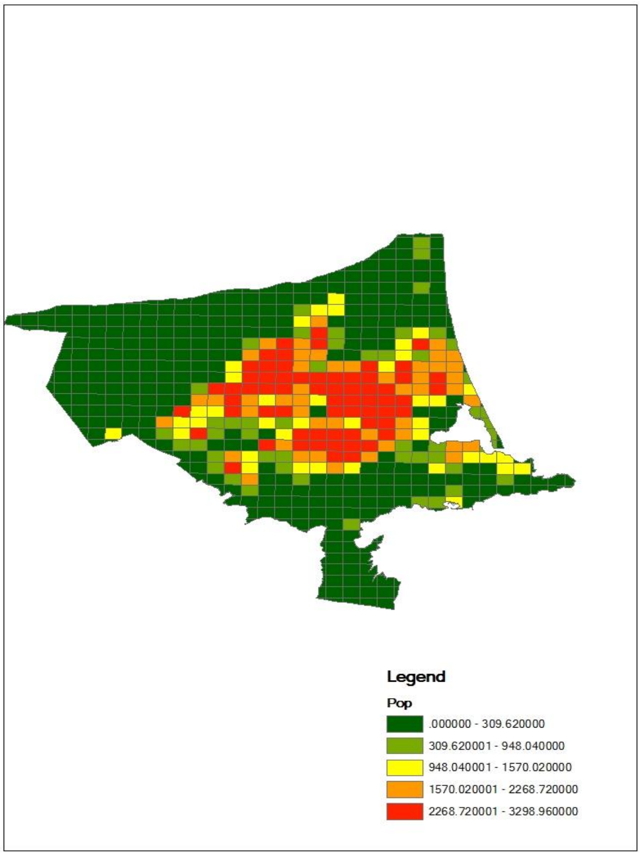

Figure 5. Population density distribution in Christchurch

(Unit: person/km²)

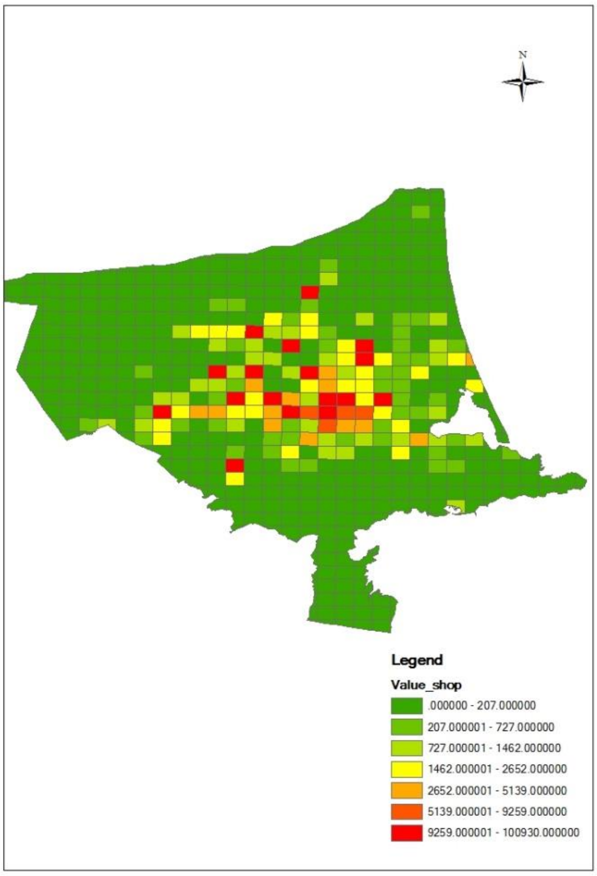

Figure 6. Shopping value distribution in Christchurch

5. Discussion and analysis

For each cell, the travel patterns and shopping values in different distance bins were calculated based on trip mode split for shopping. A cell close to the city centre of Beijing (cell A in Figure 7)and another one faraway(cell B in Figure 7) were selected as the example to show how the distance and shopping facility distribution affect trip frequency and shopping activities. Cell A is closer to the high-value shopping districts resulting in higher frequencies and better shopping service available within 5km. For people living in cell B, the motorized travel requirement is generated if they want to access more shopping facilities because of the lower level shopping services within short distance. By analysing the travel patterns in each cell, the adaptive capacity and relating shopping value at micro level could be derived as a close-up observation for analysis.

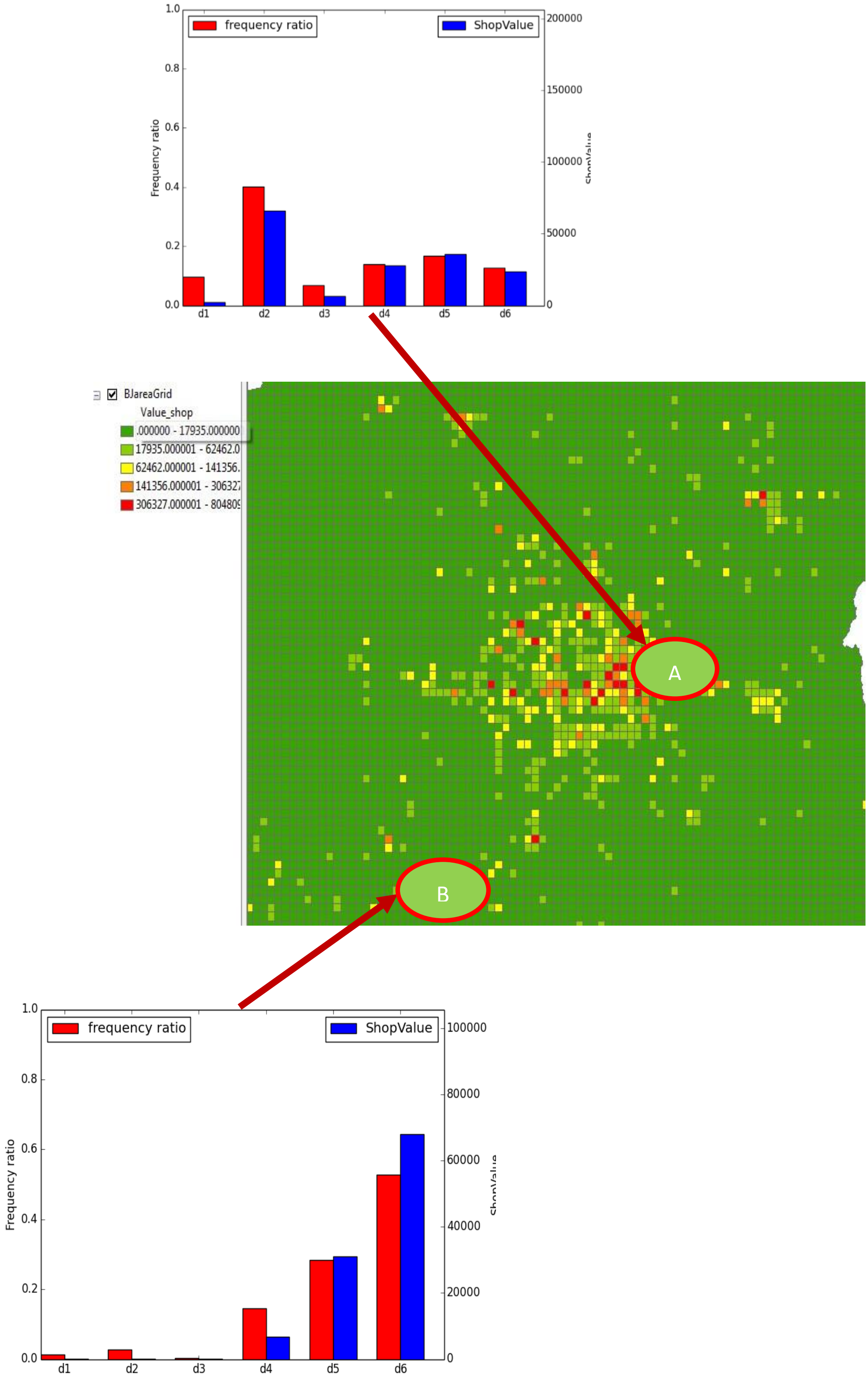

Figure 7. Example of travel patterns in each cell

The calculation of transport energy consumption in each cell was iterated throughout Beijing and Christchurch using Eq.(5) and (6) and mapped by applying the interpolation method in GIS, which is shown in Fig.8 and Fig.9. For both cities, it is similar that the city centre and surrounding areas have the lowest transport consumption because of the higher density of population and higher level of shopping services. In the outskirt of Beijing city, there exists several regions with lower transport energy use due to the long distance to the city centre. Combined with the shopping value map in Beijing, the level of shopping services in these regions are fairly good reducing the travel demand to the city centre. Also in Christchurch city, the southwest area and are of the lowest transport energy use owing to the same reason. Table. 4 is a comparative analysis on transport energy use, Vehicle Kilometres Travelled (VKT) and trip distance between Beijing and Christchurch. It is obvious that the motorized trips of Christchurch are much more than Beijing but the average trip distance is shorter owing to its smaller size of urban area. Therefore it is conceivable that a small-medium city has higher potentials for non-motorized trips than a large city. In particular, the calculated VKT value of Christchurch(1121km) based on this model is almost the same as the data (1170 VKT for shopping) derived from the travel survey by The Ministry of Transport and literature view (NZTA,2006; MOT,2015). Therefore, it might be an alternative measure to estimate the VKT data in a study area if there is no travel survey data available.

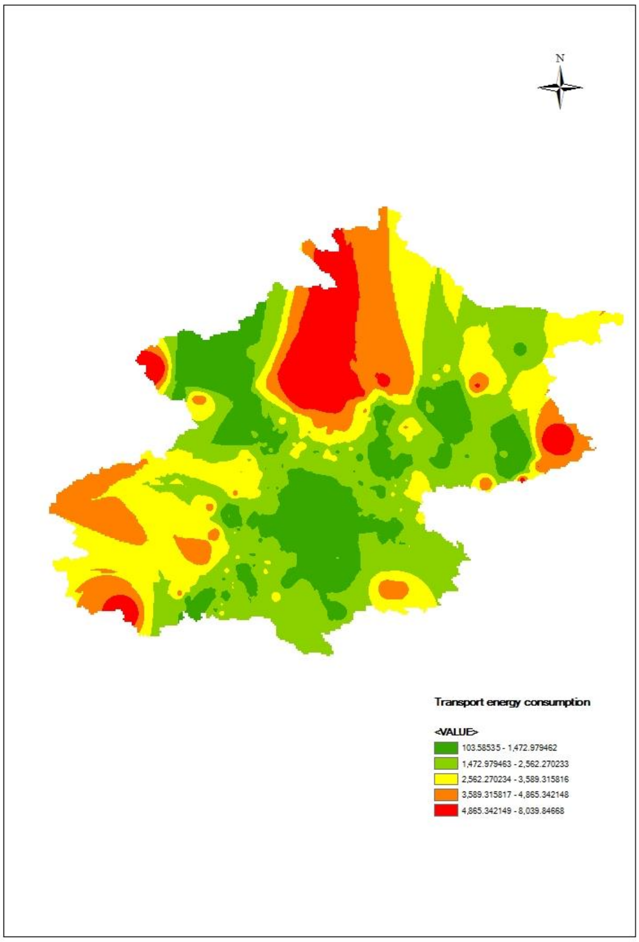

Figure 8. Transport energy consumption distribution map of Beijing

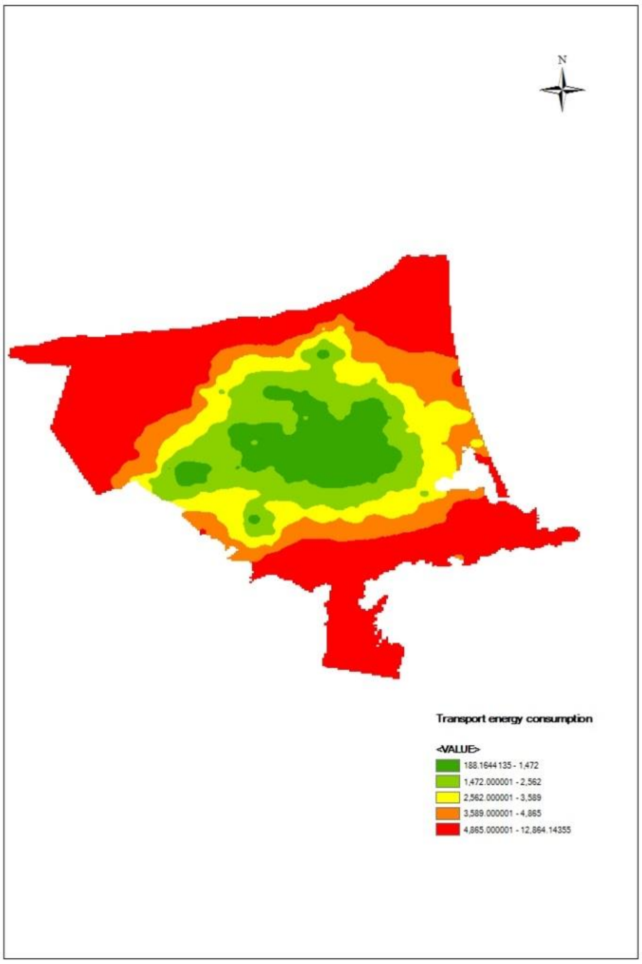

Figure 9. Transport energy consumption distribution map of Christchurch

City	Average transport energy use for shopping(MJ/person)	Average weighted VKT for shopping(km/year)	Average trip distance for shopping(km/day)
Beijing	1286.78	301	11.08
Christchurch	4137.80	1121	7.5

Table 4. Comparison on travel patterns between Beijing and Christchurch

It is generally argued that the carbon emission is negatively related to the population density, which is testified by the transport energy consumption vs. population density analysis in Fig.10 and Fig.11. All the cells in each cities were transformed into scatter chart with a division line and a trend curve highlighted in these two figures. It can be seen that both transport energy consumptions have the similar descending trend as the population density increases. Quite a few of residence in Christchurch consume more than 2000MJ/year for shopping activities, however the majority of Beijing's shoppers consume no more than 4000MJ/year, which mainly results from the differences in car ownership ratio and travel mode share.

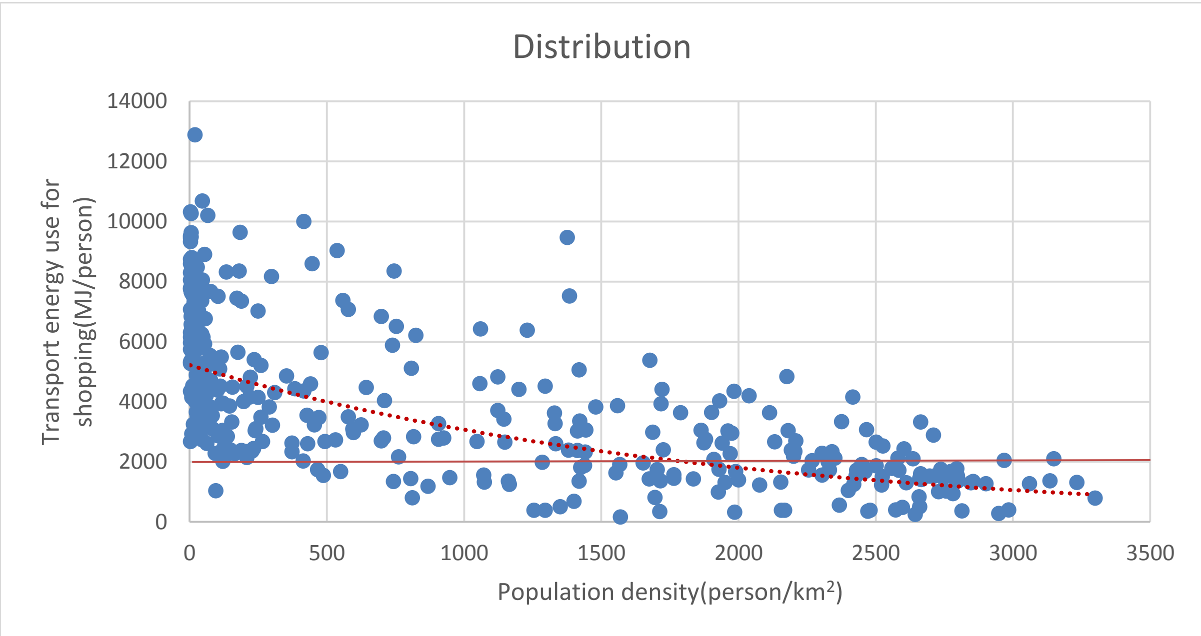

Figure 10. Correlation between transport energy use and population density in Christchurch

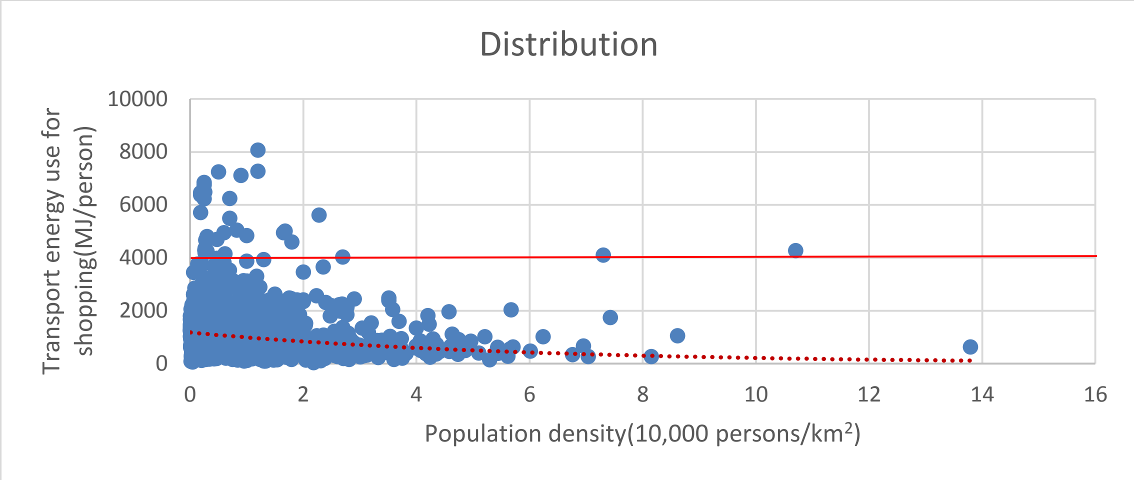

Figure 11. Correlation between transport energy use and population density in Beijing

The ratio of population with adaptive capacity greater than 25 percentile and 75 percentile were calculated in Beijing and Christchurch respectively (Table 5 and Table 6). In table 5, there is no much difference between Beijing and Christchurch in terms of meeting essential shopping activities, most essential requirements can be accessible within short distances. Nevertheless with regard to the walking accessibility, Beijing is better than Christchurch with 20 percent residence being able to shop within 1 km. In table 6, the result of Christchurch is slightly better than Beijing, nearly half of population could realize necessary shopping activities without motorization requirement, however the ratio of people in Beijing who can realize their necessary shopping activities is less than 20 percent although its shopping facility density is much higher than Christchurch. It is because in megacities, the increasing shopping facilities are more dispersed with the sprawling development of urban area, leading to more travel demand and longer trip distance (See Table. 3).

City	Ratio of people with zero transport energy consumption adaptive capacity		
	In 1km	In 3km	In 5km
Beijing	20%	53.4%	70%
Christchurch	11.4%	63%	80%

Table 5. Comparison between Beijing and Christchurch by 25 percentile shopping value

City	Ratio of people with zero transport energy consumption adaptive capacity		
	In 1km	In 3km	In 5km
Beijing	4%	12%	17.8%
Christchurch	6.7%	18.4%	43.4%

Table 6. Comparison between Beijing and Christchurch by 75 percentile shopping value

6. Conclusion

The model of this research presents a quantitative method to characterize shopping activities from the perspective of transport energy consumption. It combines Huff shopping model and Gravity model with limited travel survey data to calculate shopping transport energy use, in which a novel method to quantify the ranking of shopping facilities and relating travel patterns was proposed. Simply by shifting motorized trips that could be performed by walking and cycling, the potential of non-motorized travel patterns can be analysed based on distance bins. The model was applied to two different cities to compare the influencing factors that can contribute to the reduction of transport energy use. The results provide evidences that the development in the city centre can lead to less travel energy consumption and shorter trip distances, higher population density can help to decrease motorized trips and a small-medium sized city might has higher adaptive capacity in meeting necessary shopping activities than a large city. For megacities like Beijing, the high density development does not necessarily mean to reduce motorized travel demand if the urban boundary is not effectively contained. With the extension of urban area boundary, the average trip distance would be longer resulting in the high possibility of motorized trips. Accordingly, how to improve public transportation systems to meet longer distance travel demand is the only efficient way to offset the impact of urban sprawling.

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