# Beijing City Lab

Long Y, Shen Y, Yao X, Gao S, 2014, Spatially heterogeneous impact of urban form on human mobility: Evidence from analysis of TAZ and individual scales in Beijing. Beijing City Lab. Working paper #52

# Spatially heterogeneous impact of urban form on human mobility: Evidence from analysis of TAZ and individual scales in Beijing

Ying Long [1], Yao Shen[2], Xiaobai Yao[3], Sangni Gao[4]

[1] Beijing Institute of City Planning, Beijing 100045, China
[2] Bartlett School of Architecture, University College London, London, NW1 2BX, UK
[3] Department of Geography, The University of Georgia, Athens 30602, USA
4 Department of City and Regional Planning, Cornell University, NY 14850, USA

Abstract: The influence factors on human mobility (e.g. travel length/distance, time and count) are increasingly recognized as essential components of traffic assignment for urban sustainability. But most of the existing studies were based on individual samples, therefore neglected the spatial heterogeneity of mobility patterns. This study performs an examination of the spatially varying impacts of urban form and socioeconomic attributes on human mobility (average travel distance in this chapter) in the Beijing Area based on the Household Travel Survey in 2005. By using mixed Geographically Weighted Regression (MGWR), we incorporate the spatial stationary and non-stationary in one model to estimate the influence surfaces of elements that maters in residential mobility on the Traffic Assignment Zone (TAZ) level. Compared with the results produced by Ordinary Least Square (OLS) and Spatial Auto-Regression (SAR), the outputs of MGWR indicate that semi-parametric model has better performance in presenting the spatial variation of predictive factors' impacts. The maps further show that urban form features do impact people's mobility to various extents, both positively and negatively. Additionally, this study also yields that the analysis on the TAZ level by MGWR reveals better prediction in the spatial variability of local estimates in comparison with OLS analysis for the personal level data in the same survey. This empirical effort helps us to understand that people's mobility behaviors can be influenced by spatially exploring relevant variables of urban form.

Keywords: *urban form; human mobility; urban modelling; mixed geographically weighted regression, spatial heterogeneity*

## 1 INTRODUCTION & BACKGROUND

This chapter aims to quantitatively measure the impact of urban form on human mobility in Beijing Metropolitan Area, and to answer the question whether the impact is spatially heterogeneous so as to shed light on policy implications for decision makers in Beijing as well as other studies in relevant fields. According to the literature, three types of factors have been proved to influence human mobility, including urban form (e.g. land use characteristics), transportation system characteristics (e.g. accessibility, convenience and service quality), and socioeconomic attributes of individual or family (Wang et al., 2008). In this study, all these three aspects are addressed and the spatially heterogeneous impact of each element in urban form system is measured explicitly by controlling other factors in the statistical models.

Urban form is not only the immediate outcome of spatial plans but also the core elements affecting urban sustainability. As an important determinant for energy conservation and low carbon economy, it can impact the sustainable development of an urban system at the very beginning. Many existing research have empirically indicated that the urban form featuring poly-centers, higher density and mixed use corresponds to lower average transportation energy consumption. For example, Owens (1987) and Anderson et al. (1996) concluded that urban form has strong relationship with transportation energy consumption including passengers and cargo. Newman and Kenworthy (1989) used many cities as samples and found that average transportation energy consumption apiece decreases with population density. Holden and Norland (2005) found significant relationships between urban form and household & transportation energy consumption via analyzing eight neighborhoods in the greater Oslo region, indicating that the compact city policy corresponds with a sustainable urban form. Alford and Whiteman (2009) evaluated various types of urban form in different sub-regions of the Melbourne area in Australia and found that areas with higher residential and employment density are more likely to consume transport energy efficiently.

One important linkage between urban form and energy conservation is traveler's commuting behavior and total commuting distance. To measure the impact quantitatively, the activity-based modeling approach is widely applied using travel diaries as the basic dataset. Urban forms at housing and job places, respectively, are used as variables for quantitative evaluation. These empirical studies range from the impact of urban form on travel behavior, mobile travel behavior, children travel behavior, to pedestrian travel behavior and to non-work travel behavior (Dieleman et al., 2002; Giuliano and Narayan, 2003; Horner, 2007; Maat and Timmermans, 2009; McMillan, 2007; Pan et al., 2009; Schlossberg et al., 2006; Zhang, 2005). Moreover, Krizek (2003) indicated that the traveling behavior of a family would vary from their living neighborhood. As for land-use characteristics, another essential component of urban form, Lin and Yang (2008) found mixed land use reduces trip generation and indirectly increases the share of private mode ridership. Accordingly, the impacts of urbanization process can be statistically assessed by the relationship between the spatial distribution of commuting trips and those mobility factors associated with other urban problems in question.

Aside from urban form, socioeconomic attributes and transportation system characteristics also influence travel behavior to various extents. Some research believed that travelers' socioeconomic and demographic characteristics exert small or insignificant influence on travel demand (Lin and Yang, 2008; Pan et al, 2009). But, other research argued that socio-economic characteristics have an almost equal (Dimitris et al, 2008) or even greater influence on travel behavior than urban form (Veronique et al., 2007). Genevieve and Dhiraj (2003) indicated that females travel shorter distance than males; children and older people make less daily trips than that by the 'middle' age-groups; and trips increase with income and employment. Research also found that car ownership is an important variable to explain travel choice (Frans et al, 2002) and in-home/out-of-home recreation patterns which will affect trip generation (ARUN and RAM, 2001). For transportation system characteristics, Frans et al (2002) looked into at least 70,000 households and more than 150,000 people through Netherlands National Travel Survey (OVG) and found that the supply of good public transport clearly reduces car use. Consequently, socioeconomic factors and features of transportation system should be well considered together with the elements of urban form in one model, so as to truly count the roles of urban form in shaping mobility pattern.

The spatial nature of urban form and commuting data implies highly possible spatial dependence with the variables and spatial heterogeneity of associations between the variables. However, most of previous studies using Ordinary Least Square (OLS), a conventional global regression method, failed to consider the presence of spatial dependence and spatial heterogeneity. It is suggested that urban system is far more complex than we expected, which essentially requires the inherent spatial properties to be addressed in urban modeling. Spatial regression models can take two threads of strategies, namely the global models and local models. The global models mainly consider and account for the spatial autocorrelation. One typical model is the Spatial Auto-Regressive model (SAR) introduced by Anselin in 1988. In contrast, the local model focuses on the spatial heterogeneous, or non-stationary, relationships in the data. Geographically Weighted Regression is such an approach dealing with the issue of local variations of spatial associations (Fotheringham et al., 2002). Until now, although most urban mobility models have been established to explore the global relationships between mobility patterns and their determinants, there were some studies in which human mobility models are fitted using local regression approaches (Goetzke, 2008; Kawabata et al., 2007; Mulley, 2013). Yet, recent studies have recognized that urban data distribution is affected by the global fixed effect and local effect simultaneously. As an extended version of GWR, Mixed Geographically Weighted Regression (MGWR) was proposed to prevent the limitation of capturing purely local or global model by modeling the urban distributions by incorporating the spatial stationary and non-stationary in the same model. One such example is the modeling of urban hedonic price pattern (Wei and Qi, 2012). However, very few studies adopted this model to explore the multi-scaled relationships between urban commuting and its determinants.

The focus of this work is to explore spatial heterogeneity of urban form's impact on mobility. We choose the mixed-scaled regression techniques in order to unfold the spatial complexity in mobility modeling that is usually hidden when applying the global regression method. We are particularly interested in exploring the answers to the following questions:

1) What kinds of urban form factors are suitable predictive variables for modeling the spatial heterogeneity of urban mobility?
2) Is MGWR model a better-specified model with proper technical corrections in comparison with other standard models?
3) To what extent does urban form influence human mobility in consideration of spatial variation of the influence?

The rest of this chapter is organized as follows. Section 2 discusses the methods to account for spatial heterogeneity and introduces the proposed empirical model. Section 3 reports the datasets used for evaluating urban form and human mobility. At the next step, empirical results in Beijing Metropolitan Area are presented and summarized in section 4, before section 5 highlights the final remarks.

# 2 METHODOLOGY

## 2.1 Modeling Spatial Effects in Urban Mobility

Most of mobility models are expressed in a traditionally standard linear regression model, in which the traits of mobility, e.g. the travel distance, are regressed on a series of structural, socioeconomic and traffic characteristics. However, these traditional econometrics have largely ignored spatial dependence and spatial heterogeneity that violate the traditional Gauss-Markov assumptions used in regression modeling (Anselin, 1988). Due to the nature of spatial dependence which is widely observed in urban data, spatial regression techniques are preferred over the traditional OLS model. Spatial regression modeling is developed to address spatial autocorrelation and/or heterogeneity at the same time. Anselin (1988) introduced the most widely applied spatial regression model called Spatial Auto-Regressive model (SAR), in which spatial dependence can be incorporated in two distinct ways: as an additional operator in the form of a spatially lagged dependent variable, or in the error structure. The former is referred to as a Spatial Lag Model (SLM) and is appropriate when the focus of interest is the assessment of the existence and strength of spatial interaction. Formally, a spatial lag model, or a spatial autoregressive model is expressed as

$$y = X\beta + \rho Wy + \varepsilon \tag{1}$$

where $\rho$ is a spatial autoregressive coefficient, $\beta$ is common regression coefficient and $\varepsilon$ is a vector of error terms. A spatial lag for y is expressed as $Wy$, where W is a spatial weights matrix arbitrarily defined by the modeler reflecting the geographical continuity throughout the study landscape.

Spatial dependence in the regression disturbance term, or a spatial error model, referred to as Spatial Error Model (SEM), is appropriate when the concern is correcting for the potentially biasing influence of the spatial autocorrelation. Hence,

$$y = X\beta + \varepsilon \tag{2}$$

$$\varepsilon = \sigma W\varepsilon + \mu \tag{3}$$

is equivalent to

$$y = \sigma Wy + X\beta - \sigma WX\beta + \varepsilon \tag{4}$$

which is a spatial lag model (SLM) with an additional set of spatially lagged exogenous variables (WX) and a set of k nonlinear (common factor) constraints on the coefficients (the product of the spatial autoregressive coefficient with the regression coefficients β should equal the negative of the coefficients of WX). In this sense, the SLM model deals with the overall spatial spillover effect with defined factors, whereas the SEM model measures the extent that the predictability is interfered by other undefined key factors. In other words, if SEM is more significant, it means that there are some critical variables missed in the proposed model. Clearly, despite the fact that SAR models have taken into account the fixed regional effect with a fixed lagged operator, they are still global models. These global models are overtaken based on an assumption that all the parameters are homogenous over the geographical environment, which may be problematic to reflect the local bias in reality. Consequently, locally weighted models are hardly demanded if the locally explicit results are aimed.

Based on the observed spatial non-stationery relationships, various approaches haven been developed in order to deal with spatially varying coefficients. Among which, Geographically Weighted Regression (GWR), the most widely adopted method in the literature with relevant context, provides an elegant and easily grasped means of modeling such relationships. Actually, GWR could be considered as a local version of spatial regression that generates parameters disaggregated by the spatial units of analysis, which allows assessment of the spatial heterogeneity in the estimated relationships between the independent and a set of dependent variables (Fotheringham. et al, 2002). For a location i, GWR model is formally defined as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k_b} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i \tag{4}$$

where ($u_i$,$v_i$ ) denotes the coordinates of the $i$th location in space, $\beta_0(u, v)$ denotes to the local constant for the place $i$, and $\beta_j(u_i, v_i)$ is a realization of the continuous function $\beta_j(u,v)$ at regression point $i$, which is a parameter to be estimated. $\varepsilon_i$ is a random error term, assumed to be normally distributed. In this model, observations located closer to the regression point are weighted more heavily than the observations located far away in the study area on the basis of a distance decay function, for example, a Gaussian function. After local estimates are derived at all locations in the study area, a continuous surface of local parameters will be automatically generated. This map presents various information about each estimate which includes not only its magnitude, but also the signs which could be positive and negative according to the specific location. In a GWR model, both positive and negative values can be observed with different degrees of significance for a coefficient. In this regard, it is obvious that employing the local GWR model to estimate human mobility patterns can provide far more valuable information on the spatial variations of related variables than conventional regression model.

**2.2 Mixed-GWR: modeling mobility on multi-levels**

A recognized issue with GWR is that not all factors will present significant spatial variability across space. The reality is that both global effects and local effects may be in place. Therefore, the purely local regression model might not always be the best option to explore the relationship between the response and the explanatory variables. Some studies have discovered that socioeconomic attributes are more suitable to be treated as global variables whereas the structural features are more likely to be the local factors with significant geographical variations (Fotheringham et al., 2002). One proper solution to this issue is applying a regression model where both local and global effects are properly defined and placed. Mixed GWR (MGWR) is such a model introduced by the developer of GWR. In the MGWR model, those coefficients that were proved to be non-fluctuant across locations will be kept constant thereby improving the efficiency of prediction. Therefore, the pure local GWR model is extended to a multi-scaled one which can reflect the real spatial complexity in urban system. MGWR model can be formulated by Equation (4) as follows:

$$y_i = \sum_{g=1}^{k_a} \beta_g x_{ig}(a) + \sum_{j=1}^{k_b} \beta_j(u_i, v_i)x_{ij}(b) + \varepsilon_i \tag{5}$$

where $k_a$ and $k_b$ denote the total account of global and local parameters for the variables respectively; $x_{ig}(a)$ refers to the global variables and $x_{ij}(b)$ stands for the local variables; $\beta_g$ is the $g$th parameter associated with the global explanatory variables at all locations.

The adoptability of MGWR relies on a calibration procedure by a multiple stepwise regression algorithm to test the geographical variability for each variable. This is conducted by model comparisons between all pairs of the fitted GWR model, say the purely local GWR, and a modified model where only $k$th coefficient is fixed globally. By comparing with the difference of criterion measured by AICc, we can further decide which local factor should be assumed as global. Therefore, MGWR is more promising than standard GWR model when non-stationary and spatial stationary are detected.

Local *t*-value generated in GWR model helps us to investigate the spatial significance of local coefficient estimates. We use a significance level of 0.05 to determine the significance of the local coefficients.

## 3 DATA

### 3.1 Study area and sample data

We select the metropolitan area of Beijing as the study area and intend to measure the influence of selected factors on residents' mobility (Figure 1). Beijing household travel survey data in 2005 are employed to evaluate mobility in Beijing. The 2005 survey covers the whole administrative areas including all 18 districts with 1118 TAZs as the basic geographical survey unit (Beijing Municipal Commission of Transport and Beijing Transportation Research Centre, 2007). The sampling size is 81760 households and 174957 persons, with a sampling ratio of 1.36%. This survey adopts a travel diary form. For each trip, the survey records the departure time/location, arriving time/location, trip purpose and mode, as well as other important information including trip distance, destination building type, and transit line numbers. The household and personal information are also included in this survey. The household information consists of household size, *Hukou* (official residence registration) status and residence location, while the personal information includes gender, age, household role, job type and location, and whether having driving license or transit month pass. The trip purposes in this survey include: 1) work, 2) school, 3) back to home, 4) back trip, 5) shopping, 6) entertainment, 7) daily life (such as dining, medical, social visiting, leisure/fitness, and picking up/ delivery), 8)business, 9) other. Job types include: 1) worker, 2) researcher, 3) office employee/public employee, 4) teacher, 5) student, 6) self-employed, 7) attendant, 8) retiree, 9) specialized staff (such as medical staff, professional driver, bus/metro/taxi driver, and soldier/police), 10) farmer, 11) unemployed, 12) other. Trip modes are: 1) walk, 2) bicycle, 3) electric bicycle, 4) motor, 5) bus, 6) mini bus, 7) metro, 8) employer-provided bus, 9) private car, 10) employer-provided car, 11) legal and illegal taxi. Among all transportation modes, the share of bus ridership is 13.81% in the Beijing Metropolitan Area according to this survey.

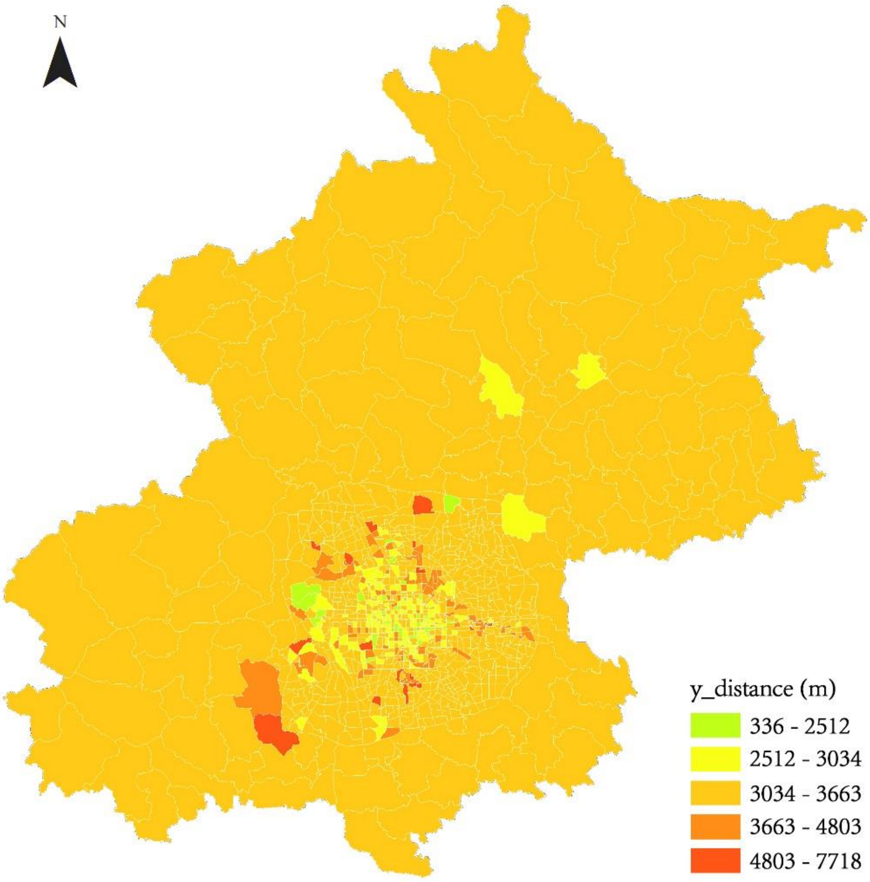



Figure 1 Spatial distribution of mobility in terms of average travel distance

In the following analysis, we aim to analyse the stimulus-response relationship between urban form and human mobility in both TAZ and individual scales. The analyses are performed at the TAZ level and individual level respectively.

3.2 Computing factors for mobility modelling

The choice of urban form indicators (UFIs) as predictive variables for mobility modeling in this study is based on the model by Pan et al (2009). There are mainly five types of explanatory variables in proposed models, including geometry, accessibility, amenities, socioeconomic properties and land uses, as listed in Table 1.

Table 1 The various types of factors in mobility modeling in the TAZ scale

| **Main type** | **Abbreviation** | **Description** |
|---|---|---|
| Geometry | A_PS | Average parcel/block size |
| Accessibilities | D_TAM | Distance to Tian'anmen square |
| | D_CBD | Distance to CBD |
| | D_ZGC | Distance to Zhongguancun |
| | D_NSC | Distance to the nearest sub-city center |
| | D_NSS | Distance to the nearest subway stations |
| Amenities | ST_D | Road / street density |
| | BS_D | Bus stops density |
| | PF_D | Density of public facilities |
| Socioeconomic | POP_D | Population density in 2005 |

| | | |
|---|---|---|
| properties | JOB_D | Job density in 2010 |
| | H_INC | Average household income (if no date in the survey, then use 3400 average value) |
| | H_CAR | Average car ownership in households |
| | A_AGE | Average age |
| Land uses | L_MIX | Land use mix index |

The land use mix index is measured by the entropy calculated from areas of various land uses. Nine types of land uses are included, denoted as C, D, F, M, R, S, U, W and X. The entropy *S* is calculated by Equation 6.

$$S = -\sum_{i=1}^{n} P_i \, log_{10} P_i \tag{6}$$

in which *n* is the number of land use types, and $p_i$ is the percentage of the area of the *i*th land use type in the TAZ.

Thus, in the theoretical regression model at the TAZ scale, a vector $y_{dis}$ is regressed on a series of determinates as follows:

$$\begin{aligned}\ln(y_{dis}) = \beta_0 + \beta_1 \ln(A_{PS}) + \beta_2 \ln(D_{TAM}) + \beta_3 \ln(D_{CBD}) + \beta_4 \ln(D\_ZGC) \\ + \beta_5 \ln(D\_NSC) + \beta_6 \ln(D\_NSS) + \beta_7 \ln(ST\_D) + \beta_8 \ln(BS\_D) \\ + \beta_9 \ln(PF\_D) + \beta_{10} \ln(POP\_D) + \beta_{11} \ln(JOB\_D) + \beta_{12} \ln(H\_INC) \\ + \beta_{13} \ln(H\_CAR) + \beta_{14} \ln(A\_AGE) + \beta_{15} \ln(L\_MIX)\end{aligned} \tag{7}$$

The data for deriving these indicators are Land use parcels in 2005, and locational GIS data in 2005, bus stops in 2005, public facilities in 2005, roads in 2005, population for parcels in 2005, and the 2005 household travel survey in 2005 (the 2005 survey) for demographic properties. The descriptive statistics are summarized in Table 2.

Table 2 Descriptive statistics for independent variables in the TAZ scale (N=1118)

| **Variables** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|
| A_PS | 0.18041 | 44.18365 | 3.38 | 3.719 |
| D_TAM | 550 | 115481 | 19900 | 17148.244 |
| D_CBD | 335 | 113185 | 20400 | 16854.603 |
| D_ZGC | 230 | 115498 | 21900 | 16403.987 |
| D_NSC | 375 | 68265 | 19500 | 9217.940 |
| D_NSS | 247 | 102121 | 10300 | 14581.321 |
| ST_D | 0 | 213.25 | 48.93 | 38.916 |
| BS_D | 0 | 2.675573 | 0.23 | 0.321 |
| PF_D | 0 | 1.079499 | 0.11 | 0.169 |
| POP_D | 0 | 938 | 82.57 | 123.588 |
| JOB_D | 0 | 21.86201 | 0.37 | 1.246 |
| H_INC | 1000 | 25000 | 3510.02 | 1521.604 |
| H_CAR | 0 | 1 | 0.13 | 0.181 |
| A_AGE | 33 | 60 | 42.86 | 2.076 |
| L_MIX | 0 | 0.85066 | 0.41 | 0.181 |

At the individual level, we add some factors regarding the personal elements including gender, age, career status (student or not) measured by variable S_STU, and the home-to-work trip distance measured by variable D_RJ. In addition, some aggregated variables at the TAZ level are replaced by the individual level data. These include income and car ownership. The descriptive statistics of all variables are presented in Table 3.

Table 3 Statistical descriptive table for variables of the person level data (N=174957)

| **Variables** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|
| SEX | 0 | 1 | 0.50 | 0.500 |
| AGE | 0 | 95 | 41.62 | 17.397 |
| S_STU | 0 | 1 | 0.13 | 0.334 |
| D_RJ | 0 | 111 | 3.67 | 6.132 |
| A_PS | 0.18041 | 23.90190 | 2.0402337 | 1.67606557 |
| D_TAM | 851.00 | 72516.0 | 12400.131 | 12440.692 |
| D_CBD | 642.00 | 75166.0 | 14188.847 | 12114.0551 |
| D_ZGC | 790.00 | 69804.0 | 15156.941 | 11565.8723 |
| D_NSC | 743.00 | 36259.0 | 18483.116 | 7711.76117 |
| D_NSS | 276.00 | 53717.0 | 5084.9656 | 9271.08157 |
| ST_D | 3.82524 | 208.025 | 77.726260 | 44.09671165 |
| BS_D | 0.00000 | 1.79886 | 0.4718081 | 0.34736583 |
| PF_D | 0.00000 | 1.07950 | 0.2469767 | 0.21420801 |
| POP_D | 0.00000 | 554.00 | 199.80923 | 134.036610 |
| JOB_D | 0.00000 | 21.86201 | 0.8413297 | 1.93712864 |
| INC | 1000 | 40000 | 3541.80 | 2733.996 |
| CAR | 0 | 3 | 0.34 | 0.491 |
| L_MIX | 0.00000 | 0.79741 | 0.4157790 | 0.13105488 |
| $y_{dis}$ | 1.95 | 12.47 | 7.5358 | 1.02938 |

The theoretical model for regression analysis of personal mobility can be formally expressed as follows:

$$\begin{aligned}\ln(y_{dis}) = \beta_0 &+ \beta_1 SEX + \beta_2 \ln(AGE) + \beta_3 S\_STU + \beta_4 \ln(D\_RJ) + \beta_5 \ln(A_{PS}) \\ &+ \beta_6 \ln(D_{TAM}) + \beta_7 \ln(D_{CBD}) + \beta_8 \ln(D\_ZGC) + \beta_9 \ln(D\_NSC) \\ &+ \beta_{10} \ln(D\_NSS) + \beta_{11} \ln(ST\_D) + \beta_{12} \ln(BS\_D) + \beta_{13} \ln(PF\_D) \\ &+ \beta_{14} \ln(POP\_D) + \beta_{15} \ln(JOB\_D) + \beta_{16} \ln(INC) + \beta_{17} \ln(CAR) \\ &+ \beta_{18} \ln(L\_MIX) \qquad (8)\end{aligned}$$

3.3 Calibration of OLS, SAR and Mixed-GWR

3.3.1 Calibration of theoretical model

Before conducting regression models, the problem of multicollinearity is examined and resolved. It happens when two or more of the variables in the model are highly correlated, which will result in an over counting bias and an unstable/unreliable model. One method to detect multicollinearity is to use the Pearson product-moment correlation coefficients, or Pearson's correlation in short. Generally speaking, two variables with Pearson's correlation above 0.8 suggest a high degree of multicollinearity. Another way to judge the degree of multicollinearity is to examine the so-called Variance Inflation Factor (VIF), which is a formal detection for multicollinearlity. If one variable has a VIF value bigger than 7, it means that it has to be dropped from the model.

In the proposed regression model at the TAZ level, four variables of accessibilities including D_TAM, D_CBD, D_ZGC and D_NSS are found to be highly correlated, which is also proved by their large values of VIF. Therefore, only one of these four variables can be kept in the theoretical model formulated by equation (7). Likewise, those four variables are also found to cause multicollinearity in the regression model based on individual data. Thus three of the distance variables are dropped in both models proposed in this study, while only D_NSC is taken into account as the measure of accessibility generated by urban form.

3.3.2 Spatial autocorrelation detection

As concisely expressed by Tobler's First Law of Geography, spatial dependence is the fundamental character of geographically distributed phenomena. When significant spatial dependence is identified, spatial autocorrelation is said to be present in the variable at issue. As a result, the classic statistical regression methods are inadequate to account for the spatial autocorrelation in the variables. Therefore, spatial regression methods have been developed in response to such inadequacy. In this study, we first performed Moran's I analysis to examine the presence of spatial autocorrelation in the data. Using the toolkit named GeoDa developed by Anselin, we calculated the value of global Moran's I and generated the map of local Moran's I by Local Indicators of Spatial Association (LISA) analysis. According to the results in Figure 2, there is significant spatial heterogeneity discovered in human mobility pattern at the TAZ level. The global Moran's I value for all the TAZs in Beijing Metropolitan Area is 0.14 (p-value equals to 0.001 by running permutation test 999 times), suggesting that there is slightly clustered when all TAZs are considered. The local analysis results in Figure 2 (d) reveal significant clusters for some TAZs. Low-Low clusters distribute both in the downtown areas and part of the suburbs. High-High clusters distribute in places which have mostly residential functions and few job opportunities. The evidence of significant spatial autocorrelation and particularly local variations suggest the possibility of spatial heterogeneity in the spatial relationships. Thus SAR and MGWR are adopted to study travel patterns in Beijing. SAR is used to account for spatial autocorrelation, while MGWR is adopted to consider spatial heterogeneity.

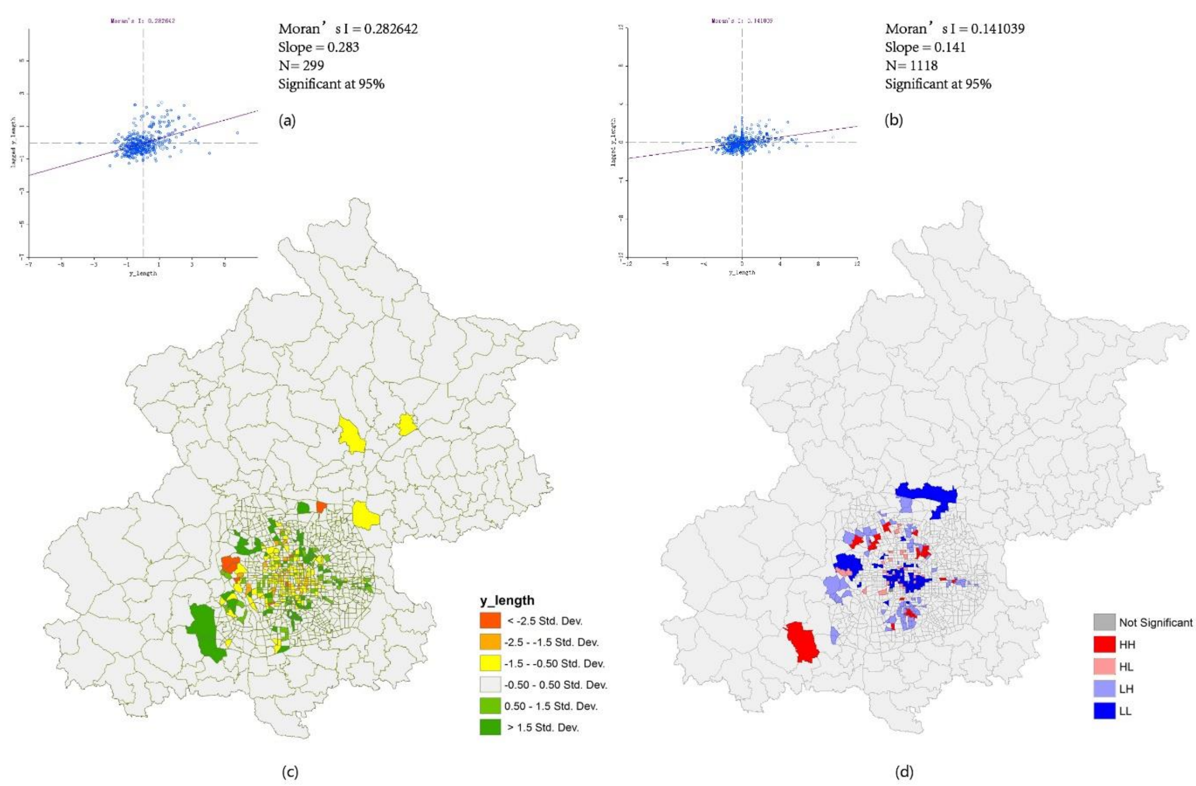



Figure 2 Spatial autocorrelation analysis for average travel distance: (a) Moran scatter plot for special TAZs (<-0.5 SD and >0.5 SD); (b) Moran scatter plot for all TAZs; (c) Hotspots TAZs (<-0.5 SD and >0.5 SD); (d) LISA analysis map

### 3.3.3 Calibration of the MGWR model

An advantage of MGWR is that it enables modelers to incorporate the fixed effects as a subset of all explanatory variables based on their prior judgment. However, it is not always easy to objectively define which factors should be fixed. We adopt the geographical variability test to solve this problem. The difference is examined between a fitted GWR model and a counterpart model in which only the *k*th coefficient is fixed globally. A positive difference indicates that *k*th variable should be identified as the global one. The critical value here is 2 in terms of AICc, which means that the switched model achieve better fitting results if it can reduce at least 2 in AIC. The results are reported in Table 4, showing that only three variables (H_INC, H_CAR, A_AGE) replicating socioeconomic characteristics are defined as local parameters, whereas others are modeled globally in GWR.

Table 4 Geographical variability test for variables

| **Variables** | **F-statistics** | **DIFF of Criterion** | **Type of parameter** |
|---|---|---|---|
| Intercept | 13.92 | -162.39 | local |
| A_PS | 0.57 | 67.57 | global |
| D_NSC | 1.60 | 17.64 | global |
| ST_D | 1.97 | 21.09 | global |
| BS_D | 0.36 | 69.22 | global |
| PF_D | 1.00 | 43.88 | global |
| POP_D | 0.67 | 58.31 | global |
| JOB_D | 1.51 | 37.64 | global |

| | | | |
|---|---|---|---|
| H_INC | 15.51 | -246.61 | local |
| H_CAR | 12.36 | -200.61 | local |
| A_AGE | 5.56 | -56.73 | local |
| L_MIX | 1.11 | 53.09 | global |

Another issue for MGWR model is the best bandwidth selection. Some exiting methods can help to select the most promising bandwidth towards the best fitting model. For instance, cross-validation (CV) procedure is such a way introduced by Cleveland in 1979 for local regression models. In the following analysis, we follow the procedure suggested by Fotheringham et al (2002) using a Gaussian Kernel function to select the golden bandwidth for minimizing the AICc value. This procedure is conducted by iterations in which only the bandwidth changes but other model settings are kept constant. The generated bandwidth in this model is 104 for the proposed MGWR model.

# 4 EMPIRICAL RESULTS

4.1 Primary findings on the TAZs level
4.1.1 OLS analysis for TAZs

Table 5 shows the coefficients generated for a stepwise OLS regression analysis. The second column from the left is the results of OLS analysis when all travel modes are combined. In addition, we conducted the OLS analysis in the TAZ scale for each of the specific traffic modes, including car, bus, bike, moto and walk. Here we regard taxi as car, metro as bus. It seems that socioeconomic features matters more significantly for all modes, while the accessibilities affect the mobility of certain mode more significantly. Furthermore, it implies that people tend to travel shorter distance when they live in the area where the urban density is higher, which is on the basis of the evidence that all the urban density features show a negative linkage to the mobility length. Meanwhile, a person is more likely to travel longer if he/she lives in the richer area with higher income and car ownership. Yet, the adjusted R square of each mode is generally low implying that the global OLS models can hardly inform a good fitted model as we have predicted. We also conducted OLS analysis for the dependent variables y_count and y_time. For y_count, $R^2$=0.06,. For y_time, $R^2$=0.03. This suggests that the explanation power of the OLS model for trip frequency and trip time is quite limited.

Table 5 Stepwise OLS results for various traffic modes (in terms of average travelling distance)

| **Variables** | **All modes** | **Car** | **Bus** | **Bike** | **Moto** | **Walk** |
|---|---|---|---|---|---|---|
| Intercept | 3209.524*** (33.726) | 15570.931 (18.2***) | 12622.127 (18.3***) | 5627.796 (23.2***) | 6179.490 (10.456***) | 531.878 (9.4***) |
| A_PS | - | - | - | - | - | - |
| D_NSC | - | 0.262 (7.5***) | 0.163 (5.6***) | - | 0.105 (3.983***) | -0.003 (-2.3**) |
| ST_D | - | -63.594 (-6.2***) | -64.969 (-8.4***) | -11.096 (-3.0***) | - | - |
| BS_D | - | -3847.367 (-3.0***) | - | - | - | - |
| PF_D | -567.579*** (110.33) | - | - | - | - | - |
| POP_D | -0.543*** | - | -6.777 | - | - | - |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.162) | | (-2.6***) | | | |
| JOB_D | -46.789*** (11.455) | - | - | - | - | - |
| H_INC | 0.02** (0.009) | - | - | - | - | - |
| H_CAR | 822.728*** (92.987) | -8082.251 (-4.0***) | -4505.999 (-2.7***) | -4717.215 (-6.2***) | -5577.429 (-5.030***) | 265.816 (3.6***) |
| A_AGE | - | - | - | - | - | - |
| L_MIX | - | - | - | - | - | -195.742 (-2.5**) |
| N | 1118 | 1015 | 982 | 848 | 597 | 1045 |
| R square | 0.111 | | | | | |
| Adjusted R square | | 0.195 | 0.195 | 0.077 | 0.063 | 0.028 |
| AIC | 16797 | | | | | |

Note: Standard errors in parentheses; *, **, and *** represent for the confident level at 90%, 95% and 99%, respectively.

4.1.2 SAR

We analyse regression diagnostics for trend surface regression models, which includes a spatial weights matrix for use in a SAR model. A linear trend surface is considered here, meaning that only explanatory variables are included but no cross-terms. Two kinds of contiguity based spatial weights matrices, Rook and Queen, are attempted in our regressions, which are provided by GeoDa. The statistics of Queen Matrix tend to be more significant. Therefore, in the following analysis the Queen Continuity Matrix is employed in SAR models.

In the next step, SLM, SEM and OLS models are compared and the results are presented in Table 5. It suggests that spatial regression models improve the fitting results (bigger R square, smaller AICc value), reduce the standard errors of almost all variables and prove the significance of spatial lag. In the comparison between SLM and SEM, we find that SLM is more appropriate for modelling spatial autocorrelation due to the robustness significance. The outputs of SAR models confirm the significant variables in OLS. However, just like OLS, the SAR models hardly have a satisfactory prediction.

Table 5 Comparison among SLM, SEM and OLS with Queen spatial weight matrix

| **Variables** | **SLM** | **SEM** | **OLS(enter)** |
|---|---|---|---|
| W_Y_distance | 0.231*** (0.043) | - | - |
| Intercept | 2827.520*** (324.588) | 3555.605*** (292.735) | 3649.306 (295.053) |
| A_PS | 1.899 (3.786) | 1.904 (3.865) | 1.839 (3.873) |
| D_NSC | 0.001 (0.002) | 0.002 (0.002) | 0.001 (0.001) |
| ST_D | -0.577 (0.485) | -0.638 (0.529) | -0.714 (0.496) |
| BS_D | -11.817 (58.460) | 1.148 (60.085) | -11.365 (59.772) |
| PF_D | -369.794*** (123.854) | -410.389*** (133.823) | -462.801*** (125.820) |
| POP_D | -0.426*** (0.165) | -0.439*** (0.169) | -0.439*** (0.169) |
| JOB_D | -44.995*** (11.259) | -44.298*** (11.213) | -45.597*** (11.517) |

| | | | |
|---|---|---|---|
| H_INC | 0.031*** (0.008) | 0.019*** (0.009) | 0.022*** (0.009) |
| H_CAR | 780.518*** (96.689) | 793.189*** (98.111) | 806.582*** (98.745) |
| A_AGE | -9.794 (6.604) | -8.784 (6.691) | -11.416* (6.753) |
| L_MIX | 45.631 (75.348) | 28.584 (78.265) | 73.715 (77.050) |
| LAMBDA | - | 0.249*** (0.047) | - |
| N | 1118 | 1118 | 1118 |
| R square | 0.146 | 0.146 | 0.116 |
| Log likelihood | -8374.74 | -8375.88 | -8389.05 |
| AIC | 16840.7 | 166775.8 | 16802 |
| Robustness | 3.994 ** | 0.300 | - |

Note: Standard errors in parentheses; *, **, and *** represent for the confident level at 90%, 95% and 99%, respectively.

4.1.3 MGWR

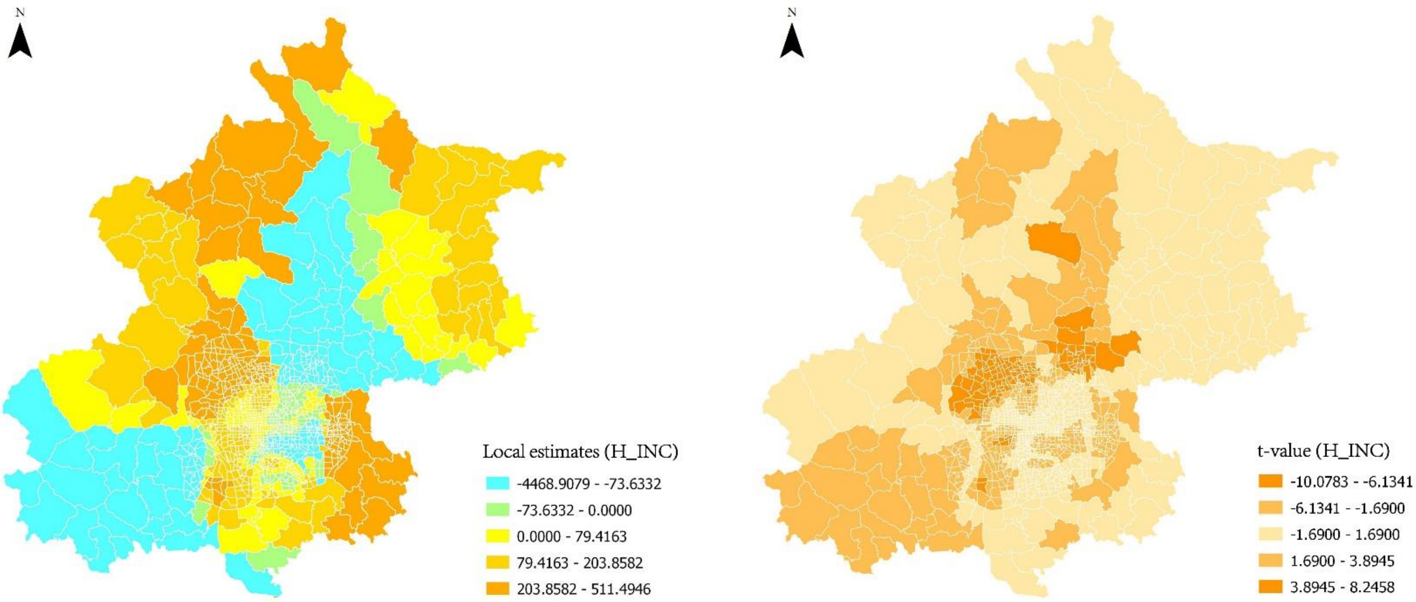
The MGWR provides both global and local estimations (see Table 6). The ranges of local estimates show that the H_INC, H_CAR and A_AGE variables are very geographically varying. All these local variables present negative and positive effects in different parts of our study area, illustrating that a constant coefficient in global models would have ignored the important particularity with locations. Moreover, it is easy to be recognised that the explanatory ability of MGWR model is much better than the OLS and SAR models based on the increased R square and the decreased AIC, suggesting that GWR models explain more about mobility patterns. Other global coefficients are recognised to be similar to the ones in OLS and SAR regressions. Consequently, we paid more attention to the spatial variability of local parameter estimates and the corresponding t-value distributions for H_INC, H_CAR and A_AGE.

Table 6 The summery of MGWR results

| **Fixed (Global) coefficients** | | **Geographically varying (Local) coefficients** | | | |
|---|---|---|---|---|---|
| Variables | Estimates (standardized) | Variables | Estimates (mean) | Estimates (min) | Estimates (max) |
| A_PS | 3.164 | Intercept | 3348.313 | 2478.510 | 4512.987 |
| D_NSC | -18.049 | H_INC | 2.224 | -4468.907 | 511.494 |
| ST_D | -6.049 | H_CAR | 184.962 | -1113.669 | 1861.479 |
| BS_D | 7.832 | A_AGE | -10.293 | -2223.535 | 2932.294 |
| PF_D | -26.263 | | | | |
| POP_D | -8.438 | | | | |
| JOB_D | -41.840 | | | | |
| L_MIX | 7.121 | | | | |
| Classic AIC | 16331.2 | | | | |
| AICc | 16353.3 | | | | |
| R square | 0.509 | | | | |
| Adjusted R Square | 0.441 | | | | |

1) *Average household income (H_INC)*

The spatial distribution of H_INC parameter estimates and corresponding t-value map are depicted in Figure 3. Figure 3(a) shows that the spatial relationship between TAZ-based average income and the travel length. It reveals that residents live in most places in the inner city of Beijing, the area within the fifth ring road, would travel to closer places if they have more income. It should be noted that about half of the TAZs show negative impacts of people's income on their travel length, which seems to be a reversed result in comparison with the OLS result. The negative peak appears in the areas in proximity to Beijing Capital International Airport in Shunyi District. This trend spreads in most of areas in Beijing except for three clusters where the income standard exerts positive effects on travel distance. Those three clusters are generally suburban areas including the area around Tongzhou District in the south-east of Beijing, the places in Changping District in the north-west and the rural areas in the very north of Beijing. The statistical reliability of this analysis is supported by the t-value pattern shown in Figure 3(b). Almost all the positively related to hot-pots and the negative ones are statistically significant at the confidence level of 95%. It suggests that high accuracy of local estimates can be explained in our case study by the significant correlation between household income and people's mobility. The reasons why the relationships in suburban areas vary differently should be explored more in further detailed studies.

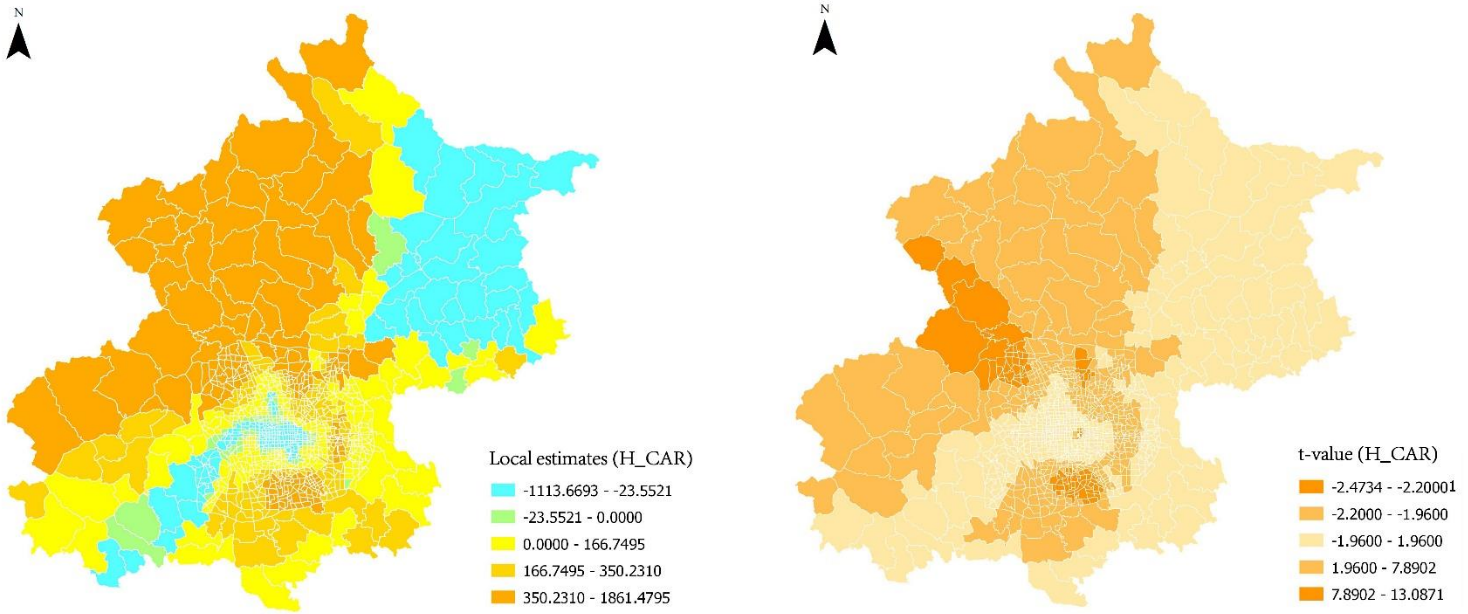



(a) (b)

Figure 3 Spatial variation of H_INC local estimates (a) and t-value map (b)

2) *Average household car ownership (H_CAR)*

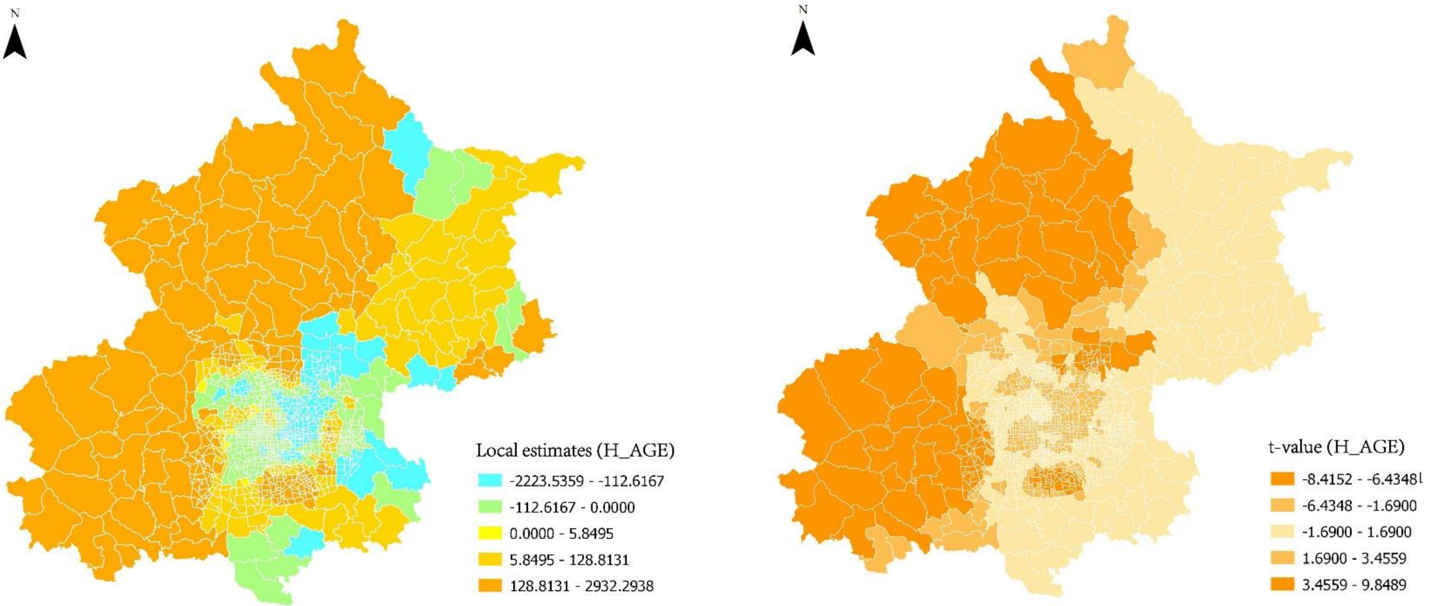
Figure 4 illustrates the local variation of the average car-ownership. It shows negative and very small values of coefficients for the inner city of Beijing, the south-west and north-east Beijing; however, these results are not significant. Other areas (darker coloring), particularly the broad areas in the northwest and the south of Beijing City exhibit higher positive local estimates, which demonstrates that people living in these areas are willing to travel further if they have more cars. It confirms the common sense that cars will encourage the traveling length to some extent, though more empirical research is to be conducted. The t-value map (Figure 4 (b)) indicates that the significant relationship between car-ownership and mobility pattern is particularly obvious in the town of Majuqiao (the dark cluster in the southeast of Beijing) and the areas around Yanqin (the clusters on the northwest in Beijing). Thus, combining the pattern of local estimates and the statistical significance distribution, the result implies a significant trend in Beijing that car ownership presents a significant factor for long-distance job opportunities.




(a) (b)

Figure 4 Spatial variation of H_CAR local estimates (a) and t-value map (b)

*3) Average age (A_AGE)*



(a) (b)

Figure 5 Spatial variation of A_AGE local estimates (a) and *t*-value map (b)

Figure 5 reveals that the inner city of Beijing and the broad east part of Beijing Metropolitan Area are found to present a negative relationship between average age and travel length. This is easy to be understood because younger people tend to be more likely and able to commute further for work and there are more old or retired people living in the inner city than the ones in the outer suburban or rural areas.

Key findings from the MGWR model are discussed here. Firstly, it is confirmed that spatial heterogeneity exists in the spatial association between trip length and the explanatory factors and can be properly modeled by MGWR. Secondly, the inner city and the suburban areas are clearly distinguished by the signs of localized coefficients. Thirdly, the western part of Beijing tends to exhibit a positive significant relationship between household socioeconomic characteristics and mobility distance, whereas the relationship in the eastern parts is generally insignificant from a statistical perspective. Finally, the empirical results indicate that socioeconomic factors impact the mobility pattern in Beijing vary spatially in the metropolitan area. Thus, more efforts should be made in understanding the mechanism between policy delivery and socioeconomic reaction, thereby making proper political and planning decisions based on socioeconomic situations to reduce traffic congestions, air pollutions and other issues caused by lengthy commuting distance. That is to say, our findings here inform that proper design of socio-economic structures can help to optimize urban mobility.

4.2 Primary findings on the individual level

Ordinary least square regression (OLS) is conducted for the person level data. The dependent variable is the natural logarithm of average trip distance of a person in a day. The regression results are listed in Table 7 in comparison with that of the GWR model. The results show that personal statues (SEX, S_STU and A_PS), local accessibilities (D_NSC, ST_D, L_MIX) and socioeconomic features (INC and CAR) are positively related to an individual's commuting length. It suggests that individual decisions about the travel distance in our observed dataset are made by considering various characteristics of the urban form rather than simply minimizing the length of travel. However, the MGWR on TAZ level tells a different story in which urban density (i.e. PF_D, POP_D, JOB_D) and local socio-economic factors play more important roles in influencing mobility on a group scale. In short, the explanatory factors function differently on various scales. For individuals, personal status, homes' accessibilities are more important, whereas for the groups of people in TAZs, the socioeconomic characteristics and urban densities of the urban form function more significantly. This also informs the urban planners that urban policies should pay specific attention to different aspects of urban form at various levels.

Table 7 The summary for comparing OLS for persons and MGWR for TAZs

| **Names** | **OLS (y_distance)** | **GWR (y_distance)** |
|---|---|---|
| Intercept | 1552.59*** | 3348.313 (mean)*** |
| SEX | 428.686*** | - |
| AGE | -0.481 | - |
| S_STU | -527.620*** | - |
| D_RJ | 283.184*** | - |

| | | |
|---|---|---|
| A_PS | 28.725*** | 3.164 |
| D_NSC | 0.008*** | -18.049 |
| ST_D | -0.731** | -6.049 |
| BS_D | -26.778 | -7.832 |
| PF_D | -17.658 | -26.263*** |
| POP_D | .024 | -8.438*** |
| JOB_D | -41.640*** | -41.840*** |
| INC | .027*** | - |
| CAR | 558.672*** | - |
| L_MIX | 269.188** | 7.121 |
| A_AGE | | -10.293 (mean) *** |
| H_INC | | 2.224 (mean)** |
| H_CAR | | 184.962 (mean) *** |
| R square | 0.146 | 0.509 |
| Adjusted R square | 0.146 | 0.441 |

Note: Standard errors in parentheses; *, **, and *** represent for the confident level at 90%, 95% and 99%, respectively.

## 5 CONCLUSIONS

This chapter analyses the impact of urban form on human mobility in Beijing using a large-scale travel survey and GIS datasets. Totally 15 indicators including geometry, accessibility, amenity, demographic and land use composition types were derived to measure the urban form at various parts of Beijing quantitatively. We aggregated urban form indicators and human mobility indicators for the 1118 TAZs in Beijing and performed analysis at the TAZ scale. The dependent variable is the average trip distance of each person for each TAZ. Classic linear regression, spatial autoregressive models, and the mixed Geographically Weighted Regression were adopted to examine the impact. MGWR enables us to understand the spatial heterogeneity of the impacts on human mobility. By comparing all three types of models, we find that MGWR model achieves the best performance with much higher explanatory capacity. In the MGWR experiment, three socioeconomic indicators of urban form are found to have significant and spatially varying impacts on human mobility. They are the average household income, average car ownership and average age in households. Meanwhile, we also conducted OLS analysis using the raw survey data on the individual level and compared it with the MGWR model. The results highlight that people’s mobility are related to their personal statuses and various urban form factors. However, the aggregated group mobility on the TAZ level is impacted by the local elements of urban density and socioeconomic characteristics to a larger extent. The findings suggest strong spatial heterogeneity in the influence of predictive variables on residents’ travel behavior in Beijing.

The contributions of this study lie in the following three aspects. First, although extensive previous studies are available on identifying the impact of urban form on human mobility, few were focused on Beijing, a mega city in the urbanizing China. The research findings of study can provide useful information for future urban planning in Beijing. Secondly, our study is based on fine-grained, best available data. We use a large-scale survey data covering the whole Beijing Metropolitan Area with a sampling ratio of about 2%, rather than small-scale survey with limited samples in only selected neighborhoods. In this research, all TAZs representing all types of urban forms in the Beijing Metropolitan Area are taken into account. Furthermore, fine-scale urban GIS datasets were used to calculate urban form indicators. Thirdly, in contrast to the conventional OLS regression, our work paid special attention to the spatial heterogeneity of the impact. Indeed it is found that the impact of each urban form indicator varies geographically, which was not addressed by previous studies. Finally, the large-scale, fine-grained survey enabled us to detect the differences between the individual level OLS results and the TAZ level regression results.

## REFERENCE

Alford G and J Whiteman, 2009, “Macro-urban form and transport energy outcomes: Investigations for Melbourne” Road & Transport Research, 18, p.53-67 [DOI: 10.1061/(ASCE)0733-9488(2006)132:3(132)]

Anderson W P and P S Kanaroglou, Miller E J, 1996, “Urban form, energy and the environment: A review of issues, evidence and policy” Urban Studies, 33, p.7-35 [DOI: 10.1080/00420989650012095]

Anselin L. (1988). *Spatial Econometrics: Methods and Models*, Dordrecht: Kluwer Academic Publishers.

Anselin L. (2005). *Exploring Spatial Data with GeoDa: A Workbook*. Champaign Urbana: University of Illinois.

Beijing Fifth Population Census Office, Beijing Statistical Bureau, 2002, “Beijing Population Census of 2000” Beijing: Chinese Statistic Press

Beijing Municipal Commission of Transport, Beijing Transportation Research Centre, 2007, “*The 3rd Transportation Comprehensive Survey Report of Beijing*” Internal Working Report. (In Chinese)

Benenson I, I Omer and E Hatna, 2001, “Agent-based modeling of householders' migration behavior and its consequences”, in Workshop on Agent based Computational Demography Ed F C P A Billari, Rostock, GERMANY p. 97-115

Box, G.E.P, & Cox, D.R. (1995). An Analysis of Transformations. *Journal of the Royal Statistical Society*. Series B (Methodological), 26, 211-252.

Brown D G and D T Robinson, 2006, “Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl” Ecology and Society 11(1). Available at http://www.ecologyandsociety.org/vol11/iss1/art46/

Cleveland, William S. 1979. "Robust locally weighted regression and smoothing scatterplots." *Journal of the American statistical association* 74.368: 829-836.

Dieleman F M, M Dijst and G Burghouwt, 2002, “Urban form and travel behaviour: Micro-level household attributes and residential context” Urban Studies, 39, p.507-527 [DOI: 10.1080/00420980220112801]

Fotheringham, A.S, Brunsdon, C., & Charlton, M. (2002). *Geographically weighted regression: the analysis of spatially varying relationships*. Chichester: John Wiley & Sons Ltd.

Giuliano G, Narayan D, 2003, “Another look at travel patterns and urban form: The US and Great Britain” Urban Studies, 40, p.2295-2312 [DOI:10.1080/0042098032000123303]

Goetzke F, 2008, “Network Effects in Public Transit Use: Evidence from a Spatially Autoregressive Mode Choice Model for New York” Urban Studies, 45, p.407-417 [DOI: 10.1177/0042098007085970]

Holden E and I T Norland, 2005, “Three challenges for the compact city as a sustainable urban form: Household consumption of energy and transport in eight residential areas in the greater Oslo region" Urban Studies, 42, p.2145-2166[DOI: 10.1080/00420980500332064]

Horner M W, 2007, "A multi-scale analysis of urban form and commuting change in a small metropolitan area (1990-2000)" Annals of Regional Science, 41, p.315-332 [DOI: 10.1007/s00168-006-0098-y]

Hourcade J C and R Crassous, 2008, "Low-carbon societies: a challenging transition for an attractive future" Climate Policy, 8, p.607-612 [DOI:10.3763/cpol.2008.0566]

Johnson R A and M C Mccoy, 2006, "Assessment of integrated transportation / land use models" Information Center for the Environment, Department of Environmental Science & Policy, University of California, Davis.

Kawabata M and Shen Q, 2007, "Commuting Inequality between Cars and Public Transit: The Case of the San Francisco Bay Area, 1990-2000." Urban Studies, 44, p.1759–1780 [10.1080/00420980701426616]

Kii M and K Doi, 2005, "Multiagent land-use and transport model for the policy evaluation of a compact city" Environment and Planning B: Planning and Design 32(4), p.485-504 [DOI:10.1068/b3081]

Krizek K J, 2003, "Residential relocation and changes in urban travel - Does neighborhood-scale urban form matter?" Journal of the American Planning Association, 69, p.265-281 [DOI:10.1080/01944360308978019]

Maat K and H J P Timmermans, 2009, "A causal model relating urban form with daily travel distance through activity/travel decisions" Transportation Planning and Technology, 32, p.115-134 [DOI:10.1080/03081060902861285]

McGarigal K, S A Cushman, M C Neel and E Ene, 2002, "FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps" Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at www.umass.edu/landeco/research/fragstats/fragstats.html

McMillan T E, 2007, "The relative influence of urban form on a child's travel mode to school" Transportation Research Part a-Policy and Practice, 41, p.69-79 [DOI:10.1016/j.tra.2006.05.011]

Mulley C, 2013, "Accessibility and Residential Land Value Uplift: Identifying Spatial Variations in the Accessibility Impacts of a Bus Transitway" Urban Studies, August, [DOI: 10.1177/0042098013499082]

Newman PWG, Kenworthy JR, 1989, "Gasoline consumption and cities: a comparison of US cities with a global survey" Journal of American Planning Association, 55, p.24-37 [DOI: 10.1080/01944368908975398]

Pan H X, Q Shen and M Zhang, 2009, "Influence of urban form on travel behaviour in four neighbourhoods of Shanghai" Urban Studies, 46, p.275-294 [DOI: 10.1177/0042098008099355]

Putman S H, 1975, "Urban landuse and transportation models: a state of the art summary" Transportation Research, 9, p.187-202 [DOI:10.1016/0041-1647(75)90056-8]

Remme U and M Blesl, 2008, "A global perspective to achieve a low-carbon society (LCS): scenario analysis with the ETSAP-TIAM model" Climate Policy, 8, p.60-75 [DOI: 10.3763/cpol.2007.0493]

Schlossberg M, Greene J, Phillips P P, Johnson B, Parker B, 2006, "School trips-Effects of urban form and distance on travel mode" Journal of the American Planning Association, 72, p.337-346 [DOI: 10.1080/01944360608976755]

Shim G E, S M Rhee, K H Ahn and S B Chung, 2006, "The relationship between the characteristics of transportation energy consumption and urban form" Annals of Regional Science 40 351-367 [DOI: 10.1007/s00168-005-0051-5]

Shukla P R, S Dhar and D Mahapatra, 2008, “Low-carbon society scenarios for India” Climate Policy, 8, p.156-176

Wei, C. and Qi, F., 2012. "On the estimation and testing of mixed geographically weighted regression models," Economic Modelling, Elsevier, vol. 29(6), pages 2615-2620.

Yi C, Q Liand G Zheng, 2008, “Commercial facility site selection simulating based on MAS” Proceedings of the SPIE - The International Society for Optical Engineering 71431N (71438 pp.)

Zellner M L, T L Theis, A T Karunanithi, A S Garmestani and H Cabezas, 2008, “A new framework for urban sustainability assessments: Linking complexity, information and policy” Computers, Environment and Urban Systems, 32, p.474–488 [DOI:10.1016/j.compenvurbsys.2008.08.003]

Zhang M, 2005, “Exploring the relationship between urban form and nonwork travel through time use analysis” Landscape and Urban Planning, 73, p.244-261 [DOI.1016/j.landurbplan.2004.11.008]

Zhuang G Y, 2008, “How will China move towards becoming a low carbon economy?” China & World Economy, 16, p.93-105 [DOI:10.1111/j.1749-124X.2008.00116.x]