Exploring the Distance-decay Effect in Commuting Behaviour at the Local-level with a Localised Spatial Interaction Model

Bowen Zhang[*1,2], Chen Zhong [3], Qi-li Gao [3] and Zahratu Shabrina [1]

[1] Department of Geography, King's College London, London, United Kingdom
[2]The Alan Turing Institute, London, United Kingdom
[3]Centre for Advanced Spatial Analysis, University College London, London, United Kingdom

Summary

Existing most spatial interaction models assume that the distance-decay effect in modelling space is spatially isogenous, but spatial heterogeneity widely exists in the modelling space. Thus, our research proposed a novel localised spatial interaction model quantitatively representing the variation of the distance-decay effect in commuting travel behaviour at the local level. Our research also confirms a positive relationship between average travel distance and distance-decay effect in commuting trips at the local level and discusses the possible reason for this phenomenon. Finally, the potential relationship between those variations and residents' social-economic characteristics has been explained by a regression model.

KEYWORDS: human mobility pattern, spatial interaction model, local modelling, commuting behaviour, distance-decay effect

1. Introduction

Spatial interaction models, one of the most powerful techniques for modelling and predicting interaction flows, forecasting the strength of spatial interaction based on the influence of distance decay. The majority of existing spatial interaction models assume that the interior space of the modelling region is spatially isogenous, meaning that the distribution of trips only obeys a general distance-decay law associated with $f(d_{ij})$. However, previous research verified that spatial heterogeneity widely exists in the spatial interaction model and may reflect the border effect of trip distribution within urban space (Zhang et al., 2022). In light of this background, "think locally" is a crucial trend in recent decades because researchers found that a global approach to spatial analysis may not be suitable for the local area within the sub-case study area due to spatial heterogeneity for the spatial interaction model (Fotheringham and Sachdeva, 2022). Previous researchers attempted different methods to highlight the local characters in spatial interaction models such as geographically weighted regression (Nakaya, 2001) Another promising study applied deep learning technics to predict flows by adding local geographical information like point of interests (POIs) (Simini et al., 2021). However, there is a lack of research to explain why variations exist in local travel behaviour within cities and the potential relationship with local residents' social-economic characteristics. By applying a localised spatial interaction model, this research proposes a novel approach to quantitatively representing the variation of distance-decay effect in commuting travel behaviour at the local level. Furthermore, this research explores the linkage between those variations and local residents' social-economic characteristics to understand the nature of human travel behaviour better.

2. Data and Case study

The Case study area is London in the United Kingdom. The is research based on the UK census data in 2001 and 2011, which includes the Origin-Destination (O-D) data and social-economic characteristics

* bowen.zhang@kcl.ac.uk

of local residences. The O-D data refers to the location of usual residence and place of work, and the social-economic data refers to the higher education rate, unemployment rate, car ownership and marriage rate. The spatial solution in the 2001 census is based on Census Ward (CAS) and there are 653 areas for the whole of London. In the 2011 census, the spatial resolution is based on the MSOA level with 983 areas in total for London. The best-fitting table published by the government has been employed to determine the successor of the local area. The rest of the area which cannot be found in the table has been matched based on the nearest distance.

3. Methodology

This research proposed a localised spatial interaction model to observe the variant of distance decay for commuting by different origins and destinations in London. The classic unconstrained (or sum constrained) gravity model is written as equation (1) below, where T_{ij} is travel flow between zone i and zone j, O_i is observed origins totals from zone i and D_j refers to observed destinations totals to zone j, d_{ij} is the main travel distance between origins and destinations, and β is a parameter related to the distance decay.

$$T = \sum_i \sum_j T_{ij} = \sum_i \sum_j K \frac{O_i D_j}{d_{ij}^{-\beta}} \tag{1}$$

This study adopted a disaggregated spatial interaction model, which divides the flows by origins then fits the flows with separate models in the formatting of the classic unconstrained gravity model. For giving specific origin, the O_i is part of the constant (equation (2)). Each sub-gravity model has its own distance-decay parameters and other indicators of travel behaviour, such as average travel distance.

$$t_i = \sum_j t_{ij} = \sum_j K \frac{D_j}{d_{ij}^{-\beta}} \tag{2}$$

$$T = \sum_i t_i \tag{3}$$

The complexity of this model is comparable with the origin-constrained gravity model since they have a similar number of parameters. This novel spatial interaction model has a better prediction ability by aggregating the predicted flows as one predicting O-D matrix (equation (3)). It performs better in statistical measurements (e.g., R-square and Root Mean Squared Error) compared with a classic constrain gravity model fitted by general linear regression models, proving the reasonability for the local distance-decay parameters.

Finally, an ordinary least squares (OLS) regression model is established to explain the relationship between distance-decay parameters and residents' social-economic characteristics to understand the nature of human travel behaviour better.

4. Results and Discussion

4.1. Localised spatial interaction model

Figure 1(a) and 1(b) below shows the local distance-decay parameters in London. The lighter colour represents that the absolute value of the distance-decay parameter is smaller. From this figure, it can be observed that the highlight values are clustering in the central area, which means the distance-decay effects for these areas is smoother. In contrast, the border area showing darker colours represents the sharper distance-decay effects within these zones.

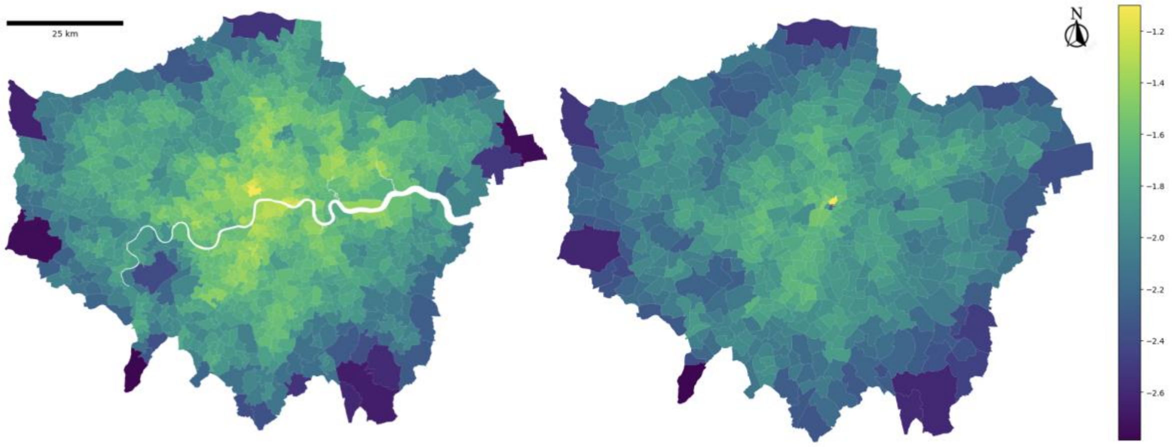

Figure 1 (a) and 1 (b) Distance-decay parameters localised by origins in London in 2001(left) and 2011 (right)

Typically, the sharper distance-decay effect means the commuters living in these areas are more sensitive about travel distance. Therefore, those people tend to travel fewer distances and live in the central areas, which means the relationship between average travel distance and the distance-decay effect should be negative. However, our results denied that statement.

Figure 2 (a) and 2(b) below illustrates another critical indicator of travel pattern, average travel distance. For this figure, the lighter colour means the average travel distance is more prolonged. Interestingly, the distribution of light colour is almost wholly contrasted with the distribution of distance-decay parameters, which means the area with the sharper distance-decay effect has a longer average travel distance. The function plot in figure 3 illustrates the obvious positive relationship between average travel distance and the distance-decay effect. Comparing the results analysed from commuting flow in 2001 and 2011, we can confirm that this trend is stable in the long-term period.

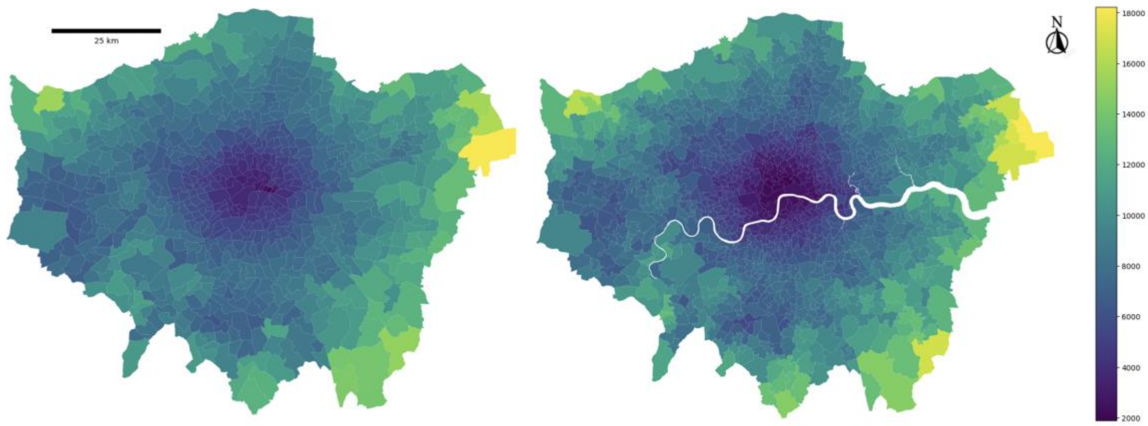

Figure 2 (a) and 2 (b) Average travel distance (in meters) by origins in London in 2001(left) and 2011 (right)

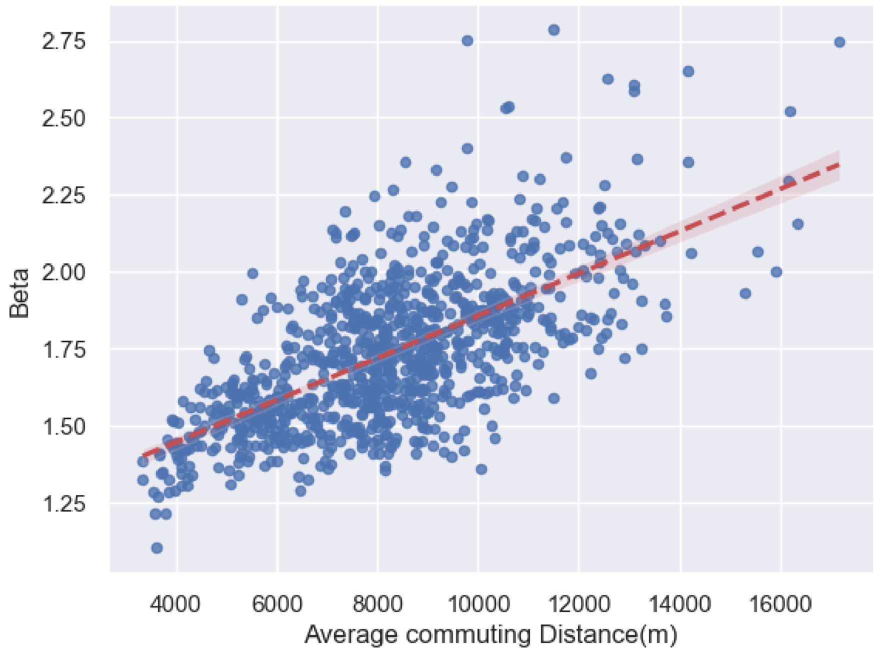

Figure 3 Scatter plot for Average commuting distance vs Distance-decay parameter

A possible explanation is most people are commuting from their residence towards city centres, but not in the opposite direction. Still, most commuters would not go beyond the central area to another side of the city. That is why the distance-decay effect of their trip distribution looks sharp. In contrast, commuters living in the central areas would freely choose their workplace without significant limitations of specific directions or areas. Thus, the distance-decay effect for those people shows smooth trends. Based on this explanation, the affordability of housing prices would significantly affect the distance decay in their commuting behaviour, which means that social-economic characteristics may have a potential relationship with this phenomenon.

4.2. Regression models

We established a linear regression model to explain the relationship between local distance-decay parameters and the social-economic characteristics of residents. Both results confirm that the higher education rate, unemployment rate, car ownership rate and marriage rate of the residents can explain 67.1 % of the variance of distance-decay parameters. The coefficient of each variable in 2001 and 2011 shows very similar trends. Education level, unemployment rate, car ownership rate and the higher marriage rate have negative relationships with the independent variable. In other words, better education level, less unemployment, more car ownership, and higher marriage rate significantly reduce the distance-decay effect of local commuters, giving them more freedom to choose working place.

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Biographies

Bowen Zhang is a PhD student at the Department of Geography, King's College London and he is also a research assistant at Alan Turing Institute. His research interests include spatial interaction models, mobility data mining and urban modelling, and the application of input-output models.

Dr Chen Zhong is Associate Professor in Urban Analytics at the Centre for Advanced Spatial Analysis (CASA), University College London (UCL). Her research interests lie in spatial data analysis, machine learning, urban modelling, and data-driven methods for urban and transport planning.

Dr Qi-Li Gao is a Research Fellow at the Centre for Advanced Spatial Analysis (CASA), University College London (UCL). She received her PhD in GIS from Wuhan University, China. Her research interests include spatial-temporal data mining, urban informatics, and human mobility analytics toward urban sustainability and human-centred urban planning.

Dr Zahratu Shabrina is a Lecturer in Spatial Data Science at the Department of Geography, King's College London. Her research interests are in the implementation of spatial data science methods for digital geography for themes including digital platforms, urban tourism, accessibility, natural language processing and mobility analysis.