Analysis The Influencing Factors of Urban Traffic Flows by Using Emerging Urban Big Data

Yue Li*[1], Qunshan Zhao†[1] and Mingshu Wang‡[2]

[1] Urban Big Data Centre, School of Social and Political Sciences, University of Glasgow, Glasgow, UK

[2] School of Geographical and Earth Sciences, University of Glasgow, Glasgow, UK

January 18, 2023

Summary

This research applies spatial Durbin model to analyse traffic flow distributions via various factors in the urban areas and traffic flow data. The results show that the overall built environment within a buffer area has more significant impact on urban traffic flow compared to the nearby location within a few meters. Areas with more young and white dwellers are associated with more traffic flows. With the influence of COVID-19, residents prefer to spend their daily life in their local neighborhood rather than having long distance travel. The initial findings from this research provide evidence of developing 20-minute city via active travel for achieving net-zero carbon target.

KEYWORDS: Traffic flow, Urban big data, COVID-19, Spatial Durbin model

1. Introduction

As a crucial component for the complex urban system, urban traffic analysis has drawn attentions from researchers and planners for decades (Batty 2008). The increasing development of Intelligent Transportation Systems with various urban sensing technologies (Buch et al. 2011), has produced a variety of traffic-related data to monitor urban traffic conditions in high spatio-temporal resolution. These data provide a near real-time understanding of the traffic flows in our cities compared to traditional travel survey methods, which offer the next level of understanding of the urban transportation system.

Many studies measuring the factors that affect urban traffic flows. Nian et al. (2020) applied the spatial lag model to explore the relationship between Point of Interest (POI) and taxi travels. Xu et al. (2019) proposed a framework to identify urban mobility patterns based on POI data. Specifically, areas with entertainment and consumption functions are more likely to generate more traffic flow. In addition to POI, land cover of urban areas also influences the mobility trends. Previous research used a sequential modelling process to analyse the impact of land use on urban mobility patterns (Bandeira et al. 2011). Recently, a study inferred urban land use from taxi trajectory data and bus smart card data (Liu et al. 2021). Besides, street imagery is a new and emerging urban big data source with high spatial resolution. Studies have reported using this data to audit road infrastructure and other built environment features. Goel et al. (2018) used Google Street View(GSV) from 34 cities in Great Britain, to predict travel pattern at the city level.

Previous researchers mostly only explored the multiple aspects of urban environment in traditional mobility pattern analysis, with limited aspects considered quantitative relationship between new forms of sensing data and traffic flow in cities. Those existing study overlooks the integrated influence of

* y.li.17@research.gla.ac.uk

† Qunshan.Zhao@glasgow.ac.uk

‡ Mingshu.Wang@glasgow.ac.uk

road characteristics, socio-demographics, and other surrounding environments on urban traffic flow, such as land use/cover, nearby points of interest and Google Street View. To tackle these issues, this research will apply spatial model to analysis the relationship between urban elements (built environment, natural environment, socio-demographics, etc.) of the city and traffic dynamic.

2. Study Area and Data

2.1. Urban Traffic Flow

The urban traffic flow data are collected from August 9, 2019 to October 16, 2021 by road detectors from Glasgow City Council (GCC). Traffic flow data of GCC area is available from Glasgow Open Data portal (M. A. A. GCC, 2022). During the study period, 1033 sites of traffic flows were recorded, from which 530 valid sites has been used in this research. In this research, the traffic data of each site are aggregated as daily average traffic flow into 4 stages based on the COVID-19.

2.2. Independent Variables

Independent variables considered in this research include land use, socio-demographics, Point of Interest (POI), Google Street Views (GSVs), and road characteristics. Data sources of the independent variables are listed as follows: land use for Functional Urban Areas (FUA) in Glasgow in 2018 comes from the Urban Atlas (Urban Atlas, 2018); census Output Areas level socio-demographic features in 2011 come from the National Records of Scotland (NRS) (Scotland's Census, 2011); POI (Points of Interest, 2021) and road characteristics (OS MasterMap Highways Network, 2019) come from the Digimap; and GSVs come from the Street View Static API (Google Developers, 2022), provided by Google Maps Platform.

All the independent variables (except GSVs) are calculated with a 200-meter buffer. GSVs are collected from the nearest position of each recorded site, with the percentages of road, building, vegetation, and car are extracted using DeepLab model from TensorFlow (Yu et al., 2020).

3. Methodology

In the selection procedure of models, spatial autocorrelation analysis has been performed to evaluate whether there is an association between daily average traffic flow and geographical locations. The calculation of the global autocorrelation coefficient Moran's I of the four periods traffic flow, for instance, daily average traffic flow before COVID-19 (Moran's I = 0.076, $P < 0.001$), suggests the existence of spatial autocorrelation. Hence, spatial models are preferred to avoid biased estimations via OLS. This study conducted the spatial Durbin model to analysis the association between urban parameters and daily average traffic flow in Glasgow.

Spatial Durbin model (SDM) (Wang et al. 2020):

$$Y = \rho WY + X\beta + WX\theta + \varepsilon \tag{4}$$

Where Y is the daily average traffic flow, X is the urban parameters. W is the weight matrix with the spatial relationship of spatial units in the sample. This research conducts k-nearest neighours algorithm (k-NN). WX represents the exogenous interaction effects on urban parameters X with a spatial autoregressive coefficient θ. WY describes the endogenous interaction effects with a spatial lag coefficient ρ. $W\mu$ refers to the correlated interaction effects with the coefficient λ.

4. Results

Table 1 presents the significant results of SDM between urban parameters and daily average traffic flow. This study reveals (1) Areas covered with natural green space are associated with fewer traffic flows; (2) Areas with more young and white dwellers are associated with more traffic flows; (3) Major roads connected between and within cities and towns are associated with more traffic flows; (4) The relationship between the percentage of vegetation covered along the roads and traffic flows is not significant from the start of the COVID-19. The contrast between (1) and (4) indicate that the overall built environment within an buffer area has more significant impact on urban traffic flow, than the nearby location within a few meters. Besides, the spatial interaction between adjacent neighbourhoods among the traffic flow and urban parameters is variable. Both the value of RLMlag and AIC reveal that the traffic flow after the COVID-19 shows the strongest spatial dependence, while the spatial dependence during the 1st lockdown is the weakest.

Table 1 Results the relationship between urban parameters and daily average traffic flow

Y=Log(flow)	Before COVID		1st Lockdown		2nd Lockdown		Post COVID	
	Beta	P	Beta	P	Beta	P	Beta	P
(Intercept)	6.751 ***	0.000	5.939 ***	0.000	5.416 ***	0.000	5.938 ***	0.000
Log(Natural areas)	-0.061 **	0.009	-0.088 ***	0.000	-0.065 **	0.004	-0.053 *	0.015
Mean age	-0.027 *	0.038	-0.031 *	0.019	-0.031 *	0.015	-0.036 **	0.003
Log(White percentage)	1.325 *	0.031	1.264 *	0.040	1.540 *	0.010	1.602 **	0.004
Major Road (km/sq.km)	0.037 *	0.044	0.038 *	0.039	0.039 *	0.027	0.031	0.062
Log(Vegetation)	-0.039 *	0.036	-0.017	0.358	-0.010	0.569	-0.022	0.207
RLMlag	17.754	0.000	10.299	0.001	23.185	0.000	28.977	0.000
AIC	956.13		962.76		934.19		888.75	

5. Conclusions

This study analyses the urban factors that influence the traffic flow before, during and after the COVID-19. First, the overall built environment within an buffer area has more significant impact on urban traffic flow, than the nearby location within a few meters. Besides, areas with more young and white dwellers are associated with more traffic flows, since most of the youngsters live in areas with high population density. Second, the traffic flow after the COVID-19 has much stronger spatial dependence than before the pandemic. The variation of spatial dependence indicates that with the influence of COVID-19, residents prefer to spend their daily life in their local neighborhood rather than having long distance travel. According to the result, cities may contain multiple "liveable neighborhood" in the future, for example the 20-minute neighborhood concept proposed by the Glasgow City Council (GCC, 2022), which could offer the basic needs for residents within a 20-minute round trip from home walking or cycling. The development of 20-minute city acts an important role in contribution to the active travel and achieve net-zero carbon target in the future.

6. Acknowledgements

The first author is funded by the China Scholarship Council (CSC) from the Ministry of Education of P.R. China. Dr. Qunshan Zhao has received UK ESRC's on-going support for the Urban Big Data Centre (UBDC) [ES/L011921/1 and ES/S007105/1]. Authors would also like to express their appreciations to the Urban Big Data Centre (UBDC) and Glasgow City Council (GCC) for their data supports.

References

Bandeira, J.M., Coelho, M.C., Sá, M.E., Tavares, R., Borrego, C., 2011. Impact of land use on urban mobility patterns, emissions and air quality in a Portuguese medium-sized city. Science of The Total Environment 409, 1154–1163. https://doi.org/10.1016/j.scitotenv.2010.12.008
Batty, M., 2008. The Size, Scale, and Shape of Cities. Science 319, 769–771. https://doi.org/10.1126/science.1151419
Buch, N., Velastin, S.A., Orwell, J., 2011. A Review of Computer Vision Techniques for the Analysis of Urban Traffic. IEEE Transactions on Intelligent Transportation Systems 12, 920–939. https://doi.org/10.1109/TITS.2011.2119372
GCC, 2022. Liveable Neighbourhoods. URL https://www.glasgow.gov.uk/liveableneighbourhoods (accessed 1.19.23).
GCC, M.A.A., 2022. Home. Microsoft Azure API Management - developer portal. URL https://gcc.developer.azure-api.net/ (accessed 11.20.22).
Goel, R., Garcia, L.M.T., Goodman, A., Johnson, R., Aldred, R., Murugesan, M., Brage, S., Bhalla, K., Woodcock, J., 2018. Estimating city-level travel patterns using street imagery: A case study of using Google Street View in Britain. PLOS ONE 13, e0196521. https://doi.org/10.1371/journal.pone.0196521
Google Developers, 2022. Google Maps Platform Documentation | Street View Static API. Google Developers. URL https://developers.google.com/maps/documentation/streetview (accessed 11.20.22).
Liu, Q., Huan, W., Deng, M., Zheng, X., Yuan, H., 2021. Inferring Urban Land Use from Multi-Source Urban Mobility Data Using Latent Multi-View Subspace Clustering. ISPRS International Journal of Geo-Information 10, 274. https://doi.org/10.3390/ijgi10050274
Nian, G., Peng, Bozhezi, Sun, D. (Jian), Ma, W., Peng, Bo, Huang, T., 2020. Impact of COVID-19 on Urban Mobility during Post-Epidemic Period in Megacities: From the Perspectives of Taxi Travel and Social Vitality. Sustainability 12, 7954. https://doi.org/10.3390/su12197954
OS MasterMap Highways Network, 2019. OS MasterMap Highways Network. URL https://digimap.edina.ac.uk/ (accessed 11.20.22).
Points of Interest, 2021. Points of Interest. URL https://digimap.edina.ac.uk/ (accessed 11.20.22).
Scotland's Census, 2011. Home. Scotland's Census. URL https://www.scotlandscensus.gov.uk/ (accessed 11.20.22).
Urban Atlas, 2018. Urban Atlas — Copernicus Land Monitoring Service. URL https://land.copernicus.eu/local/urban-atlas (accessed 11.20.22).
Wang, M., Chen, Z., Mu, L., Zhang, X., 2020. Road network structure and ride-sharing accessibility: A network science perspective. Computers, Environment and Urban Systems 80, 101430. https://doi.org/10.1016/j.compenvurbsys.2019.101430
Xu, Z., Cui, G., Zhong, M., Wang, X., 2019. Anomalous Urban Mobility Pattern Detection Based on GPS Trajectories and POI Data. ISPRS International Journal of Geo-Information 8, 308. https://doi.org/10.3390/ijgi8070308
Yu, H., Chen, C., Du, X., Li, Y., 2020. TensorFlow Model Garden. GitHub. URL https://github.com/tensorflow/models (accessed 11.21.22).

Biographies

Yue Li is a PhD student in Urban Studies in the Urban Big Data Centre at University of Glasgow. Her research interests span geographic information science, spatio-temporal analysis, machine learning and deep learning.

Qunshan Zhao is a Senior Lecturer in Urban Analytics in the Urban Big Data Centre at University of Glasgow. His research interests span urban analytics, spatial optimization/statistics, remote sensing, and geographic information science, with applications in transportation, housing, public health, sensing technologies, and environmental monitoring.

Mingshu Wang is a Senior Lecturer in Geospatial Data Science at the School of Geographical & Earth Sciences, University of Glasgow, UK. His research focuses on developing and applying methods of geographical information systems, remote sensing, spatial analysis, machine learning, artificial intelligence, and econometrics to understand urban systems.