The effect of the built environment on spatial-temporal pattern of traffic congestion in a satellite city in emerging economies

Bao, Zhikang; Ng, S. Thomas; Yu, Gang; Zhang, Xiaoling; Ou, Yifu

Published in: Developments in the Built Environment

Published: 01/01/2023

Document Version: Final Published version, also known as Publisher's PDF, Publisher's Final version or Version of Record

License: CC BY-NC-ND

Publication record in CityU Scholars: Go to record

Published version (DOI): 10.1016/j.dibe.2023.100173


Citing this paper
Please note that where the full-text provided on CityU Scholars is the Post-print version (also known as Accepted Author Manuscript, Peer-reviewed or Author Final version), it may differ from the Final Published version. When citing, ensure that you check and use the publisher's definitive version for pagination and other details.

General rights
Copyright for the publications made accessible via the CityU Scholars portal is retained by the author(s) and/or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights. Users may not further distribute the material or use it for any profit-making activity or commercial gain.

Publisher permission
Permission for previously published items are in accordance with publisher's copyright policies sourced from the SHERPA RoMEO database. Links to full text versions (either Published or Post-print) are only available if corresponding publishers allow open access.

Take down policy
Contact lbscholars@cityu.edu.hk if you believe that this document breaches copyright and provide us with details. We will remove access to the work immediately and investigate your claim.

Download date: 25/09/2023
The effect of the built environment on spatial-temporal pattern of traffic congestion in a satellite city in emerging economies

Zhikang Bao a, S. Thomas Ng a, Gang Yu b,*, Xiaoling Zhang c,*, Yifu Ou d

a Department of Architecture and Civil Engineering, City University of Hong Kong, Kowloon Tong, Hong Kong, China
b SILC Business School, Shanghai University, Shanghai, China
c Department of Public and International Affairs, City University of Hong Kong, Kowloon Tong, Hong Kong, China
d Department of Urban Planning and Design, The University of Hong Kong, Pokfulam, Hong Kong, China

A R T I C L E   I N F O

Keywords:
Built environments
Spatial-temporal traffic congestion modelling
Satellite city
Emerging economies

A B S T R A C T

Traffic congestion has been widely perceived as an inevitable byproduct in the process of global urbanization, leading to significant negative economic and environmental impacts. Existing studies have attached significant importance to revealing the interaction between traffic congestion patterns and built environment features in many metropolises with little attention, if any, paid to their counterparts of satellite cities (SC). For being aware that developing SCs has been a main trend to address many urban issues of metropolises in the rapid urbanization process of emerging economies, this study makes one of the first research attempts to investigate how traffic congestion temporally and spatially evolves with the built environment characterized by land use and transportation network features in Foshan, a typical SC of Guangzhou in China by using valuable hyperlocal travel data. The results show that while weekdays experience traffic peaks in both morning and evening, weekends or holidays generally only have the evening peak. The traffic congestion in Foshan during the pre-weekend is found much heavier compared with normal weekdays and weekends with a long-lasting effect possibly due to Foshan’s role as a SC of Guangzhou. Additionally, the rising traffic congestion in a SC associated with company land use during the peak hours can be partly offset by the increasing supply of public transit, suggesting urban planners increase the density of public transit where there is a denser distribution of companies. This study provides new knowledge on travel behaviors in SCs in emerging economies, supplying urban governors with new insights for improving their traffic conditions generally.

1. Introduction

Stimulated by rapid economic development, a growing number of people swarm into towns and cities to seek greater access to education, housing, and labor markets. This urbanization process has inevitably caused a series of byproducts, including traffic congestion (Yang et al., 2023; Huang et al., 2021). In the United States (US), traffic congestion was estimated to additionally cost the drivers over $88 billion in the single year of 2019 (McCarthy, 2020). In China, at least 24% of additional travel time is required to commute during peak periods in major cities such as Beijing, Shijiazhuang, and Chongqing (Buchholz, 2021; Chang et al., 2017). Not only does traffic congestion cause direct economic loss, it also raises a series of negative environmental issues, such as anabatic carbon emissions and deteriorative greenhouse effects (Chang et al., 2017; Grote et al., 2016). Existing studies have found that built environments, in terms of the “3Ds” (density, diversity, and design) proposed by Cervero and Kockelman (1997), can directly affect how people connect and travel (Cao et al., 2019; Clifton et al., 2009; Ou et al., 2022; Van Wee et al., 2019; Chen et al., 2022a, 2022b; Liang et al., 2023), and how traffic congestion is formed also strongly correlates to built environments. Understanding the dynamic interrelation between traffic congestion and built environments has strong policy implications, providing important insights for urban planners and transportation managers to optimize the traffic flows, which ultimately contributes to
the development of sustainable cities (Liu et al., 2017; Wang et al., 2018). In this study, we focus primarily on the land use aspect of the built environment, and we identify built environments with land use characteristics hereafter.

Efforts have been made to explore the land use effects of traffic behavior in metropolises, including New York (Tracy et al., 2011), Shanghai (Pan et al., 2009), Singapore (Lee and Cheng, 2023), and Hong Kong (Yang et al., 2021). Sarzynski et al. (2006) suggested that traffic congestion is affected by residence-workplace proximity, continuity/density and housing centralization. Similarly, Litman (2008) explored the effects of a range of land use factors, such as regional accessibility, density, and roadway connectivity, on traffic conditions, indicating a synergistic and cumulative influence of these factors on travel behavior. Zhang et al. (2017) conducted a study by linearly modelling the correlation between traffic congestion and points of interest (POI) distribution, showing that commercial land use adversely affects traffic conditions. Liu et al. (2012) found that land use types of commercial, industrial, institutional, recreational, and residential are strongly related to road traffic, using taxi trajectory datasets in Shanghai. In addition, a study by Sider et al. (2013) revealed a strong connection between a set of transportation infrastructures (highway, road, and bus stop) and traffic emissions in Montreal, Canada. However, these findings cannot be simply applied to satellite cities (SCs) in emerging economies, given their underdeveloped public transit systems and different functionalities (Bao, 2023; Bao et al., 2023). For example, as of 2020, the metro network in Guangzhou with a rail length of 531.6 km (China Association of Metros, 2021) covers all eleven urban districts, effectively meeting the needs of commuters living in urban core and suburban areas. In contrast, the metro network in Guangzhou’s neighboring SC, Foshan, which connected to the metro system of Guangzhou, is placed in urban core areas of the city only with a rail length of 28.1 km by 2020 (China Association of Metros, 2021), serving mostly those commuters who travel between Guangzhou and Foshan. This would inevitably result in varying traffic and congestion patterns between the two cities. With a great share of population living in SCs, it is important to enhance our current understanding of how built environments affect congestion patterns in these areas.

In addition, previous studies seem to place more focus on investigating the “built environment-congestion” dynamics on a larger scale (e.g., urban or even regional level), trying to gain policy implications for regional development strategies. Indeed, the debates on whether the sprawl or compact development strategy is preferable have been ongoing for decades (Ewing et al., 2016; Litman, 2008; Pendall, 2003; Sarzynski et al., 2006; Wang, 2011). While the former is criticized for generating more long-distance travels, and thus presumably heavier congestion for its scattered and segregated land use forms (Ewing et al., 2016; Pendall, 2003), the latter has induced more frequent trips in a local scale and resulted in more frequent localized congestion in the short term (Sarzynski et al., 2006; Wang, 2011). The congestion levels in these studies are usually measured by some macro-level metrics, reflecting the overall traffic condition of a place over a relatively long period, e.g., average daily traffic/lane, commuting time and delay/Fast PG, generally disregarding the fine-grained traffic condition at a neighborhood level.

The pattern of traffic conditions is subject to the change of time (Bao et al., 2022; He et al., 2016; Kinham et al., 2011; Wen et al., 2014; Zhang et al. 2011). For example, congestion during weekdays is most likely to occur in the morning or at nightfall because of the concentrated commuting demands in those periods. Such commuting-induced congestion tends to be influenced by urban main stems that connect workplaces and residential areas. Travel behaviors during the weekend, on the other hand, are comparatively dispersive, and the congestion tends to occur in commercial or recreational areas. Due to the lack of effective tracking technologies and location-based services, early studies fall short of characterizing such time-varying effects using traffic status data with sufficient granularity. The recent proliferation of localization technology and smartphone-enabled navigation offers new tools to overcome the limitation, providing hyperlocal travel data (e.g., floating car data) with unprecedented resolution and granularity (Tayarani et al., 2020; Tomer et al., 2020; Chen et al., 2020; Chen et al., 2022c). Based on such fine-grained data, the latest studies have attempted to explore the spatial-temporal pattern of traffic congestion (Di et al., 2019; Song et al., 2019; Xu et al., 2013). However, these studies are primarily oriented to the big city contexts. Much remains unclear on how time-varying traffic condition is spatially affected by land use characteristics in SCs.

Using a typical SC in China, this research aims to explore how the traffic congestion pattern evolves spatially and temporally based on spatial-temporal traffic congestion modeling (STCM) of a valuable hyperlocal travel dataset. It differs from existing literature in several aspects. First, although few previous studies may have already probed into this field with seemingly similar modelling approaches, this study is unique for its contextualization in a SC in emerging economies. Amid a myriad of previous studies, a seemingly similar one is conducted by Bao et al. (2022), who investigated the interplay between the built environment and traffic congestion in typical smaller urban areas of Xining in China. However, these two studies are distinctively different in four aspects. Firstly, as indicated by Bao et al. (2022), various land use categories in Xining are distributed around a single central focus for its position as smaller urban areas with underdeveloped urban forms, aligning with the well-known central place theory (Osth et al., 2021). Contrastingly, various land use categories may be much more dispersed across the whole city along with the traffic line (e.g., Guangfo Line in this study) mainly due to its role as a SC affiliated to the main city (e.g., Foshan and Guangzhou in this study). Secondly, since various land use categories are aggregated around a single central focus in Xining, the effect on how traffic congestion is affected by the built environment may not be evidently demonstrated by Bao et al. (2022). Comparatively, different land use categories may be distributed more distinctively and dispersively in Foshan, for which more insights on the interaction between the built environment and traffic congestion are expected to be derived from this study. Thirdly, the study conducted by Bao et al. (2022) researched the built environment effect on traffic congestion by directly adopting each land use category as explanatory variables without considering their significant intercorrelation, likely leading to multicollinearity issue and biased results. Notably, our Foshan study has well addressed this issue to aggregate a total of twelve land use categories into three composite land use indices by adopting a widely applicable PCA dimension reduction technique, thus producing more reliable results with more referential values. Finally, in our Foshan study, we further investigate the effects of transportation network characteristics and their interaction with land use on traffic conditions in our regression models, providing new insights into the integrated land use and transportation planning.

Second, our study focuses specifically on a SC, supplementing the existing literature that focuses solely on large metropolises. Third, instead of a large-scale study, it zooms into examining the interaction between traffic congestion and neighborhood-level built environments, supplying urban governors with more fine-grained insights for further formulation of targeted strategies. Fourth, distinctive scales, including daily, weekly, and holidays of temporal factors, are taken into account, allowing for a more comprehensive understanding of the impacts of built environments on congestion formation. The paper adds to the depth of the body of knowledge on traffic behaviors in SCs, providing insights into the traffic congestion pattern in these areas. Our study has significant policy implications, aiming to improve traffic resilience and environmental health. The STCM methodology adopted in this study,
which is also applicable to a general context, can also provide a useful reference for other researchers of interest to explore the nexus between congestion and built environments in SCs.

2. Conceptual framework

To provide readers with a clear flowchart of the study, a conceptual model is developed to examine the spatial-temporal traffic congestion pattern contextualized in SCs (see Fig. 1). The spatial dimension means the physical structure of the built environment features, embracing not only land use patterns, but also transportation network distributions. The measurement of land use factors is according to how different POI categories are distributed spatially in our research contexts, such as sports, catering, and healthcare. Then, we take factors including roadway density, proximity to arterial roads, and public transit accessibility into consideration for the transportation network. Furthermore, we perform statistical analyses, including principal component analysis (PCA) and bivariate correlation (BC) with an aim of selection and conversion of typical metrics for capturing smaller built environment features effectively. We also classify the temporal dimension into three scales, namely, daily pattern, weekly pattern, and national holiday pattern. Finally, a comprehensive spatial-temporal model incorporating these factors is employed for the prediction of traffic congestion in a typical SC in China. Based on the model, what and how land use factors affect traffic congestion can be revealed.

With mathematical language, the spatial-temporal model can be defined conceptually below:

\[ C_t = f(L, TP, [t]) \]  
\[ L = f_l(POI_1, POI_2, \ldots, POI_m) \]  
\[ TP = f_p(I_1, I_2, \ldots, I_n) \]

Where \( C_t \) refers to the congestion level at time \( t \), \( L \) and \( TP \) are metrics to characterize the patterns of land use and transportation network distribution, respectively; \([t]\) denotes the temporal control variable, ensuring only traffic conditions occurring simultaneously are taken into consideration. To explore time-varying impacts, the model constructed according to corresponding congestion levels at different times \( C_t \) will be compared. By conducting BC and PCA analysis for the density pertaining to different categories of POI, \( m \), the metric characterizing the patterns of land use, \( L \) can be extracted. The transportation network metric \( TP \) is obtained based on the analysis of different transportation network distribution index \( I_i \) (\( i = 1, 2, \ldots, n \)), e.g., road density, proximity to arterial roads and public transit accessibility.

3. Research methodology

3.1. Data and materials

Foshan, a prefecture-level Chinese city in Guangdong province, is selected as our research focus. With a history of over 2000 years, Foshan is developed from township. As shown in Fig. 2, Foshan is adjacent to the western border of Guangzhou and is divided into five administrative districts, amongst which we incorporate Chancheng, Nanhai, and Shunde, the three most developed districts into our study. The study area occupies a total land area of 2034 km\(^2\) and houses more than 6 million residents. In 2020, Foshan achieved its Gross Domestic Product (GDP) of about CNY 1081.6 billion (CMAB, 2018), which is still largely lagging behind many large metropolises in China. Foshan is widely regarded as a satellite city of Guangzhou in China’s context (He, 2017; Zhong et al., 2003), especially since the opening of the Guangfo Line in 2010, which connected the two cities with an integrated inter-city metro system.

The materials used in this study were collected from multiple sources. For land use data, the application programming interface (API) enabled by the AutoNavi (https://lbs.amap.com/) is used to extract a total of twelve categories of POI within our research scope, including healthcare, tourist attraction, shopping, residence, government institution, education institution, hospitality, company, financial services, catering, life services, and sports. For the transportation network, we
used OpenStreetMap to extract information on the city’s road networks, intersections, and public transit.

With an aim to acquire real-time traffic conditions, we also used the AutoNavi API. The congestion level is captured by a top-down system, with scores of 4, 3, 2, 1, and 0, aligning to AutoNavi API. The congestion level is captured by a top-down system, intersections, and public transit.

3.3. The definition and quantification of variables

To more precisely capture different sources of data, we purposely divided our study area into grid cells. This approach has been commonly applied to existing studies (Cutsinger et al., 2005; Martinez et al., 2009; Salomons and Pont, 2012). As per Fig. 3, by starting from designating the geographical center of the focused region as the centroid of a cell, a mesh of cell grids is consequently extended outward. While some studies, such as Sarzynski et al. (2006) and Cutsinger et al. (2005), adopted 1.0 × 1.0 mile as the cell size, another group of researchers, such as Mendel et al. (2019) and Wang (2011) suggested a more stable size of 2.5 × 2.5 mile to measure urban form. Two commonly applied cell sizes in measuring urban form in existing studies are 1.0 × 1.0 mile (Sarzynski et al., 2006; Cutsinger et al., 2005) and 2.5 × 2.5 mile (Mendel et al., 2019; Wang, 2011). We choose the former over the latter, given that finer cell size could capture more details in congestion patterns. Consequently, a total of 698 cell grids are obtained after quantization for the study area.

3.3. The definition and quantification of variables

Our key explanatory variables, land use features, are characterized by the number of POIs for the 12 POI categories defined in Section 3.1 within each of the 1.0 × 1.0 mile (2.59 km²) cell as shown in Fig. 3.

The transportation network is characterized by four variables, which are road density $Dr$, intersection density $Ds$, public transit density $Dp$, and proximity to arterial roads $d_{rd}$. The variables are defined as follows from Eq. (4) to Eq. (7):

$$\frac{\sum_{i} w_{len,Rd_i}}{\text{cellArea}}$$ (4)

$$\frac{N_{sec}}{\text{cellArea}}$$ (5)

$$\frac{N_{bus} + N_{metro}}{\text{cellArea}}$$ (6)

$$d_{rd} = \min(dist(C_{cell}, M_{Rd}))$$ (7)

Where $len,Rd_i$ is the total length of roads of class i in the cell of interest, and $\alpha$ is the weighted factor of road lanes for road class i. In OpenStreetMap, there are seven road classes, including "motorway", "trunk", "primary", "secondary", "tertiary", "unclassified", and "residential". We are only interested in a subset $M$ of them (i.e., $M = \{"motorway", "trunk", "primary"\}$). $\alpha$ is specified as 4, 3, and 3 for "motorway", "trunk", and "primary", respectively. $N_{sec}$, $N_{bus}$ and $N_{metro}$ are, respectively, the number of intersections, bus stops and subway stations in a cell; $dist(C_{cell}, M_{Rd})$ provides the distance from cell center $C_{cell}$ to arterial road $M_{Rd}$. In the study area, there are three arterial roads, which are the Foshan Avenue, Guangyun Road, and Guangzhu Road. $S$ is the set of the three roads, i.e., $S = \{"Foshan Avenue", "Guangyun Road", "Guangzhu Road"\}$.

We measure traffic congestion using average traffic condition. Specifically, the mean value of the traffic volume reported at all observation points that fall inside a given cell is calculated. (Note: an absolute value representing the traffic volume at observation points captured directly from the raw data.)

We calculate the values of these variables for all the 698 cells, and the detailed statistics are presented in Table 1.

### Table 1: Statistics of the explanatory and response variables.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Average</th>
<th>St. dev.</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use (Explanatory variables)</td>
<td>Catering</td>
<td>29.1</td>
<td>32.3</td>
<td>236.3</td>
</tr>
<tr>
<td></td>
<td>Shopping</td>
<td>41.5</td>
<td>60.0</td>
<td>437.5</td>
</tr>
<tr>
<td></td>
<td>Life services</td>
<td>21.2</td>
<td>33.0</td>
<td>212.4</td>
</tr>
<tr>
<td></td>
<td>Sports</td>
<td>3.4</td>
<td>5.4</td>
<td>40.9</td>
</tr>
<tr>
<td></td>
<td>Healthcare</td>
<td>4.9</td>
<td>8.6</td>
<td>62.5</td>
</tr>
<tr>
<td></td>
<td>Hospitality</td>
<td>2.6</td>
<td>4.6</td>
<td>53.3</td>
</tr>
<tr>
<td></td>
<td>Tourism</td>
<td>1.9</td>
<td>2.8</td>
<td>34.7</td>
</tr>
<tr>
<td></td>
<td>Residence</td>
<td>7.8</td>
<td>13.0</td>
<td>113.5</td>
</tr>
<tr>
<td></td>
<td>Government</td>
<td>6.6</td>
<td>10.4</td>
<td>122.0</td>
</tr>
<tr>
<td></td>
<td>Education</td>
<td>5.6</td>
<td>9.9</td>
<td>88.8</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>2.2</td>
<td>4.3</td>
<td>44.0</td>
</tr>
<tr>
<td></td>
<td>Company</td>
<td>26.4</td>
<td>30.3</td>
<td>182.2</td>
</tr>
<tr>
<td>Transportation (Explanatory variables)</td>
<td>$Dr$</td>
<td>2.6</td>
<td>3.2</td>
<td>18.4</td>
</tr>
<tr>
<td></td>
<td>$Ds$</td>
<td>0.7</td>
<td>2.3</td>
<td>36.7</td>
</tr>
<tr>
<td></td>
<td>$Dp$</td>
<td>1.1</td>
<td>2.2</td>
<td>18.5</td>
</tr>
<tr>
<td></td>
<td>$d_{rd}$</td>
<td>5.9</td>
<td>4.3</td>
<td>19.4</td>
</tr>
<tr>
<td>Traffic condition (Response variables)</td>
<td>MTS$^*$</td>
<td>1.06</td>
<td>0.17</td>
<td>3</td>
</tr>
</tbody>
</table>

Fig. 3. The quantized study area comprising 698 square-mile cells.
\[ y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \epsilon \]  
(8)

where \( y_i \) is the congestion level of cell \( i \) at time \( t \); \( x_i \) is a vector of land use factors; \( z_i \) is a vector of transportation factors; \( \beta_0, \beta_1, \) and \( \beta_2 \) are parameters to be estimated; and \( \epsilon \) is the error term. Given that built environment and transportation features are regarded as constant under the time scale of our study. Therefore, the explanatory variable \( x \) and \( z \) has no time dimension. By collecting different traffic condition data at different times, congestion models with time-varying effects of \( y \) can be obtained. Through a comparison of the relative contribution of various built environment features to \( y \) over time, our understanding on how land use and transit accessibility impact traffic congestion over time may be obtained.

To further explore the potential interaction effects between land use and transportation factors on traffic congestion, we add interaction terms \( x_i \times z_i \) to the regression model, where \( z_i \) is a vector of dummy variables equal to 1 if they are higher than the average values of \( z_i \). All other notions are as defined in Eq. (8). 

\[ y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i \times z_i + \beta_3 z_i + \beta_4 z_i + \epsilon \]  
(9)

4. Findings and analyses

4.1. Time-varying impacts of traffic congestion

Built environments affect traffic conditions in different manners in SCs when the time evolves. In this section, we investigate the time-varying impact of traffic conditions in Foshan, through which the most likely time for the occurrence of congestion will be identified for subsequent correlation analysis. While people have a concentrated demand for road infrastructure for commuting purposes during the weekdays, it is usually not the case during the weekends or national holidays. In addition, literature has also revealed a higher travel demand on the day prior to holidays or weekends than on normal workdays (Wen et al., 2014; Zhao and Hu, 2019). Therefore, the traffic condition data are categorized into these three typical conditions, including “weekdays”, “pre-weekends”, and “weekends” in subsequent analysis.

Fig. 4 shows the average traffic condition at representative time points during (1) pre-weekends by averaging the data during December 25–31, 2020, (2) weekdays by averaging the data during December 23–24 and December 28–30, 2020, and (3) weekends by averaging the data during December 26–27, 2020, and January 1, 2021. An observation universally applicable to all the three different conditions is that around 6:30 p.m. of the day is the rush hour with the heaviest traffic pressure. Both the pre-weekend and weekdays experience traffic peaks twice a day, one at around 8:00–10:00 in the morning and the other at around 16:30–18:30 in the afternoon, whereas the weekend seems to have no morning peak. This is probably because during the weekend, people have no need to commute to work, or even if overtime working is required, the office time can be adjusted flexibly. Many people may just choose to stay at home with more time for rest in the weekend morning (Zhao and Hu, 2019), thus significantly relieving the traffic demand and disappearing the morning peak.

When combining Fig. 4 with Fig. 5, some interesting in-depth traffic congestion phenomena can be indicated by comparing the three different conditions at the same time point. First, by comparing the traffic congestion pattern during the three different conditions at 16:30 p.m., the traffic congestion during pre-weekend happens much earlier than that during normal weekdays and weekends. By taking Fig. 5 as a reference, those corresponding land use categories characterized as congestion at 16:30 p.m. mainly include either company or those related to leisure activities, such as catering, shopping, and sports. This interesting phenomenon can be attributed to a possible situation that many people may get off work earlier during pre-weekend (Balbin et al., 2020). Second, with a focus on 18:30 p.m. during the three different conditions, the traffic congestion during pre-weekend is found much
heavier than that during weekdays and weekends. By referring to Fig. 5, those land use categories correlating to the pre-weekend congestion are mostly with the attribute of entertainment, such as catering, shopping, life services and sports, which could be owing to two possible reasons. Firstly, many people are likely to celebrate their weekend during pre-weekend after finishing one week’s hard work by participating in various leisure activities (Singh et al., 2020). Secondly, for being widely recognized as a SC of Guangzhou, many people with family and friends in Foshan may work in Guangzhou. They may get used to living in Guangzhou on normal weekdays to save time and money from daily commuting. When weekends or holidays are approaching, they could have higher willingness to swarm into Foshan for visiting family and friends, even with long-distance or cross-jurisdictional travel (Yin et al., 2023). As such, the role of Foshan as a SC of Guangzhou also intensifies its traffic congestion during pre-weekend. Third, when taking 20:00 p.m. as a focus, the traffic congestion during pre-weekend still exists in many leisure-related land use categories, such as catering, shopping, and healthcare by referring to Fig. 5, while during normal weekdays or even weekends, such a clear congestion pattern has not been found. Foshan’s role as a SC of Guangzhou also has an additional effect on its long-lasting traffic congestion during pre-weekend as many people from Guangzhou are still continuously swarming into Foshan at around 20:00 p.m.

4.2. Land use correlation analysis

Fig. 5 visualizes how the 12 POI categories are distributed in our study context. It is observed that some POI categories follow very similar distribution patterns, e.g., catering, shopping, life services, and healthcare, which are densely concentrated in the downtown area of the Chancheng District and cluster at a few suburban places. The observation is confirmed by a quantitative BC analysis, the results of which are presented in Table 2. The distributions of shopping, catering, healthcare, life services, hospitality, government institution, residence, educational resources, and financial services are highly correlated with each other, while the land use for tourism and companies/enterprises has a different distribution pattern.

The significant intercorrelation indicates a great potential for dimension reduction. Here, we use principal component analysis, a widely used dimension reduction technique (Lever et al., 2017), to find components that can best characterize the variance of the land use features. To eliminate the effect exerted by the variant scales, we normalized all the variables to the range of [0, 1] according to the equation as follows:

$$DPOI_i' = \frac{DPOI_i - \min(DPOI_i)}{\max(DPOI_i) - \min(DPOI_i)}$$

Fig. 5. The distribution of 12 categories of POI.
4.3. Spatial-temporal traffic congestion modeling (STCM)

We considered the composite land use factors (\(Cm\), \(Cp\), and \(Ct\)) and transportation network indices (i.e., \(Dr\), \(Ds\), \(Dp\), and \(d_{4}\)) as explanatory variables. Then multivariable regression models can be created to reconstruct the STCM by taking the traffic conditions with time-varying effects as response variables. Based on the analysis in Section 4.1, five temporal scenarios of travel conditions are considered in the study: (1) the evening peak in a typical weekday (Wd-en-peak); (2) the morning peak in a typical weekday (Wd-mn-peak); (3) the evening peak in a typical pre-weekend day (pWk-en-peak); (4) the morning peak in a typical pre-weekend day (pWk-mn-peak); and (5) the evening peak in a typical weekend day (Wk-en-peak).

The outcomes of MLSR pertaining to each of the five above scenarios are presented in Table 4. The normalized coefficients in absolute values reflect the relative influence of the respective variables on the traffic condition (i.e., response variable), with greater coefficients (in absolute values) indicating more important influencing factors. The factors at the 5% level of significance are highlighted in bold font style in Table 4.

Table 4 shows valuable insights into how SC’s built environments exert different influences on traffic conditions as time changes. In all the five temporal scenarios, the \(Cm\) is observed to be positively correlated to congestion, while the \(d_{4}\) is inversely related. The observation suggests that neighborhoods in the SC with more concentrated commercial land use and closer to arterial roads probably experience heavier congestion in peak periods, no matter whether it is weekdays, pre-weekends, weekends, or holidays. Fig. 6 demonstrates the pattern vividly, where it can be clearly observed that clusters with the most severe congestion are concentrated in areas around the main roads of Foshan City. Our results indicated that the distance to major trunk roads plays an important role, which in fact, has the largest contribution to the occurrence of congestion amongst all built environment dimensions.

For a normal weekday, \(Cm\) and \(d_{4}\) seem to be the only two influencing factors during the morning peak periods, while during the evening peak periods, \(Cp\) (the density of company land use) and \(Dp\) (public transit density) have a certain level of influence as well: the higher the \(Cp\) or the lower the \(Dp\), the heavier the congestion elevation occurs, which is in conformance with daily experience. Densest distribution of companies means more jobs in the same unit area, indicating higher demand for commuting. As for \(Dp\), densely distributed bus stops and (or) subway stations provide commuters with easier access to public transit, which can reduce the need for private cars and thus improve the traffic condition (Ewing and Cervero, 2010; Ou et al., 2022; Yang et al., 2020; Li et al., 2019).

For pre-weekends, it is interesting to find that tourism land use exerts a negative effect on the congestion during the morning peak (with a coefficient of \(-0.121\)). Correlation does not necessarily reflect causality (Hu et al., 2012; Pearl and Mackenzie, 2018), and the interplay between \(Ct\) and traffic conditions certainly does not mean allocating more land for tourism can alleviate congestion. Instead, it can be attributed to the fact that many tourist attractions are located in suburban areas where the commuting swarm does not normally pass. The congestion in the evening peak of pre-weekends is the most severe among all the investigated scenarios. Similar to a normal weekday evening peak, it is
positively related to commercial and company land use, and negatively related to distance to major arterial roads. However, the influence of $Dp$ has been turned down, whereas the $Ds$ contributes positively to the congestion level. The observations imply that roadway intersections are potential hotspots of traffic congestion during evening peaks of pre-weekends. In addition, as more people choose to take long-distance and cross-region travels to spend their weekends or holidays, the effects of public transit, which are primarily oriented to short-distance local trips, in mitigating traffic conditions have diminished.

For evening peaks during holidays/weekends, the congestion is observed to be positively correlated to commercial land use but negatively related to tourism land use, implying a preference for shopping or other leisure activities in downtown areas over suburban tourist attractions. As such leisure activities are confined to local areas in the downtown, a densely developed public transit system can help alleviate the traffic congestion, as indicated by the negative coefficient of public transit density ($Dp = -0.152$).

Given that congestion effects of land use characteristics may be partly influenced by the provision of transportation infrastructure, we further investigate the interaction effects of land use and transportation network features on traffic conditions (Table 5). As presented in Column [1], commercial and company land use and road intersection density are positively associated with the average congestion level during the five temporal scenarios, while public transit density and distance to arterial roads are negatively correlated with the average congestion level, consistent with the findings drawn from Table 4. When interaction terms between land use and public transit dummies are included in Column [2], the coefficient of $-0.131$ for the interaction term $Cp \times Dp_H$ is significant at the 5% level, suggesting that the rising traffic congestion associated with company land use during the peak hours can be partly offset by the increasing supply of public transit. In comparison, the coefficients for the other two interaction terms, $Cm \times Dp_H$ and $Ct \times Dp_H$, are statistically insignificant, reflecting that the traffic congestion relief effects of public transit services in places with high commercial or tourism land use share are mild during the peak hours. This reveals that public transit serves as a primary travel mode for commuting trips in Foshan's context, while it is probably not the first choice for leisure trips. Then, the interaction terms between land use and arterial road proximity dummies are further added into Column [3]. The coefficients for the interaction terms ($Cm \times d_{rd}_H$, $Cp \times d_{rd}_H$, and $Ct \times d_{rd}_H$) are also statistically insignificant, demonstrating that proximity to arterial road do not affect the impacts of land use features on traffic conditions.

5. Discussion

5.1. Limitations

No study can escape from limitations. The present research has four main limitations thus demanding further exploration in future studies. First, due to data constrains regarding its limited coverage in geographical scope, limited comprehensiveness to include other influencing factors of traffic congestion and limited duration, the results derived from this study are by no means conclusive. Future studies are suggested to conduct larger-scale traffic congestion analyses by covering larger geographical scope and embracing more influencing factors during a longer study period when finer data become available. Second, in this study, land use features are measured by POI density (number of POIs within a given cell), which may not necessarily reflect the actual
Third, as a SC plays a role complementary to a megacity in terms of their differences theoretically. Although this study is of the first of its kind to further examined in future studies using different land use measures (e.g., a higher density of branch roads is suggested to be incorporated into planning, policymaking and transportation management in SCs in terms affect traffic conditions in SCs.

The research findings have several aspects of implications for urban planning, companies. Finally, more shared mobility services, e.g., bicycle and e-scooter, could be deployed at many metro stations to solve the “last mile” problem (Rosenberg et al., 2021), further facilitating to relieve the traffic congestion.

6. Conclusions

Traffic congestion has been widely perceived as an inevitable byproduct in the process of global urbanization. If not properly managed, traffic congestion is bound to impose significant adverse economic and environmental impacts to governmental authorities, transportation planners, developers, and the public, thus preventing cities from sustainably transitioning towards developed cities in the long run. As such, worldwide researchers and practitioners have spared no efforts to investigate how to effectively mitigate traffic congestion with different strategies deployed, amongst which a mainstream is to better take advantage of the built environment for being aware of their mutual interplay. However, past studies have attached significant importance to revealing the interaction between traffic congestion patterns and built environment features in many metropolises with little attention, if any, paid to their corresponding SCs. Discerning that developing SCs has been a main trend to address many urban issues of metropolises in the rapid urbanization process of emerging economies, this study makes one of the first research attempts to investigate how traffic congestion temporally and spatially evolves with the built environment characterized by land use and transportation network features in Foshan, a typical SC of Guangzhou in China by using valuable hyperlocal travel data.

The results indicate that the traffic congestion in Foshan during the pre-weekend is found much heavier compared with normal weekdays and weekends or holidays with a long-lasting effect (e.g., 16:30 p.m.–20:00 p.m. in our Foshan’s study), more consolidated traffic management measures are suggested to be deployed. For example, the traffic police may be deployed to have more time on duty to channel through the traffic congestion during the pre-weekend. The traffic management department may also consider arranging a higher frequency of public transits (e.g., buses and metros) by shortening the interval between trips to reduce the use of private cars and further alleviate the traffic congestion during the pre-weekend. Third, according to Table 5, the rising traffic congestion associated with company land use during the peak hours can be partly offset by the increasing supply of public transit. Therefore, urban planners are suggested to increase the density of public transit (e.g., establishing more bus stops and metro stations) where there is a denser distribution of companies or enterprises, which contradicts many previous studies that suggest concentrating more on commercial land use (Cervero and Duncan, 2002). Finally, as more traffic congestion may happen along with the traffic line between the SC and the main city (e.g., Guangfo Line in our Foshan’s case), more shared mobility services, e.g., bicycle and e-scooter, could be deployed at many metro stations to solve the “last mile” problem (Rosenberg et al., 2021), further facilitating to relieve the traffic congestion.

5.2. Practical implications

The research findings have several aspects of implications for urban planning, policymakers and transportation management in SCs in emerging economies. First, according to the significant contribution of arterial roads to congestion, a direction toward sustainable urban planning for transportation optimization may be suggested. To undertake high traffic volume of arterial roads leading to potential congestion, a higher density of branch roads is suggested to be incorporated into SCs’ urban transportation network, which allows drivers to have more optional routes to arrive the same destination. Second, as long-lasting traffic congestion may occur during the pre-weekend for SCs (e.g., 16:30 p.m.–20:00 p.m. in our Foshan’s study), more consolidated traffic management measures are suggested to be deployed. For example, the traffic police may be deployed to have more time on duty to channel through the traffic congestion during the pre-weekend. The traffic management department may also consider arranging a higher frequency of public transits (e.g., buses and metros) by shortening the interval between trips to reduce the use of private cars and further alleviate the traffic congestion during the pre-weekend.

Table 5
Regression results of average traffic congestion at peak hours.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cm</td>
<td>0.225**</td>
<td>0.319**</td>
<td>0.320**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Cp</td>
<td>0.086*</td>
<td>0.161**</td>
<td>0.202*</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.005)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Ct</td>
<td>0.066</td>
<td>0.145**</td>
<td>0.148*</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
<td>(0.004)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Cm × Dp_H</td>
<td>0.126</td>
<td>0.121</td>
<td>(0.089)</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cp × Dp_H</td>
<td>0.131*</td>
<td>0.159*</td>
<td>(0.042)</td>
</tr>
<tr>
<td></td>
<td>(0.094)</td>
<td>0.095</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Ct × Dp_H</td>
<td>0.090</td>
<td>0.095</td>
<td>(0.063)</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cm × d_a_H</td>
<td>0.018</td>
<td>0.010</td>
<td>(0.040)</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cp × d_a_H</td>
<td>0.043</td>
<td>0.042</td>
<td>(0.442)</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ct × d_a_H</td>
<td>0.043</td>
<td>0.042</td>
<td>(0.442)</td>
</tr>
<tr>
<td></td>
<td>(0.462)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dp_H</td>
<td>0.072</td>
<td>0.084*</td>
<td>0.080</td>
</tr>
<tr>
<td></td>
<td>(0.080)</td>
<td>(0.044)</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Ds</td>
<td>0.113**</td>
<td>0.105**</td>
<td>0.105**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Dp</td>
<td>0.017*</td>
<td>0.013</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.064)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>d_a</td>
<td>0.333**</td>
<td>0.343**</td>
<td>0.336**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
</tbody>
</table>

Note: *p < 0.05; **p < 0.01; p-values are in parentheses.
use and transportation facilities to improve traffic resilience and environmental health.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The research was supported by Natural Science Foundation of Shanghai, China [Grant number: 21ZR1423800] and National Natural Science Foundation of China [Grant number: 71834005].

References


Z. Bao et al. Developments in the Built Environment 14 (2023) 100173


