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Urban morphology and traffic congestion: Longitudinal evidence from US cities

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ABSTRACT

Traffic congestion is an ever-increasing issue across urban environments in the US. One potential mitigation strategy is to improve our understanding of how the geographical patterns of urban land use influence congestion. Unfortunately, there is no consensus regarding if more sprawling or dense urban morphologies help mitigate congestion issues. To potentially clarify the conflicting findings of previous studies, we used a detailed spatial metric-based approach and panel regression to quantify the relationships between urban development patterns and congestion in 98 US urban areas from 2001 to 2011. We found that the abundance and spatial configuration of urban land uses were correlated with traffic congestion. Specifically, high degrees of polycentricity for both high-intensity and low-intensity urban land uses were associated with more congestion, while contiguous residential development was correlated with less congestion. Important distinctions were also observed between different congestion measures, as urban morphology exhibited a more substantial influence on overall congestion than rush-hour congestion. Our findings can potentially inform future land use planning by clarifying which urban morphologies alleviate traffic congestion issues.

1. Introduction

Traffic congestion is a global phenomenon influenced by economics, population growth, transportation infrastructure, and the ever-increasing availability of ridesharing and delivery services. Although larger cities generally exhibit higher congestion levels (Chang, Lee, & Choi, 2017), the negative consequences of traffic, including the loss of time, increase of urban pollution, and rise of accidents, are pervasive throughout many urban centers. The delays caused by congestion have effectively contracted business markets and raised production costs by reducing urban agglomeration economies (Weisbrod, Vary, & Treyz, 2003). For example, congestion enhances the price of freight movement by increasing operating costs and decreasing reliability. The estimated annual total congestion cost in the freight sector alone was $74.5 billion in 2018 (Hooper, 2018). In terms of human health, congestion reduces air quality by enhancing traffic-related air pollutants such as NO_x and CO (Zhang & Batterman, 2013; Zheng, de Beurs, Owsley, & Henebry, 2019), and it also jeopardizes road safety by increasing the fatality and injury accident rates (Wang, Quddus, & Ison, 2013).

Within auto-dependent US cities, traffic congestion is a particularly challenging and growing problem. Total travel delays accounted for 6.9 billion hours in 2014 (or $160 billion 2014 USD), which was 2.8 times greater than the equivalent value in 1982 (Texas A&M Transportation Institute, 2015). Additionally, congestion-related delays were four times worse than the 1982 baseline in urban areas with a population of less than half a million. INRIX Research (2019) found that several large US cities, including Boston, Washington DC, Philadelphia, New York City, and Chicago, were amongst the world's top 25 most congested cities. The US was also home to 22% of the top 50 most congested urban areas worldwide, highlighting the pervasiveness of traffic congestion issues throughout the country (INRIX Research, 2019). Because traffic congestion is expected to increase due to continued urbanization (Downs, 2004), exploring potential mitigation strategies through effective land use planning will be critical.

Unfortunately, there is a general lack of consensus regarding the relationships between the spatial arrangement of urban land uses and traffic congestion despite the rich body of scholarship focused on the topic (e.g., Ewing, 1997; Gordon & Richardson, 1997). The inconclusive

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findings are partly due to the general reliance upon various proxy measures of urban morphology (e.g., population density, job distribution, residential density), highlighting the need for more direct and nuanced empirical analyses of urban form and its influences on congestion. This study aims to elucidate the contradictory results of previous research and clarify which urban morphologies enhance traffic congestion by utilizing a detailed spatial metric-based approach to quantify urban development patterns. Specifically, we address the following research questions:

- What spatial configuration of urban development (e.g., monocentric vs. polycentric) exacerbates urban traffic congestion?
- Which types of urban land use (e.g., high-intensity vs. low-intensity) exhibit the strongest associations with congestion?
- How notably do the relationships between urban morphology and congestion vary depending on the specific type of congestion analyzed?

Addressing these research questions that more fully acknowledge the potential heterogeneous influence of different aspects of urban morphology on various types of congestion using robust quantitative techniques will help inform land use planning measures aimed at mitigating traffic congestion, which is a major challenge facing urban centers in the US. The following section provides additional background on spatial metrics and discusses the contradictory findings of past studies that motivated this research. Section 3 outlines the cities incorporated in the analysis, the methods used to quantify urban form and congestion, and the statistical approach utilized to analyze the relationships. The results are presented in Section 4, with additional discussion provided in Section 5. Finally, the conclusion summarizes the major findings and highlights potential policy implications.

2. Literature review: spatial metrics, urban morphology and congestion

One tactic to mitigate traffic congestion within cities is to improve our understanding of how it is influenced by the spatial configuration and abundance of various urban land uses. Spatial metrics offer a methodological approach to clarify these linkages and potentially inform land use planning strategies that seek to minimize congestion issues. Although spatial metrics were initially developed within landscape ecology to address the relationships between habitat fragmentation and ecological processes (Forman & Godron, 1986; Gustafson, 1998; Naveh & Lieberman, 1984), they have been increasingly adopted within urban studies (Herold, Scepan, & Clarke, 2002). Urban applications of spatial metrics initially focused on quantifying the development patterns of individual urban centers, comparing urban morphologies of various cities, and monitoring the temporal evolution of urban forms (Herold, Couclelis, & Clarke, 2005; Huang, Lu, & Sellers, 2007; Ji, Ma, Twibell, & Underhill, 2006; Luck & Wu, 2002). More recently, studies have utilized spatial metrics to examine the relationships between urban morphologies and various urban processes, such as the urban heat island effect, urban streamflow, and urban air quality (Connors, Galletti, & Chow, 2013; Debbage & Shepherd, 2015; Debbage & Shepherd, 2018; Kim & Park, 2016; Makido, Dhakal, & Yamagata, 2012).

Despite the overall growth of research exploring the linkages between urban form and urban processes, spatial metrics remain underutilized within traffic congestion studies. Spatial metrics have been more frequently used to analyze the influence of urban morphologies on congestion-related outcomes, such as air pollution, noise pollution, and carbon emissions (e.g., Margaritis & Kang, 2016; Ou, Liu, Li, & Chen, 2013; Wang, Madden, & Liu, 2017; Weber, Haase, & Franck, 2014), than congestion itself. Conversely, studies directly analyzing the relationships between urban development patterns and traffic congestion have relied upon other measures to evaluate urban form. Population density (Izraeli & McCarthy, 1985), employment outside central cities (Gordon, Lee, & Richardson, 2004), and composite indices that account for numerous variables (Ewing, Pendall, & Chen, 2003; Sarzynski, Wolman, Galster, & Hanson, 2006) are all more commonly used than spatial metrics to quantify urban form when assessing its influence on traffic congestion.

Importantly, these previous studies utilizing proxy measures of urban morphology have reached conflicting conclusions regarding if sprawling or dense urban development increases congestion and commute times. On the one hand, sprawling urban development enhances the need for frequent, long trips via automobile, which results in greater vehicle miles traveled and may exacerbate traffic congestion (Ewing, 1997). However, Gordon and Richardson (1997) argued that sprawl reduces congestion primarily by dispersing origins and destinations over a larger area. Empirical analyses quantifying the relationships between urban form and several congestion measures have not entirely clarified this debate. Several studies observed positive relationships between population or residential density and commute duration (Gordon, Kumar, & Richardson, 1989; Izraeli & McCarthy, 1985), while others discovered negative relationships (Gordon et al., 2004; Malpezzum, 1999). Insignificant statistical relationships between sprawl/compactness and congestion have also been documented in the literature, which potentially illustrates the complex countervailing forces of sprawl where greater distances traveled are offset by higher travel speeds (Ewing, Prendall, & Chen, 2002; Ewing, Tian, & Lyones, 2018).

Of course, the contradictory findings are at least partly due to the different study cities considered, specific congestion measures analyzed, and various methodologies used to quantify urban form. However, the work of Sarzynski et al. (2006) highlighted how complex findings could emerge within a single study, as two of the urban form measures analyzed indicated that more compact development enhanced traffic congestion while the third suggested the opposite. Overall, these conflicting findings suggest that proxy measures of urban morphology might be overly simplistic and ignore the heterogeneity of urban development patterns within cities. For example, vastly different underlying urban morphologies could be described by a similar population or housing density value. Spatial metrics provide an approach that more fully addresses the complexities of urban form because the abundance and spatial configuration of different urban development intensities can be analyzed independently. Therefore, spatial metrics help isolate and quantify specific dimensions of urban morphology, which could be obfuscated by coarser proxies.

The general lack of consensus is complicated further by the support for polycentric urban development in planning and policy circles due to its purported economic and environmental benefits (e.g., Cortinovis, Haase, Zanon, & Geneletti, 2019). While urban polycentricity has been observed in many cities around the world, including those in the US (Meijers & Burger, 2010) and China (Liu & Wang, 2016), it is unclear if polycentric morphologies encourage more frequent and perhaps longer commuting trips between individual urban centers or facilitate more efficient public transport systems (Ewing & Rong, 2008). Nevertheless, a recent simulation study in Singapore showed potential synergies between shorter commuting trips and urban polycentricity (Wu, Smith, & Wang, 2021). From an environmental perspective, Lee and Lee (2014) illustrated how a polycentric urban structure could shorten commuting distances and reduce carbon emissions. Conversely, Wang et al. (2017) revealed that polycentricity might be associated with greater carbon emissions, likely due to the excess vehicle miles traveled. Li, Xiong, and Wang (2019) similarly discovered a non-linear relationship between polycentricity and traffic congestion. In terms of urban economic outcomes, Meijers and Burger (2010) found that a polycentric city was associated with improved labor productivity in US cities, suggesting that the agglomeration economies of polycentrism offset any congestion costs. However, a more recent study conducted by Wang, Derudder, and Liu (2019) reached the opposite conclusion based on Chinese cities. Applying spatial metrics to quantify urban form offers an opportunity to clarify these conflicting empirical findings and provide a more holistic view of how urban polycentricity and other aspects of urban form influence congestion within US cities.

In recent years, various real-time big geodata sources have helped further model traffic congestion with impressive granularity and accuracy. One source of such data that has been particularly transformational is GPS devices, which are often either mounted in vehicles or embedded in smartphones. For example, Kan et al. (2019) utilized taxi GPS data to detect multi-dimensional congestion at the turn level. Zhou, Wang, and Li (2019) also leveraged GPS data from taxis in addition to GPS information from bikes affiliated with a bike-sharing program to develop a travel mode choice model. Compared to vehicle-mounted GPS, smartphone-embedded GPS devices used in conjunction with navigation apps have provided a more nuanced understanding of traffic speeds (e.g., Hoseinzadeh, Liu, Han, Brakewood, & Mohammadnazar, 2020), flow patterns (e.g., Kohan & Ale, 2020), and road conditions (e.g., Li & Goldberg, 2018). Furthermore, Gately, Hutyra, Peterson, and Wing (2017) integrated mobile phone and vehicle GPS data to derive hourly vehicle speed information for congestion and pollution modeling. Such detailed traffic information has often been commercialized, and the congestion data source used in this study, which is discussed in the following section, incorporates a similar level of granularity.

3. Data and methodology

3.1. Study area and datasets

This study analyzed a large sample of Urbanized Areas (UAs) within the conterminous United States. According to the US Census Bureau, a UA is composed of a densely settled core of at least 50,000 people and includes adjoining non-residential urban land uses with low population densities that link outlying densely settled areas to the urban core. Over 70% of the US population lived in UAs as of the 2010 US Census.

The data describing the UAs were primarily obtained from two sources. First, congestion statistics were collected from the Urban Mobility Scorecard (UMS) produced by the Texas A&M Transportation Institute. The UMS aggregates speed data provided by INRIX (http://inrix.com/) with volume and roadway inventory information produced by the Highway Performance Monitoring System maintained by the US Federal Highway Administration (FHWA). The dataset measures congestion in a unified framework, which allows for accurate comparisons between various UAs. INRIX utilizes real-time traffic data to determine the 'real' rush hour speeds of vehicles, while overnight vehicle speeds are used to evaluate free-flowing conditions. Overall, the UMS dataset contains (1) congestion statistics for 52 UAs at a quarterly time interval from 2008 to 2015; and (2) congestion statistics for 101 UAs at a yearly time interval between 1982 and 2014. The second data source was the National Land Cover Database (NLCD), created by the Multi-Resolution Land Characteristics (MRLC) Consortium. The NLCD 2011 Edition contains detailed land cover datasets for the US in 2001, 2006, and 2011. Urban land use information obtained from the NLCD was used to evaluate each UA's urban morphology, which is described further in subsection 3.3.

Specifically, this study utilized the yearly UMS congestion statistics for several reasons. First, the yearly statistics provided a considerably larger sample size relative to the quarterly congestion data (i.e., 101 vs. 52 UAs). Second, only the long historical record of the yearly congestion statistics overlapped all the years included in the 2011 Edition of the NLCD. This ultimately enabled the longitudinal structure of the study. The final sample included a balanced panel dataset of 98 UAs within the conterminous United States, where each UA had an observation in 2001, 2006, and 2011, respectively. Three of the 101 UAs incorporated in the UMS were omitted because they were located outside the continental US. Fig. 1 shows the spatial distribution of the 98 UAs, which highlights the variety of urban forms, city sizes, and geographical regions captured by the sample.

3.2. Congestion measures

Three congestion measures from the UMS were considered because previous studies have highlighted the sensitivity of findings to the

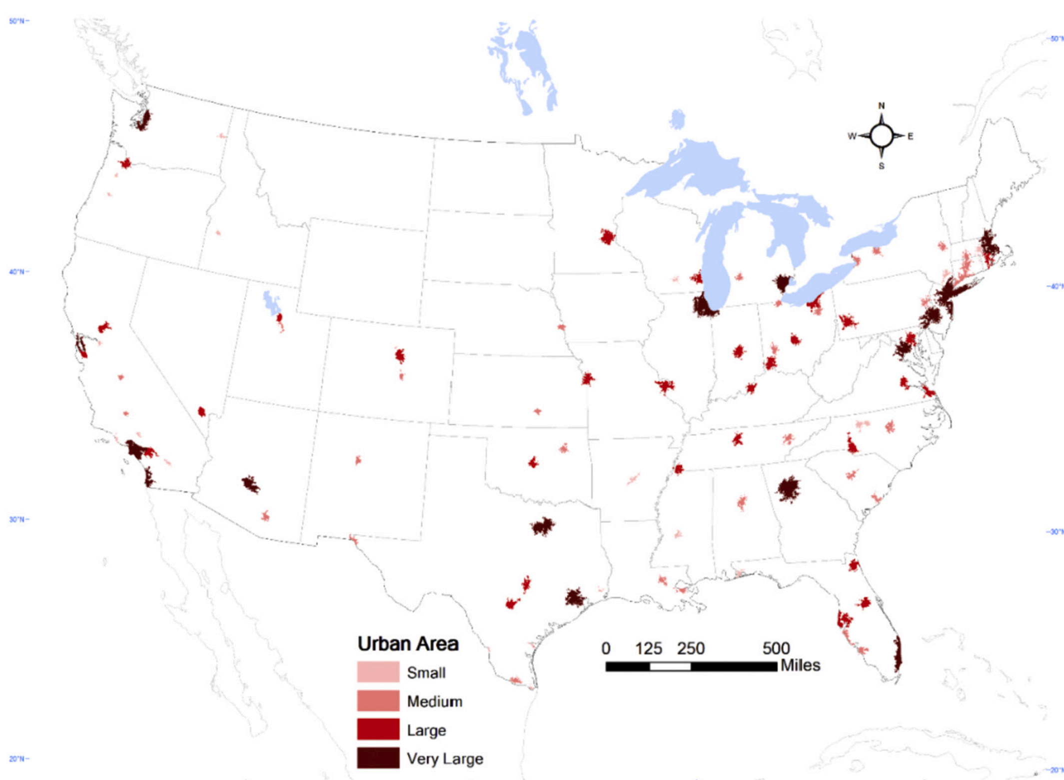


Fig. 1. Location of the 98 urbanized areas (UAs) included in the study. UAs are color-coded by their population sizes: Small = less than 500,000; Medium = 500,000 to 1 million; Large = 1 million to 3 million; Very Large = more than 3 million.

specific type of congestion analyzed (Sarzynski et al., 2006). The included congestion variables evaluated different aspects of traffic congestion using distinct metrics (e.g., delays, fuel consumption, etc.). The first congestion measure was total annual excess fuel consumed (*AEFC*, in thousands of gallons), which has been previously used in congestion studies (e.g., Wang & Zhou, 2017). *AEFC* is determined by

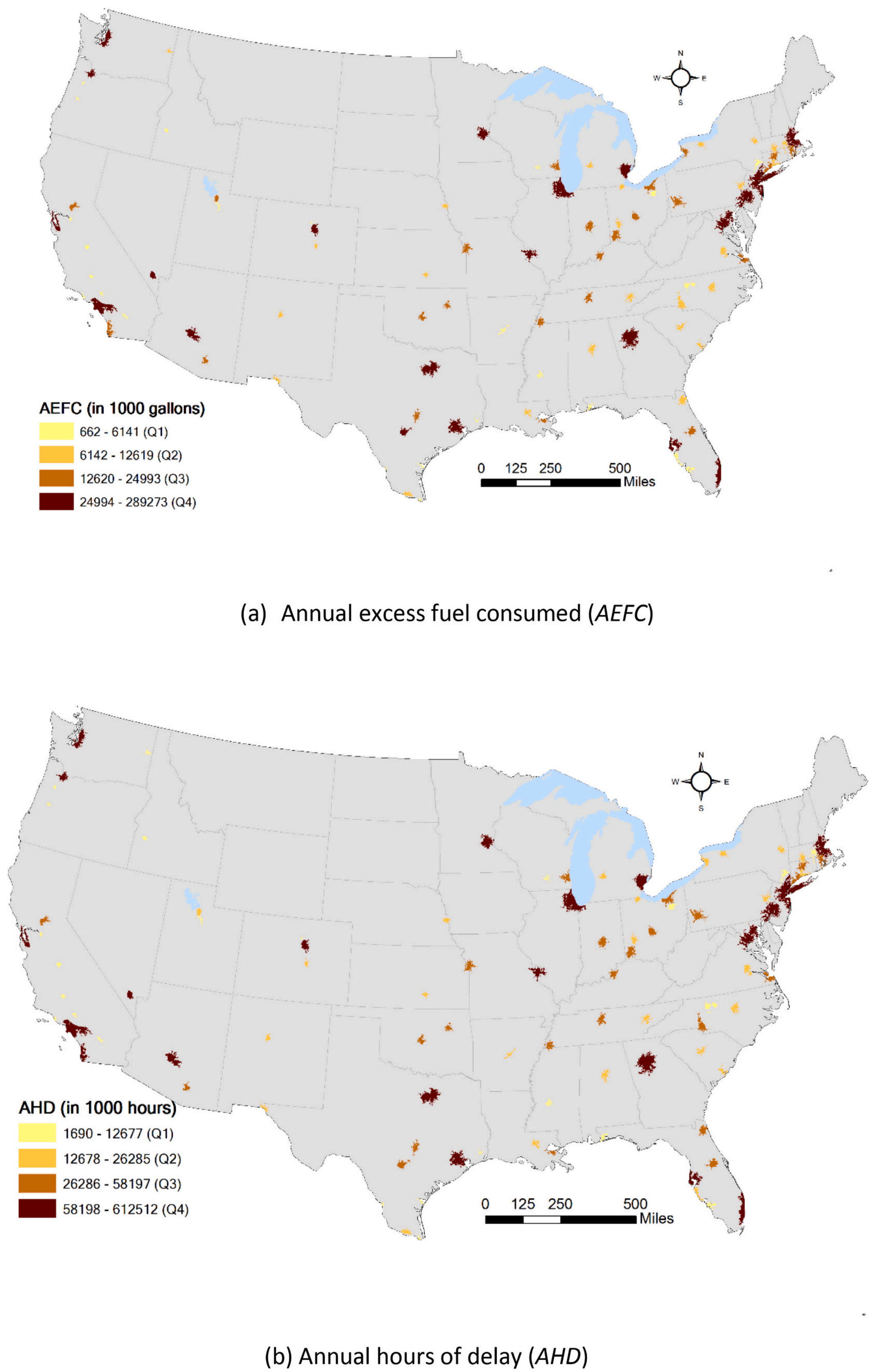
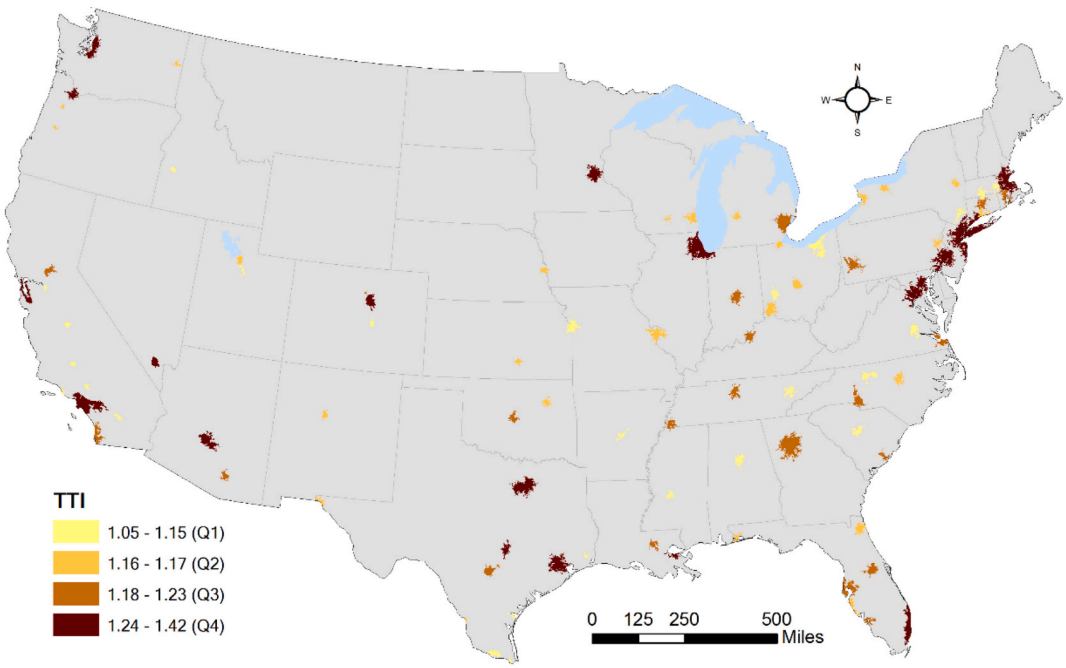


Fig. 2. Spatial distributions of the three traffic congestion measures in 2011.



(c) Travel Time Index (*TTI*)

Fig. 2. (*continued*).

comparing fuel consumption during congested conditions with fuel consumption during free-flowing conditions, which quantifies the overall congestion level within a UA. Annual hours of delay (*AHD*, in thousands of hours) was selected as the second measure of overall congestion because it evaluates traffic congestion from a temporal perspective. Conceptually, *AHD* is calculated as the cumulative difference between daily travel hours at actual speed and daily hours of travel at free-flowing speed throughout a year.

Finally, we adopted the Travel Time Index (*TTI*) to measure rush-hour congestion and enable comparisons with the two overall congestion variables. *TTI* is defined as the ratio of the travel time during rush hour divided by the time of the same trip under free-flowing conditions, which essentially captures congestion during work commutes. A *TTI* value of 1.1 can be interpreted as an 11-minute trip during rush hour that would only require 10 minutes in free-flowing conditions (i.e., 1.1 = 11/10). Rush hour includes the morning peak between 6 am and 10 am and the evening peak between 3 pm and 7 pm. Because it is a unitless measure, *TTI* enables us to compare trips of various distances and evaluate excess commuting travel time relative to a free-flowing baseline. Fig. 2 shows the geographical distributions of the three congestion measures. The varying spatial patterns suggest that the different variables are indeed capturing distinct dimensions of traffic congestion, which will help clarify if urban morphology influences these various types of congestion in a similar manner.

3.3. Spatial metrics

To quantify both the abundance and configuration of urban development within the UAs, spatial metrics were calculated using version 4.2.1 of FRAGSTATS (McGarigal, Cushman, & Ene, 2012). An extensive number of metrics are available within the FRAGSTATS software, but this study focused on spatial metrics previously used to quantify the geographical patterns of urban development (e.g., Debbage, Bereitschaft, & Shepherd, 2016; Herold et al., 2005; Kang, Ma, Tong, & Liu, 2012). Specifically, for each NLCD urban land use category, three spatial metrics that evaluated distinct dimensions of urban morphology were analyzed, including Percentage of Landscape (PLAND), Largest Patch Index (LPI), and Percentage of Like Adjacencies (PLADJ). PLAND is a basic composition metric, which determines the relative quantity of urban land use within a city. Monocentricity was assessed by LPI, which measures the relative dominance of the largest urban patch. LPI shares similarities with the centrality and nuclearity dimensions investigated by Sarzynski et al. (2006). Finally, PLADJ quantifies the contiguity of urban development through an evaluation of the number of like adjacencies (i.e., urban pixels neighboring other urban pixels), which is comparable to the continuity concept also considered in Sarzynski et al. (2006). Several other spatial metrics, including patch density, edge density, and area-weighted mean fractal dimension, were also initially evaluated but ultimately not included since they did not improve the specifications of the regression models. The reader is referred to the FRAGSTATS help documentation for additional technical details describing the spatial metrics and the specific formulas used for their calculation.

The spatial metrics were derived from the 2011 Edition of the NLCD using data available for 2001, 2006, and 2011. The NLCD is a land use and land cover (LULC) dataset produced primarily through the unsupervised classification of satellite imagery obtained by Landsat. The dataset includes 20 LULC categories with a 30–meter spatial resolution and an overall accuracy of approximately 80% (Wickham et al., 2017). Prior to calculating the spatial metrics in FRAGSTATS, the NLCD data were clipped to each UA to align with the spatial extent of the congestion information. The three spatial metrics were then determined for the four NLCD urban categories (Classes 21–24) in each of the three study years. Importantly, the four NLCD urban categories were analyzed individually rather than utilizing a simplistic urban/non-urban binary since it was hypothesized that different urban development intensities would exhibit distinct relationships with congestion. This additional level of detail will also potentially help disentangle the conflicting findings of previous studies.

The least intense NLCD urban class is developed open space (Class 21), which generally includes large-lot single-family homes and vegetation within urban settings (e.g., urban parks, golf courses, etc.). Denser single-family housing units are generally incorporated within both the low-intensity developed (Class 22) and medium-intensity developed (Class 23) categories. High-intensity developed (Class 24) encompasses those areas where individuals reside/work in large quantities, such as row houses/apartments, commercial/industrial complexes, and city centers. Substantively, the interpretation of the metrics depends on the urban intensity category from which they are derived. For example, greater values of PLAND for Class 21 are generally indicative of more sprawling urban morphologies, whereas larger Class 24 PLAND values correspond with denser urban forms (Debbage et al., 2016). When evaluating Class 24, higher PLADJ and LPI values represent more contiguous, monocentric urban configurations that are also generally associated with less sprawling urban environments. Fig. 3 maps the five UAs with the smallest and largest values for select spatial metrics in 2011. The spatial distributions highlight the regional differences in urban morphologies, particularly between the eastern and western portions of the US.

3.4. Control variables

In addition to the spatial metrics, we included several widely adopted control variables to account for the potential influence of confounding factors such as socioeconomics and travel behavior. These variables were gathered from the UMS and US Census. The two control variables obtained from the UMS were the total population and the percentage of autocommuters. Total population (*Population*, in thousands) accounted for the different sizes of the UAs included in the study. The percentage of autocommuters (*AutoProp*), defined by dividing the total number of autocommuters by the total population, addressed the distinctive commuting behaviors within each UA. From the US Census, we incorporated variables for median household income and median age to control for the heterogeneous socioeconomic characteristics of the different UAs. American Community Survey (ACS) five-year estimates were used for the 2011 and 2006 study years. Conversely, the 2000 Decennial Census was utilized for 2001 since the ACS began in 2005. These specific control variables were selected because previous studies (e.g., Ewing et al., 2018; Wang & Zhou, 2017) have highlighted their significant influence on traffic congestion. Descriptive statistics for all the variables included in the models are reported in Table 1.

3.5. Panel regression and robustness tests

For the empirical analysis, all the control variables and dependent variables were transformed by taking natural logarithms to reduce the influence of potential outliers and enhance the linearity of the relationships. We employed a two-way fixed-effect panel regression model (Eq. (1)), where Y_{it} corresponds to the traffic congestion in the ith urban area during the year t. X_{it} is a suite of time-varying spatial metrics, while Z_{it} represents a set of time-varying control variables both for the ith urban area during year t. θ_i corresponds to the fixed-effect control variable for omitted variables that are time-invariant for the ith urban area, and δ_t is the fixed-effect control variable for trends in urban areas during year t. Finally, ε_{it} symbolizes the random error term for the ith urban area during year t. Wang and Zhou (2017) successfully utilized a similar panel regression approach to understand how bike-sharing systems influence congestion, so the model structure was adapted to analyze the relationships between urban morphology and traffic congestion. Panel regression provides several important advantages relative to more commonly utilized cross-sectional approaches. For example, panel data typically contain more degrees of freedom and sample variability, while panel regression provides a greater capacity for capturing complex relationships than a singular cross-sectional analysis (Hsiao, 2003; Ou et al., 2013).

$$Y_{it} = \beta X_{it} + \gamma Z_{it} + \theta_i + \delta_t + \varepsilon_{it} \quad (1)$$

Before reporting the results, we conducted several robustness tests to evaluate model assumptions and rule out other possible model specifications. First, we used the variance inflation factor (VIF) to examine the degree of multicollinearity amongst the independent variables. As a rule of thumb, a specification suffers from multicollinearity issues when the VIF is greater than 10 (Kutner, Nachtsheim, Neter, & Li, 2005). Second,

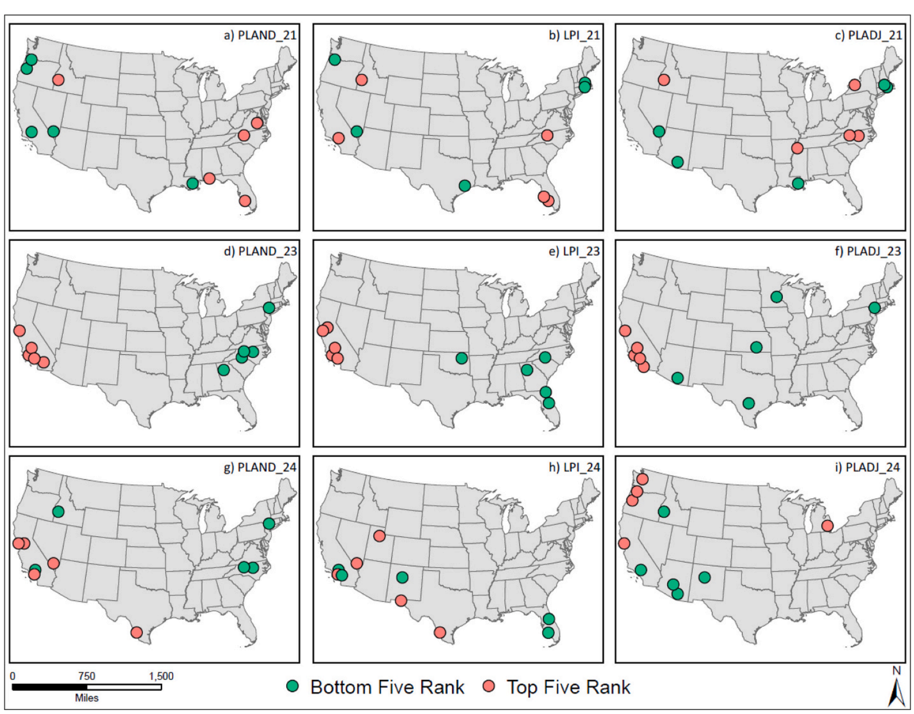


Fig. 3. Locations of the Urbanized Areas (UAs) with the five largest and smallest values for select spatial metrics in 2011: PLAND = Percentage of Landscape, LPI = Largest Patch Index, PLADJ = Percentage of Like Adjacencies, 21 = Developed Open Space, 23 = Medium-Intensity Developed, and 24 = High-Intensity Developed.

Table 1
Descriptive statistics of the variables included in the panel regression (N = 294).

Variable	Description	Mean	Std. Dev.	Min	Max
Population	Total population (in thousands)	1,632.551	2,451.684	95	18,860
med_Age	Median age	34.946	3.523	23.200	51.200
Income	Median household income (in USD)	49,624.290	9,987.363	24,352	92,031
AutoProp	Proportion of autocommuters	0.486	0.041	0.260	0.550
PLAND	Total urban land use for Classes 21, 23, and 24 (%)	42.698	8.298	25.729	68.185
PLAND_21	Developed open space urban land use (%)	19.712	6.080	6.984	37.466
LPI_21	Largest patch index of developed open space urban land use (%)	1.070	1.525	0.050	9.249
PLADJ_21	Like adjacencies of developed open space urban land use (%)	61.832	5.261	47.550	76.308
PLAND_23	Medium-intensity urban land use (%)	16.820	8.394	4.352	42.710
LPI_23	Largest patch index of medium-intensity urban land use (%)	3.345	6.385	0.030	37.921
PLADJ_23	Like adjacencies of medium-intensity urban land use (%)	54.976	7.232	43.189	78.397
PLAND_24	High-intensity urban land use (%)	6.165	3.057	0.570	14.873
LPI_24	Largest patch index of high-intensity urban land use (%)	0.840	0.939	0.022	4.526
PLADJ_24	Like adjacencies of high-intensity urban land use (%)	63.388	7.083	37.632	74.354

the F-test for individual and/or time effects and the Lagrange Multiplier (Breusch-Pagan) test for balanced panels were utilized to evaluate if a panel model (i.e., either a fixed-effects or random-effects model) was preferable to an OLS alternative. Third, the Hausman test, which evaluates the null hypothesis that panel regression with random effects is superior to a fixed-effects model, was used to verify the specification of the two-way fixed-effects model. Fourth, the Augmented Dickey-Fuller test was performed to evaluate the stationarity of the congestion variables with a first-order lag. If the test fails to reject the null hypothesis of the unit root, the first-order difference of the congestion variables must be taken to stabilize the time series. Finally, we reported robust standard errors grouped at the UA level for all the estimates to account for any potential issues associated with heteroscedasticity (Arellano, 1987).

4. Results

Several panel regression models were estimated to quantify the relationships between the three congestion measures and the urban morphological characteristics evaluated via the spatial metrics (Tables 2–4). Notably, the diagnostic tests confirmed the appropriateness of the model specifications. The VIF values ranged from 1.394 (*MedAge*) to 5.921 (*PLAND*), with an average of 2.768. The VIFs never exceeded 10, which indicated that the models did not suffer from multicollinearity issues. A significant F-test for individual effects (F = 2931.4, $p < 0.001$) and a significant Lagrange Multiplier (Breusch-Pagan) test (Chi-sq. = 238.86, $p < 0.001$) demonstrated that a panel regression model with either fixed-effects or random-effects, respectively, was superior to an OLS specification. Therefore, the Hausman test was applied to determine which panel regression model was more appropriate. A significant result for the Hausman test (Chi-sq. = 35.585, $p < 0.001$) suggested that a fixed-effect model was preferable. Finally, a significant Augmented Dickey-Fuller Test ($p = 0.01$) indicated that we did not need to take the variable's first-order difference. Overall, the various diagnostic checks demonstrated that a two-way fixed-effect panel regression model provided a robust modeling approach.

The baseline model that included only control variables (Table 2, Model 1) explained 74% of the variability in annual excess fuel consumed (*AEFC*). Because all the control variables and dependent variables were log-transformed, the beta coefficients can be interpreted as elasticities. Specifically, the coefficients indicated that population size and median age had a substantial and statistically significant influence on congestion. A 1% increase in UA population (*Population*) was associated with a 0.92% increase in annual excess fuel consumed, while a 1% increase in median age (*MedAge*) was associated with a 1.37% decrease. Although the control variables for income and percentage of autocommuters were also statistically significant, their coefficients exhibited relatively modest magnitudes. A 1% increase in median household income (*Income*) or the percentage of autocommuters (*AutoProp*) was associated with only a 0.53% and a 0.61% increase in annual excess fuel consumed. Overall, the highly significant coefficients highlighted the importance of incorporating control variables when modeling the relationships between urban morphology and traffic congestion.

Table 2
Panel regression results for Annual Excess Fuel Consumed (*Dependent variable: AEFC;* N = 294).

	Model 1 (Baseline)	Model 2 (Full model)	Model 3 (Low intensity)	Model 4 (Medium intensity)	Model 5 (High intensity)
Population	0.9212*** (0.0903)	0.7312*** (0.0831)	0.8223*** (0.0899)	0.8025*** (0.0913)	0.8737*** (0.0868)
MedAge	−1.3699*** (0.4740)	−1.4044*** (0.4405)	−1.3418*** (0.4415)	−1.4276*** (0.4599)	−1.4197*** (0.4783)
Income	0.5253*** (0.1726)	0.5625*** (0.1559)	0.6292*** (0.1840)	0.4810*** (0.1535)	0.5238*** (0.1731)
AutoProp	0.6128** (0.2964)	0.3425 (0.2927)	0.4362 (0.2865)	0.7495*** (0.2764)	0.4395 (0.3203)
PLAND		0.0228*** (0.0072)			
PLAND_21			0.0233* (0.0130)		
LPI_21		−0.0743** (0.0292)	−0.1078*** (0.0367)		
PLADJ_21		−0.0063 (0.0087)	−0.0115 (0.0092)		
PLAND_23				0.0249** (0.0125)	
LPI_23		0.0026 (0.0063)		0.0017 (0.0073)	
PLADJ_23		−0.0212 (0.0130)		−0.0271* (0.0147)	
PLAND_24					0.0463** (0.0234)
LPI_24		−0.1747*** (0.0544)			−0.1585*** (0.0398)
PLADJ_24		0.0007 (0.0044)			−0.0018 (0.0053)
Adjusted R^2	0.74	0.77	0.76	0.76	0.75
F Statistic	158.11*** (df = 6; 193)	14.48*** (df = 13; 183)	112.46*** (df = 9; 187)	112.40*** (df = 9; 187)	109.17*** (df = 9; 187)

Notes: *p < 0.1; **p < 0.05; ***p < 0.01; Year fixed effects and UA fixed effects are controlled. Robust standard errors clustered at UA level are in parenthesis.

Table 3
Panel regression results for Annual Hours of Delay (*Dependent variable: AHD;* N = 294).

	Model 6 (Full model)	Model 7 (Low intensity)	Model 8 (Medium intensity)	Model 9 (High intensity)
Population	0.7315*** (0.0831)	0.8224*** (0.0898)	0.8028*** (0.0913)	0.8738*** (0.0867)
MedAge	−1.4048*** (0.4405)	−1.3422*** (0.4415)	−1.4281*** (0.4598)	−1.4201*** (0.4783)
Income	0.5623*** (0.1558)	0.6290*** (0.1840)	0.4808*** (0.1535)	0.5237*** (0.1730)
AutoProp	0.3421 (0.2927)	0.4360 (0.2865)	0.7488*** (0.2763)	0.4390 (0.3203)
PLAND	0.0228*** (0.0072)			
PLAND_21		0.0232* (0.0130)		
LPI_21	−0.0743** (0.0292)	−0.1077*** (0.0367)		
PLADJ_21	−0.0063 (0.0087)	−0.0115 (0.0092)		
PLAND_23			0.0248** (0.0125)	
LPI_23	0.0026 (0.0063)		0.0017 (0.0073)	
PLADJ_23	−0.0212 (0.0130)		−0.0270* (0.0147)	
PLAND_24				0.0462** (0.0233)
LPI_24	−0.1745*** (0.0543)			−0.1584*** (0.0397)
PLADJ_24	0.0007 (0.0044)			−0.0018 (0.0053)
Adjusted R^2	0.77	0.76	0.76	0.75
F Statistic	84.85*** (df = 13; 183)	112.51*** (df = 9; 187)	112.44*** (df = 9; 187)	109.21*** (df = 9; 187)

Notes: *p < 0.1; **p < 0.05; ***p < 0.01; Year fixed effects and UA fixed effects are controlled. Robust standard errors clustered at UA level are in parenthesis.

Table 4
Panel regression results for Travel Time Index (*Dependent variable: TTI;* N = 294).

	Model 10 (Full model)	Model 11 (Low intensity)	Model 12 (Medium intensity)	Model 13 (High intensity)
Population	−0.0320** (0.0152)	−0.0235 (0.0147)	−0.0258* (0.0145)	−0.0242* (0.0139)
MedAge	−0.1441** (0.0601)	−0.1334** (0.0571)	−0.1430** (0.0589)	−0.1405** (0.0583)
Income	0.0738*** (0.0168)	0.0742*** (0.0192)	0.0678*** (0.0176)	0.0681*** (0.0181)
AutoProp	−0.0803 (0.0537)	−0.0631 (0.0526)	−0.0413 (0.0473)	−0.0744 (0.0571)
PLAND	0.0018* (0.0009)			
PLAND_21		0.0012 (0.0017)		
LPI_21	−0.0022 (0.0032)	−0.0049 (0.0035)		
PLADJ_21	−0.0010 (0.0010)	−0.0010 (0.0011)		
PLAND_23			0.0018* (0.0011)	
LPI_23	−0.0004 (0.0009)		−0.0004 (0.0010)	
PLADJ_23	−0.0022 (0.0018)		−0.0025 (0.0018)	
PLAND_24				0.0066** (0.0031)
LPI_24	−0.0182*** (0.0056)			−0.0207*** (0.0056)
PLADJ_24	0.0002 (0.0009)			−0.0003 (0.0009)
Adjusted R^2	0.266	0.243	0.251	0.270
F Statistic	16.64*** (df = 13; 183)	22.25*** (df = 9; 187)	30.72*** (df = 9; 187)	23.80*** (df = 9; 187)

Notes: *p < 0.1; **p < 0.05; ***p < 0.01; Year fixed effects and UA fixed effects are controlled. Robust standard errors clustered at UA level are in parenthesis.

Including the spatial metrics for each of the urban land use intensities slightly improved the Adjusted R^2 of the full model to 0.77 (Table 2, Model 2), which indicated that urban morphological characteristics helped further explain congestion. A one percentage point increase in the relative abundance of urban land use (*PLAND*, the summation of developed open space, medium-intensity, and high-intensity urban land use percentages) was associated with a 2% (i.e., (exp (0.023) – 1) * 100%) increase in annual excess fuel consumed. This suggests that more urbanized cities generally exhibited significantly higher levels of congestion. Notably, the LPI for both the developed open space and high-intensity urban land use categories displayed a significant negative relationship with congestion. A one percentage point increase in *LPI_21* or *LPI_24* corresponded with a 7.2% and 16.0% decrease in annual excess fuel consumed, respectively. The result for *LPI_24* highlighted the notable influence of polycentricity, as more monocentric urban cores were associated with less traffic congestion. At the same time, the *LPI_21* finding suggested that a dominant patch of developed open space also helped moderate congestion but to a lesser degree.

Models 3–5 (Table 2) explored the heterogeneous influences of the different urban land use intensities on traffic congestion by examining the spatial metrics for each urban category individually. Because the goodness-of-fit for these three models was better than the base model, the inclusion of spatial metrics derived from any urban land use intensity appeared to improve the predictability of traffic congestion. However, the Adjusted R^2 values for Models 3–5 were smaller than the value for the full model, which suggested that including spatial metrics for all the urban land use intensities simultaneously was superior to any partial inclusion. Nevertheless, Models 3–5 helped disentangle the specific roles of the individual urban land use categories and supplemented the insights provided by the full model. The coefficients for PLAND demonstrated that the relative abundance of high-intensity urban development was the most influential composition metric. Specifically, a one percentage point increase in either *PLAND_21* or *PLAND_23* was associated with a ~ 2% increase in annual excess fuel consumed, while a one percentage point increase in *PLAND_24* resulted in a 4.7% increase. The LPI results demonstrated a similar trend as the coefficient for *LPI_24* displayed a larger magnitude than the coefficient for *LPI_21*. This mirrored the full model results but again emphasized the important influence of high-intensity urban development on congestion. Interestingly, *PLADJ_23* exhibited a marginally significant relationship, as a one percentage point increase in like adjacencies was associated with a 2.7% decrease in annual excess fuel consumed. The *PLADJ_23* finding indicated contiguity might be another urban morphological characteristic that influences congestion, with more contiguous urban forms reducing traffic congestion issues.

In Table 3, we re-estimated Models 2–5 with annual hours of delay (*AHD*) serving as the dependent variable. The coefficients for the *AHD* models (Models 6–9) were remarkably similar to the results for *AEFC*. The high degree of similarity was likely due to the two measures both evaluating general congestion, even though they relied upon different metrics (i.e., hours versus gallons). The panel regression results provided a starker contrast for the travel time index (*TTI*), which evaluated rush hour congestion (Table 4). The overall explanatory power of the *TTI* models was substantially lower, as only approximately one-quarter of the variability in the travel time index was explained by the control variables and spatial metrics. The high-intensity model (Model 13) displayed a superior Adjusted R^2 to the full model (Model 10), highlighting the elevated influence of high-intensity urban land uses on rush-hour congestion relative to the other urban categories. Specifically, the coefficients indicated that urban morphologies with a greater abundance of high-intensity urban land use arranged in a more polycentric manner were associated with larger travel time index values. The spatial metrics derived from the developed open space and medium-intensity categories were never significantly related to *TTI* at the $p < 0.05$ level. Finally, although most of the control variables in Models 10–13 exhibited directions identical to the *AEFC* and *AHD* models, the UA population was a notable exception because it was negatively related to *TTI*. This suggests that less populated cities generally exhibited greater travel times during rush hour relative to non-rush hour for a given urban morphology. The following section outlines how the results compared to previous studies and elaborates upon the notable differences observed between general and rush-hour congestion.

5. Discussion

The models performed favorably relative to previous regression studies that considered similar congestion measures. For example, when analyzing the influence of urban morphology on delay per capita, which is analogous to our Model 6 (Adjusted $R^2 = 0.77$), the multiple regression models estimated by Ewing et al. (2003) and Sarzynski et al. (2006) produced Adjusted R^2 values of 0.63 and 0.69, respectively. The superior Adjusted R^2 of Model 6 suggests that the two-way fixed-effect panel regression modeling technique provided a robust approach to quantifying the relationships. Additionally, the favorable comparison reflects the overall utility of leveraging spatial metrics to quantify urban morphological characteristics when analyzing urban form's influence on traffic congestion. In each of the models, the control variables were also highly significant, which reaffirmed the importance of controlling for potentially confounding influences on congestion (Sarzynski et al., 2006).

In terms of the specific urban morphology results, the models indicated that cities with a greater relative abundance of urban land use were associated with higher congestion levels. Thus, the findings empirically supported the longstanding notion that traffic congestion is a negative externality of urbanization. Importantly, the modeling results highlighted that the relative quantity of high-intensity urban land use was particularly influential in enhancing congestion. The magnitudes of the coefficients for *PLAND_24* were approximately two and five times greater than the *PLAND_21* coefficients for general congestion and rush-hour congestion. These notable differences observed between the various urban intensities demonstrated the importance of considering the urban categories individually rather than grouping them into a simplistic urban/non-urban binary.

The spatial configuration of urban development was also significantly related to congestion. The *LPI_24* variable suggested that more monocentric urban morphologies characterized by a single dominant high-intensity urban core were associated with lower traffic congestion levels. This result supports the findings of Ewing et al. (2003), who observed a similar significant negative relationship between a “degree of centering” factor and annual hours of traffic delay per capita. Additionally, Sarzynski et al. (2006) included a “nuclearity factor” in their models that displayed a negative relationship with most of the congestion measures considered, although not at a statistically significant level. The findings for *LPI_24* also closely align with previous studies that have linked enhanced levels of carbon emissions with polycentric urban forms (Wang et al., 2017). The panel regression provided marginal evidence that more contiguous medium-intensity development (Model 4 & 8) was associated with less general congestion. This contradicts the findings of Sarzynski et al. (2006), which documented a significant positive relationship between a density/continuity factor and several congestion measures. This difference was perhaps due to the density/continuity factor of Sarzynski et al. (2006) incorporating a density dimension, whereas the spatial metric (*PLADJ_23*) solely evaluated contiguity.

Finally, substantial differences were observed between the general congestion (Tables 2 & 3) and rush hour congestion (Table 4) models. The lower Adjusted R^2 values for the *TTI* models indicated that rush hour congestion was more challenging to predict. This was potentially due to the idiosyncrasies of rush hour commuting patterns that are specific to a given urban area and less directly influenced by urban morphology. A second noteworthy discrepancy was the dominant influence of high-intensity urban land use on rush-hour congestion, while both developed open space and high-intensity development were significantly associated with general congestion. The elevated importance of the high-intensity category for rush hour congestion can likely be attributed to the concentration of rush hour travel within urban cores and along highly urbanized arteries. These important differences were only detected because each urban category was evaluated independently via spatial metrics. In fact, the *PLAND* variable included in Model 10 that grouped the urban categories appeared to obscure the importance of high-intensity urban development, which resulted in a less significant coefficient and a lower Adjusted R^2 for the full model. A final discrepancy worth nothing involved the coefficients of the population control variable, which were negative in the rush hour congestion models but positive in the general congestion models. This switch of direction highlights the potential volatility of the relationships between population and population-based measures of urban form and congestion. Overall, it appeared that the spatial metrics identified more consistent relationships, perhaps because they provided more direct evaluations of urban morphology.

Nevertheless, there are some limitations of this study, which also provide opportunities for future investigations. First, while we adopted a suite of well-established and widely applied urban morphology metrics (e.g., Debbage et al., 2016; Herold et al., 2005; Kang et al., 2012; Sarzynski et al., 2006) to highlight the importance of the spatial configuration of urban development on traffic congestion, they are by no means exclusive or exhaustive. Future studies could investigate additional urban morphology metrics that may provide further insights into the relationships between urban form and traffic congestion. Alternatively, policy-aware and context-aware urban morphological measures could be applied to understand the effectiveness of particular policies on traffic congestion in a specific geographical locale. For example, a recent paper by Derudder et al. (2021) emphasized the necessities of conceptual, mathematical, and empirical concerns when developing and using a polycentric urban development measure. Second, while both the land cover and urban congestion data utilized in this study were the most granular data that we could obtain, they are at an aggregated level where the spatiotemporal details could be strengthened in the future. From a spatial perspective, while the NLCD from the MRLC consortium provides a consistent dataset for decades, it only produces such data at a 30-m spatial resolution. LULC information with additional granularity may produce more nuanced knowledge of urban spatial configuration. From a temporal perspective, the urban congestion data are aggregated annually, which obfuscates the intra-annual or seasonal variability of traffic congestion. Relatedly, because the congestion data are provided for entire urban areas, we could not capture any intra-urban variations of urban congestion. In large and very large US urban areas, the explanations and predictions of heterogeneous traffic congestion within individual urban areas may provide more practical knowledge for urban planning and management. Finally, this study focused on the US context and provided longitudinal evidence regarding the relationship between urban morphology and traffic congestion. Therefore, the findings may not be relevant to other geographical contexts.

6. Conclusion

This study analyzed 98 urban areas throughout the US using spatial metrics and robust panel regression modeling to clarify the relationships between urban morphology and traffic congestion. In terms of the original research questions, the results indicated that:

- Polycentric urban morphologies were associated with greater levels of congestion
- The abundance and polycentricity of high-intensity urban land use exhibited the strongest relationships with the congestion measures
- Urban morphology influenced general congestion to a greater extent than rush-hour congestion

Importantly, deriving the spatial metrics from individual urban categories provided a more nuanced understanding of how both the abundance and spatial configuration of various urban land uses influenced traffic congestion.

From a landscape management and urban planning perspective, the detailed spatial metric findings demonstrated the significant influence of both the abundance and spatial configuration of urban development on congestion. This suggests that land use policies guiding urban configuration can play an equally important role in alleviating congestion as measures designed to limit the overall quantity of development. Most of the relationships indicated that a monocentric urban morphology characterized by a single dominant high-intensity urban core was beneficial to reducing general and rush-hour congestion. Additionally, contiguous medium-intensity development and monocentric developed open space appeared to alleviate general congestion further. This indicates that policies influencing the configuration of both the urban core and urban periphery could be advantageous.

Of course, future research analyzing a larger number of cities will be necessary to understand how these relationships might vary when incorporating smaller urban areas. Exploring alternative quantitative approaches to capture the complex influence of urban morphology on congestion, such as machine learning algorithms, could also prove helpful. Nevertheless, these findings provide further evidence that compact and monocentric urban forms could potentially remedy the growing congestion issues amongst cities in the United States.

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