Megaregion Truck Flow Estimation Model

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16. Abstract

Freight transportation has played a critical role in the growth of megaregion economies. However, most of the existing freight studies have focused on goods movement at the national, state, or metropolitan levels. Megaregion truck transportation has not received much attention. This research intends to develop an analytical model for estimating megaregion truck flows, which is an extension of the regional freight model developed in our previous studies. It utilizes the data from the most recent Freight Analysis Framework (FAF) and implements the extended analytical framework to estimate baseline truck flows in megaregion highway networks. Because the FAF data ignores the details of truck movement within large metropolitan areas, the centroids in the FAF's zonal system will be redesigned by adding multiple freight external stations or intermodal facilities as network centroids. The estimated link-level truck flows are expected to support the evaluation of freight mobility and facilitate the decision-making process of policy makers for megaregion freight transportation planning. In addition to an understanding of the spatial patterns of megaregion truck flows, it also explores their temporal patterns, especially the night time truck traffic patterns. It selects Texas Triangle as an empirical case to demonstrate the implementation of the megaregion truck flow model.

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1. Introduction

According to “Beyond Traffic 2045”, the US population is expected to increase by about 70 million in 30 years, from 320 million in 2015 to 390 million by 2045. The US economy GDP is forecasted to grow by 115% to $36.7 trillion during the same period. America 2050 has identified 11 megaregions in the US, shown in Figure 1. About 75 percent of US population and employment are located in these megaregions, which are defined as a network of metropolitan centers and their surrounding areas that are spatially and functionally linked through environmental, economic, and infrastructure interactions (Rose 2009). This definition regards metros not only as the ‘space of places’ but the ‘space of flows’ such as transportation, information, and business networks (Lang and Dhavale, 2005). In planning practice, the megaregions are usually identified as adjacent urban areas clustered together based on their socio-economic relationships, common interests, and connections through transportation and communication channels. These megaregions are projected to absorb most of the growing population, which means they are expected to meet the increasing demands for jobs, goods, and public services. They are expected to face more significant pressures on infrastructure adequacy suggesting they will need substantial improvements to bring their infrastructure up to acceptable levels of service (Amekudzi et al. 2007).

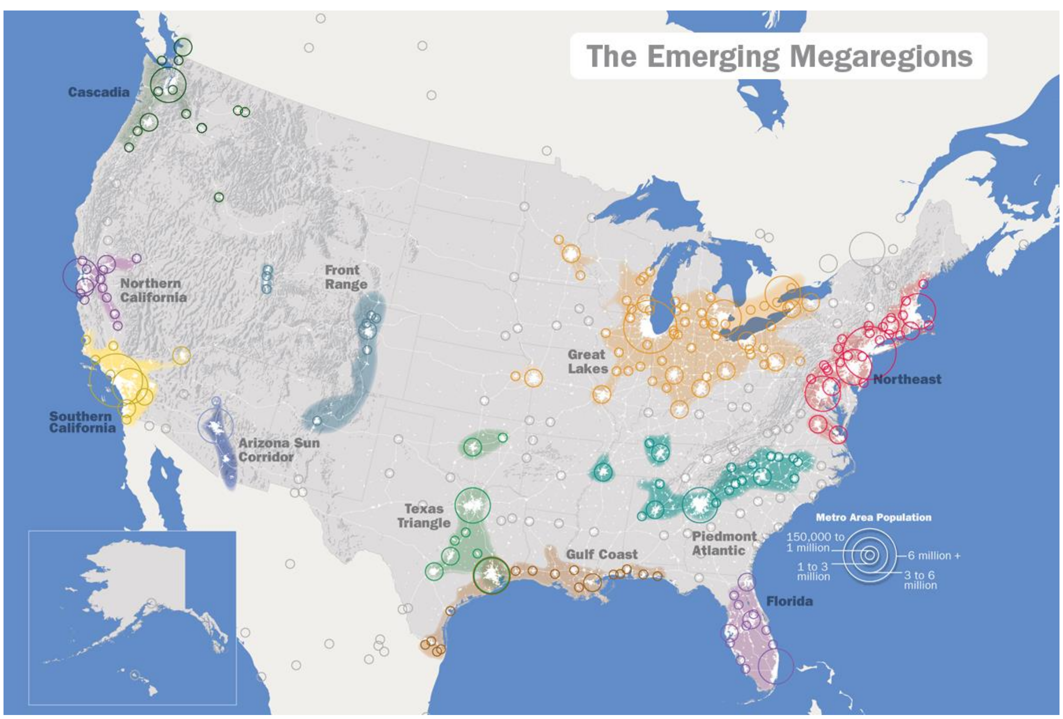


Figure 1. Megaregions in the US identified by America 2050
(Source: http://www.america2050.org/content/megaregions.html)

With rapid growth of population, employment, domestic and international trade, demands for freight transport has grown as well. Transportation planning has been facing the challenges of moving goods in an efficient way, reducing the various nuisances associated with freight transport, and facilitating the improvement of freight mobility. Truck mobility has become one of the major concerns of transportation planners because trucks are the dominant mode of freight transportation and also one of the major contributors to congestion and emissions on highways. To facilitate efficient freight transport, improved competence of the regions, and ensure the success of the megaregional economy, it is necessary to gain a better understanding of the patterns of truck movement in megaregions. It is hard for decision makers to gain a comprehensive overview of megaregion truck movement due to the lack of sufficient data and appropriate approaches. Many existing studies and analytical models for truck transportation are available at federal, state, and metropolitan levels. Few, if any, have examined truck transportation at the megaregion level.

Federal and state transportation departments have prepared their transportation improvement plans and developed freight analysis models. Bureau of Transportation Statistics (BTS) and Federal Highway Administration (FHWA) worked together to produce the Freight Analysis Framework (FAF) by integrating data from a variety of sources to estimate commodity flows and related freight transportation activities among states, major metropolitan areas, and major international gateways by all major modes of transportation. The average daily truck flows on the national highway system estimated by FAF is shown in Figure 2.

Many states also have their analytical models or transportation management systems for passenger and freight movement. Texas Department of Transportation (TxDOT), for instance, has developed and maintained the Texas Statewide Analysis Model (SAM) as a multi-modal model with statewide coverage and freight components developed using TransCAD. In addition to the development of freight analysis models at state level, TxDOT also supported a number of freight studies within the state boundary. Michael Walton and his colleagues analyzed relevant freight data and started engaging Texas shippers and freight stakeholders in a dialogue to provide insights into how freight moves on the Texas transportation infrastructure (Prozzi et al. 2011). Harrison et al. (2006) implemented freight performance measures (FPMs) to evaluate the accomplishment of goals and objectives of freight highway corridors in Texas.

Figure 2. Average Daily Long-Haul Truck Traffic on the National Highway System: 2012
Source: U.S. Department of Transportation, Bureau of Transportation Statistics and Federal Highway Administration, Freight Analysis Framework, Version 4.3.1, 2016 (BTS 2018).

There are also freight analysis models developed in other U.S. states. The California Department of Transportation (Caltrans) has released multiple versions of its Intermodal Transportation Management System (ITMS) since 1996. As a GIS software package, ITMS was designed to bring together information about personal and freight transportation traffic flows into a consistent database and provide a quick response statewide transportation analysis tool for planning and policy studies on both person travel and freight movement. ITMS estimated freight movement by different modes based on data from a variety of sources (Caltrans 1996). The ITMS traffic analysis zones are based on existing zip code areas. As a major metropolitan area in California, the Los Angeles area was covered by ITMS and disaggregated freight data for the region were partially available from ITMS (Pan 2006).

In addition to the state transportation agencies in Texas and California, the Florida Department of Transportation (FDOT) developed the Florida Intermodal Statewide Highway Freight Model (FISHFM) to support the project-related work of FDOT and Florida's metropolitan planning organizations (MPOs). The goal of the model was to identify the needs and deficiencies that can be easily identified at the local level and may affect efficient freight transportation, and also to test solutions on those major freight corridors throughout the state, that have suffered from considerable congestion as they pass through metropolitan areas.

There are also several other statewide studies described in the National Cooperative Highway Research Program (NCHRP) report prepared by Cambridge Systematics (2008), such as the Minnesota Trunk Highway 10 Truck Trip Forecasting Model, Ohio Interim Freight Model, New Jersey Statewide Model Truck Trip Table Update Project, Indiana Commodity Transport Model, and Oregon Statewide Passenger and Freight Forecasting Model. Few of these state-level freight models have explicitly addressed issues about freight movement in megaregions.

At the metropolitan levels, the core functions of metropolitan planning organizations (MPOs) include the development of a transportation improvement plan (TIP) and the maintenance of a regional transportation plan (RTP). However, most state transportation agencies and MPOs have failed to encourage greater cooperation among individual MPOs (Seedah and Harrison, 2011). They lack analytical methods to estimate travel demands and measure the performance of transportation infrastructure on moving people and goods at the megaregion level. Zhang et al. (2007) argued that a megaregion approach can provide provocative and imaginative answers to growing problems of congestion, development disparity, and air pollution facing individual metropolitan areas or cities but are unlikely to be solved by each region individually. A megaregion transportation plan should integrate individual metropolitan transportation plans with consideration of inter-metropolitan people and goods movements within the megaregion.

Besides the development of freight analysis models at state or MPO levels, some state and local transportation departments have also sponsored freight movement studies of megaregions. Harrison et al. (2012) examined freight issues in the megaregions of Texas and tried to answer the question whether statewide freight planning can be enhanced through a megaregional approach. They progressed by conducting interviews and workshops with stakeholders from a variety of public and private sector entities. These freight research projects mainly focused on freight data and policy analysis.

There are few studies that explore the temporal patterns of truck flows, especially the night time truck traffic patterns. The Defense Meteorological Satellite Program (DMSP) / Operational Linescan System (OLS) data have been used to obtain nighttime lights generated by urban infrastructures. However, most of the relevant studies focus on measuring socioeconomic development, using remote sensing data as a proxy for the intensity of human activity, such as geographic extents, population density, and energy consumption. Even fewer, if any, examine the characteristics of night time truck flows.

To fill gaps in the existing literature and gain a better understating of the patterns of megaregion truck flows to facilitate the improvement of freight mobility, this research will develop an analytical model for estimating spatial and temporal patterns of truck flows in megaregions based on the available datasets. Texas Triangle is selected as an empirical case to demonstrate the implementation of the megaregion truck flow model.

2. Previous Studies

In the available literature, most studies of megaregions are still limited to pure academic interest. Dewar and Epstein (2007) analyzed the state of megaregion planning in the United States through the work of America 2050. They explained the public data available for the analysis of commute flows and truck flows. But their discussions are conceptual and descriptive, involving no quantitative methods for freight transportation analysis.

As Harrison et al. (2012) pointed out, applied research on megaregional freight planning is still at an early stage. For example, as one of the most discussed US megaregions, Texas Triangle includes these large metropolitan areas as the major bottlenecks for truck movement in Texas. The study by Harrison et al. (2012) has explored how the freight planning structure can be strengthened by adding a megaregional component. However, there is as yet no analytical model developed to estimate both the intra- and inter-metropolitan truck flows within the megaregion. It also lacks discussions on the temporal patterns of the truck flows. The study of megaregions is still limited to academic research.

Historical and economic census data were employed by Zhang et al. (2007) to discuss the complementarities and interconnectedness of the metros within the Texas Triangle. They reviewed the historical development and examined the economic structure of the triangle cities. They took both a normative view and heuristic modeling to understand the nature of future transportation demands in the Triangle region. They projected mobility change, mode shares, and total travel by mode for the Texas Triangle for 2020 and 2050. But their study did not project goods movement.

Seedah and Harrison (2011) explored the strategies for maintaining efficient future freight movement and to find multimodal solutions to moving freight to, between, and within the metropolitan economies of the megaregion. By selecting the Texas Triangle as a case study, they reviewed population growth, economic profile, and freight patterns of the Triangle and discussed megaregional planning strategies. Freight patterns were examined using the datasets from Freight Analysis Framework (FAF), version 3.1. But it was difficult to obtain the details of freight movement within individual metropolitan areas from the FAF data and connect freight demands to economic activities at the sub-metropolitan level.

As a part of the effort to develop a regional freight transportation model, a freight O-D matrix, mainly truck O-Ds, was constructed by Gordon and Pan (2001) and Pan (2006) via a low-cost approach, using secondary data sources. As an advance of these regional freight studies, Giuliano et al. (2007) extracted freight data automatically from online sources, which further reduced the cost of modeling freight movement. Cho et al. (2015) integrated a multiregional input–output (I–O) model with the US national highway network to simulate the economic impacts and changes in transportation system performance in the disruptions of highway infrastructure failures. The freight data and highway network from freight analysis framework (FAF) 2002 are employed in this study. It extended regional freight transportation models discussed in Pan (2006) and Giuliano et al. (2007) to analyze interregional and interstate freight flows. However, megaregion freight transportation was not discussed in this study.

Most of the existing freight studies model truck traffic at peak hours or day time. Existing research shows that it is possible to model truck flows at night using nighttime light data collected from remote sensing datasets. Dobson et al (2000) employed DMSP/OLS images to develop population database at global scale. In their study, not only DMSP/OLS images but also geospatial data, land cover and topology information, were used in the model. For greater accuracy, they proposed a potential research to explain the differences between daytime population pattern and nighttime one.

Doll et al (2000) parameterized the association between socioeconomic patterns and CO_2 emission using nighttime lights. It highlighted that DMSP/OLS images provided a significant advantage with the information relating the size and location of each urban district over a large area. Its uniqueness makes it possible to easily transform socioeconomic status to spatial information using pixel values.

DMSP/OLS images can also be utilized to understand electric energy consumption. He et al (2013) demonstrated that nighttime lights are practical resource to measure energy consumption. Nighttime light images have been used to explore damage levels driven by natural disasters (Kohiyama et al, 2004). Its estimation is based on measuring the reduction of urban lights by comparing their values before and after a disaster event. It implied the potential applications of estimating the impacts of disasters on human activities as an indirect effect.

Visible Infrared Imaging Radiometer Suite (VIIRS) images can overcome some weakness of DMSP/OLS data generated by the spatial resolution. As of now, the applications of VIIRS are not as much as DMSP/OLS because they are a relatively new source that brings some unexpected technical challenges. Nevertheless, the VIIRS data has started to be utilized in recent studies. Ma et al. (2014) estimated the magnitude of socioeconomic activity using VIIRS images. They found that nighttime lights induced significant positive associations with airport performance, population, gross domestic product, electronic energy consumption, and surface road traffic. A higher spatial resolution of images with nighttime light data makes it possible to extract built-up areas at global scale. Sharma et al (2016) estimated urban impervious coverage by integrating VIIRS images to MODIS data. Shi et al. (2015) parameterized freight traffic in China. They conducted statistical analysis using the amount of total freight traffics within each province. Their study highlighted the potential applications of VIIRS to explore transportation infrastructures and regional economic status.

To gain a better understating of megaregional truck flows and also facilitate the improvement of freight mobility, transportation planners and scholars call for a megaregion approach with an analytical framework for estimating spatial and temporal patterns of truck flows in megaregions on the base of available datasets.

3. Methodology

This research addresses issues of megaregion truck flows and develops an analytical framework for estimating truck flows at a megaregion level. Many existing freight studies have employed aggregate-level methods that are implemented as spreadsheet-based models. These have not taken into account the special characteristics of megaregions as networked metropolitan areas nor fully grasped the impacts of individual freight facilities like seaports, airports, airports, and rail yards on truck flows. They also maintain the unrealistic assumption that the attraction of freight movement to a zone is simply a function of the land use type within the zone and strength of relationship between zones. This does not consider the spatial location of the zones and the accessibility effects of other zones. They also ignored the temporal patterns of truck flows. These shortcomings have limited the effectiveness of freight models in policy analysis. All of these problems in freight studies call for an operational model designed for truck flow estimation in megaregions that can be developed at low costs. We have developed methods to examine spatial and temporal patterns of megaregion truck flows.

3.1 Estimate megaregion truck flows and examine their spatial patterns

To examine freight movement via a low-cost approach, Gordon and Pan (2001) and Pan (2006) constructed a freight O-D matrix, mainly truck O-Ds, using secondary data sources. Giuliano et al. (2007) further reduced the cost of modeling freight movement by acquiring freight data automatically from online sources. Their freight models can be extended for freight analysis at the megaregion level.

Similar to the freight models developed by Pan (2006), the analytical framework for megaregion truck flow estimation separates truck flows in a megaregion to the various inter-metropolitan and intra-metropolitan parts. The intra-metropolitan component refers to the truck movements within an individual metropolitan area of the megaregion while the inter-metropolitan part refers to the truck movement between the adjacent metropolitan areas of the megaregion.

This model is an integration inter-metropolitan goods movements by truck in Federal Highway Administration (FHWA)'s Freight Analysis Framework (FAF) database and the intra-metropolitan freight flows for metropolitan area highway networks. The commodity value and tonnage data are obtained from the FAF and other publicly available sources. FAF data are based mainly on the CFS and other components of the Economic Census. The original version of FAF provides estimates for 1998 and forecasts for 2010 and 2020 while the new version of FAF, i.e. the FAF version 4 (FAF4), includes the regional and state database of 2012-2015 and the forecasts through 2045 in 5-year intervals. The commodity origin-destination (O-D) database in the FAF estimates tonnage and value of goods shipped by type of commodity and mode of transportation among and within 132 predefined areas used in the 2012 CFS, as well as to and from eight international trading regions (Hwang et al. 2016). These predefined areas are called economic centroids. The FAF also provides highway link and trucking data in GIS format, as well as the models to disaggregate interregional flows from the Commodity O-D Database into flows among individual counties, which allows to estimate county-to-county O-D flows and loads the flows onto regional highway networks.

Because there is only one centroid typically defined even for a very large metropolitan area, the FAF's truck origin-destination (O-D) flows do not provide enough details about truck freight movements *within* a megaregion. In this research, the centroids in the FAF's zonal system will be redesigned by adding more detailed zonal system plus multiple freight external points such as seaports, airports, rail yards and highway entry-exit points in large metropolitan areas. Data for the freight external points can be manually added or obtained from local MPOs and public agencies that manage seaports, airports, rail yards, and highway weight stations. These freight external points are called network centroids.

To estimate detailed truck flows within metropolitan areas, the small number of economic centroids representing the FAF4 predefined areas with associated origin-destination (O-D) can be disaggregated to network centroids that are added to represent freight zonal system and external points. By following the procedures described by Pan (2006), attractions and productions of commodities are calculated for each network centroids. The analytical methods similar to those proposed by Pan (2006) can be adopted to estimate commodity flows and convert them to O-Ds for intra-metropolitan truck flows.

When the data for both intra-metropolitan and inter-metropolitan truck flows are ready, a user equilibrium (UE) freight model will be developed to estimate the truck freight values on each link of the roadway network. The truck freight values by link calculated via the analytical method proposed in this research can support the evaluation of freight mobility and facilitate the decision-making process of policy makers for megaregion freight transportation.

The equilibrium-based model employed to load freight flows by considering the network overloading condition is described as follows,

$$\text{Min} \sum_a \int_0^{x_a} C_a(x)dx \tag{2.1}$$

$$\text{subject to } x_a = \sum_o \sum_d \sum_p \delta_{a,p}^{od} h_p^{od} \quad \forall a \tag{2.2}$$

$$\sum_p h_p^{od} = T_{od} \qquad \forall o, d \tag{2.3}$$

$$h_p^{od} \geq 0 \qquad \forall p, o, d \tag{2.4}$$

where x_a is the total flow on link a.

$C_a(t)$ is the cost-flow function to calculate average travel cost on link a.

$\delta_{a,p}^{od}$ is link-path incidence variable; equal to one if link *a* belongs to path *p* connecting OD pair o and d,

h_p^{od} is flow on path *p* connecting OD pair o and d,

T_{od} is total trips between origin node o and destination node d,

p is a network path, o and d are two end nodes on the network.

This equilibrium-based freight model is usually computed using an iterative scheme, which repeats to load O-D truck trips onto network using link travel times that are continuously updated in response to loaded flows on network links and stops until the criterion of network condition is satisfied. The minimization of travel costs requires the solution of all feasible values to be generated at each step of iteration. When the results become convergent, the total travel costs of the network are minimized. The process is summarized as follows, Step 0: **Initialization**. Perform all-or-nothing approach for assigning freight trips simultaneously using free flow travel costs $C_a = C_a(0)$, for each link a on the empty network. Link flows x_a are obtained.

Step 1: **Update link travel times**. The travel time on link a is updated as $C_a = C_a(x_a)$.

Step 2: **Find a feasible descent direction**. Use the updated travel time $\{C_a\}$ for an all-or-nothing assignment for freight trips, which yields a set of auxiliary link flows $\{u_a\}$ combining both freight trips in PCEs.

Step 3: **Find optimal parameter**. A linear approximation algorithm (LPA) such as the Golden section or Bisection method described in Sheffi (1985) is applied to obtain optimal parameter α satisfying the following equation:

$$\text{Min} \sum_a \int_0^{x_a+\alpha(u_a-x_a)} C_a(x)dx$$

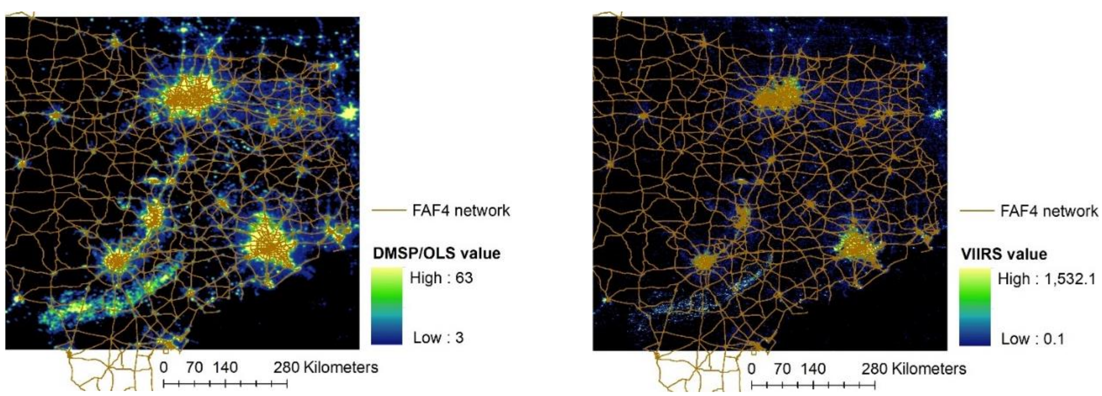
Step 4: **Update link flows**. Link flows x_a is changed to be $x_a+\alpha(u_a-x_a)$

Step 5: **Test Convergence.** The process stops when a convergence criterion is satisfied and link flows are the optimal link flows at equilibrium condition. Otherwise, go back to Step 1 and continue the process.

This approach has been utilized to model the integrated passenger and freight flows in a congested highway network system under a user equilibrium condition by Pan (2006). It can be employed to load truck flows to megaregion highway networks in a congestion situation.

3.2 Examine the nighttime truck flows in a megaregion using remote sensing data

Nighttime lights observed via remotely sensed data are used to extract diverse surface characteristics of urban activities. In our study, both DMSP/OLS and VIIRS instruments have been used to obtain nighttime images for diverse applications. Previous research demonstrated their applications in interdisciplinary research topics, such as urban population, socio-economic activity, energy consumption, urban expansion, natural disaster damage, and forest fires (Dobson, et al., 2000; Doll, et al., 2000; Fuller & Fulk, 2000; Kohiyama, et al., 2004; Sutton & Costanza, 2002; He, et al., 2013). While most of these studies employed DMSP/OLS in different ways and in different topics, the spatial resolution of the DMSP/OLS is 30 arc second, about 1 km in equator, which limits their applications at a large geographical scale (Li & Zhou, 2017). To obtain more specific information from nighttime images, VIIRS data have been used. It contributes to the understanding the relationships between urban density and the amount of truck mobility at a fine scale. The unit cell of VIIRS images is 15 arc second or 0.5 km in equator, which is approximate 2 times smaller than the images produced by DMSP/OLS (Elvidge, C., et al., 2017). Figure 3 shows the areas covering the Texas Triangle on DMSP/OLS and VIIRS images. The image by DMSP/OLS is composed of 1,009,785 cells. As for VIIRS data, the total number of cells is 2,020,648 and each cell represents a spatial unit.



(a) DMSP/OLS image (b) VIIRS image

Figure 3. Texas Triangle imagery

Spatial regression models are used to explain the relationship between Average Annual Daily Truck Traffic (AADTT) and VIIRS information with NLCD. First, it employs a spatial lag (SAR) model as follows,

$$AADTT = \alpha + \rho WAADTT + X\beta + \varepsilon \quad (2.5)$$

where W is the normalized spatial weight matrix, where the element w_{ij} is non-zero if cells i and j are neighbors and their values are zero otherwise,

WAADTT represents the average value of the neighboring observations of AADTT,

X is an independent variable,

β is the coefficients of the independent variables X,

ρ is the spatial lag coefficient, a measure of the strength of the SA,

α is constant coefficient and ε is the error term.

Second, it employs an SEM model as follows,

$$AADTT = \alpha + X\beta + \varepsilon \quad (2.6)$$
$$\varepsilon = \lambda W\varepsilon + u \quad (2.7)$$

where λ is the lag coefficient of the error term ε,
u is an error term with a normal distribution,
α, X, and β are the same as those in Equation (2.5).
For more information, see LeSage and Pace (2009).

4. Analysis

Our analysis employs Texas Triangle as an empirical case study to demonstrate the implementation of the megaregion truck flow model. Texas Triangle is one of the most discussed US megaregions. Its total population was 19.7 million in 2010, which was projected to reach 24.8 million by 2025 and 38.1 million by 2050 (RPA 2017).

The Freight Analysis Framework (FAF) 2012 provides link and node geographic reference data for the highway network. The commodity data are also obtained from the FAF dataset. The most recent version of FAF, i.e. the FAF version 4 (FAF4), has defined 132 domestic regions, which are called economic centroids in this study. There are nine domestic regions or economic centroids located within the state of Texas, including Austin, San Antonio, Dallas-Fort Worth, Houston, Laredo, Beaumont, Corpus Christi, El Paso, and the rest of Texas. Four of them, i.e. Austin, San Antonio, Dallas-Fort Worth, and Houston, represent the large metropolitan areas that form Texas Triangle, a megaregion completely located within Texas.

4.1. Truck flow estimation for Texas Triangle

This study has identified 38 border entry points for trucks moving in and out of Texas, which separate the state from the rest of the country. It also categorizes these border entry points as major entries or minor entries according to their truck volumes obtained from the FAF4 datasets, which reports the long-distance truck volume estimated based on the FAF 4 Origin-Destination truck tonnage. Empty trucks are included in the datasets.

The number of predefined domestic regions or economic centroids are too small to estimate the detailed patterns of truck flows in a megaregion. It has also been considered unrealistic to load trucks onto highway network through a single network node connecting to the economic centroid of a domestic region. It is possible to add multiple network nodes at the highway interchanges to connect a regional centroid to the highway network based on econometric and spatial analysis. The network nodes or so-called network centroids in this study are selected as freight external points such as seaports, airports, rail yards, and highway intersections to fine-tune the truck movements in a megaregion, especially for truck flows within a metropolitan area. This study has selected 579 network centroids manually by identifying the truck infrastructures in Texas Triangle and the rest of Texas. By adding two centroid connectors to each network centroid and incorporating those centroid connectors to the network links based on the FAF 2012 data set, the total number of network links is 80,260 in Texas (Figure 4).

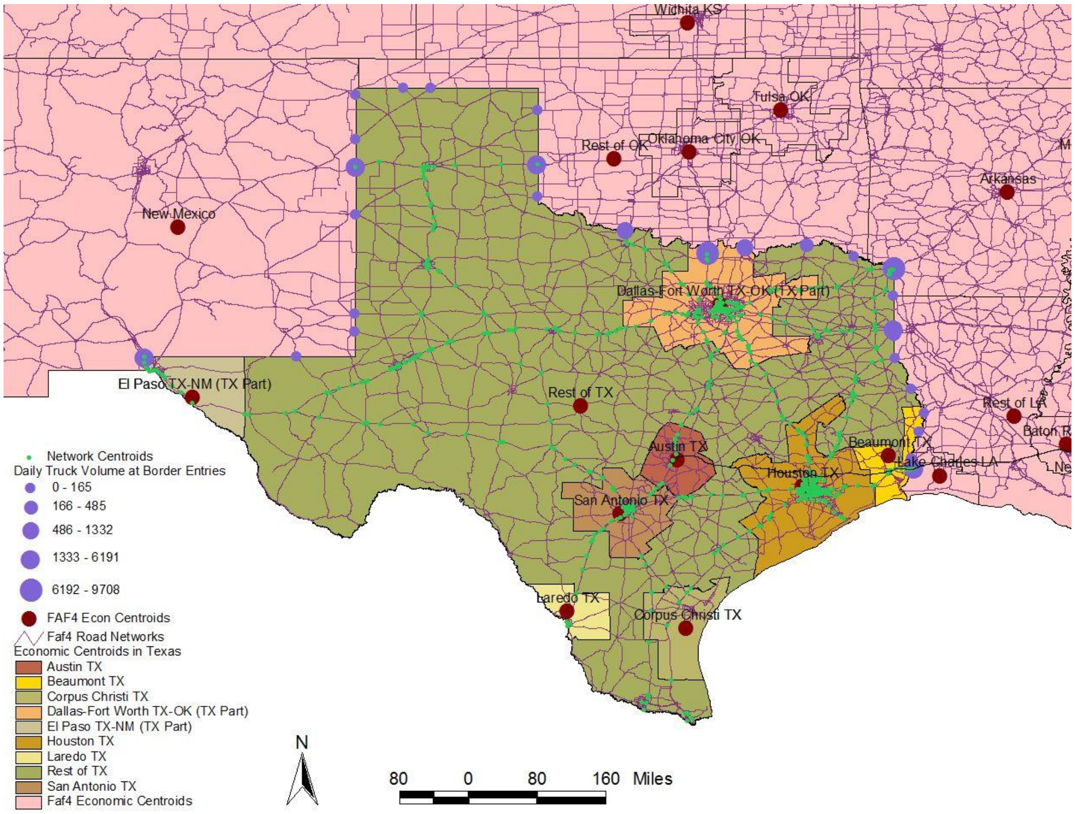


Figure 4. Economic Centroids, Network Centroids, and Border Entries of Truck Movement

In this empirical study, the 80,260 highway network links in Texas are reorganized in the forward star data structure that represents a network as a list of links and a list of node pointers and stores the node adjacency of each node as a single array. In addition to from-node, to-node, and length, the network link attributes also include capacity and speed data. The link capacity is obtained from FAF 2012 data set, which estimates capacity using the methodology in Highway Capacity Manual (HCM). The link speed is estimated based on the link classification.

The user-equilibrium based model with capacity constraints and the iterative processes described in the methodology section are applied to estimate freight flows in the state of Texas, especially in Texas Triangle. The model has run multiple iterations in the freight trip assignment step to reach convergence. The freight tonnage in FAF 2012 OD database is converted to passenger car equivalent (PCE) value based on the ton-per-PCE ratio estimated by Giuliano et al. (2007). The baseline link volumes in PCE per hour estimated by the user equilibrium assignment with link capacity constraints are shown in Figure 5.

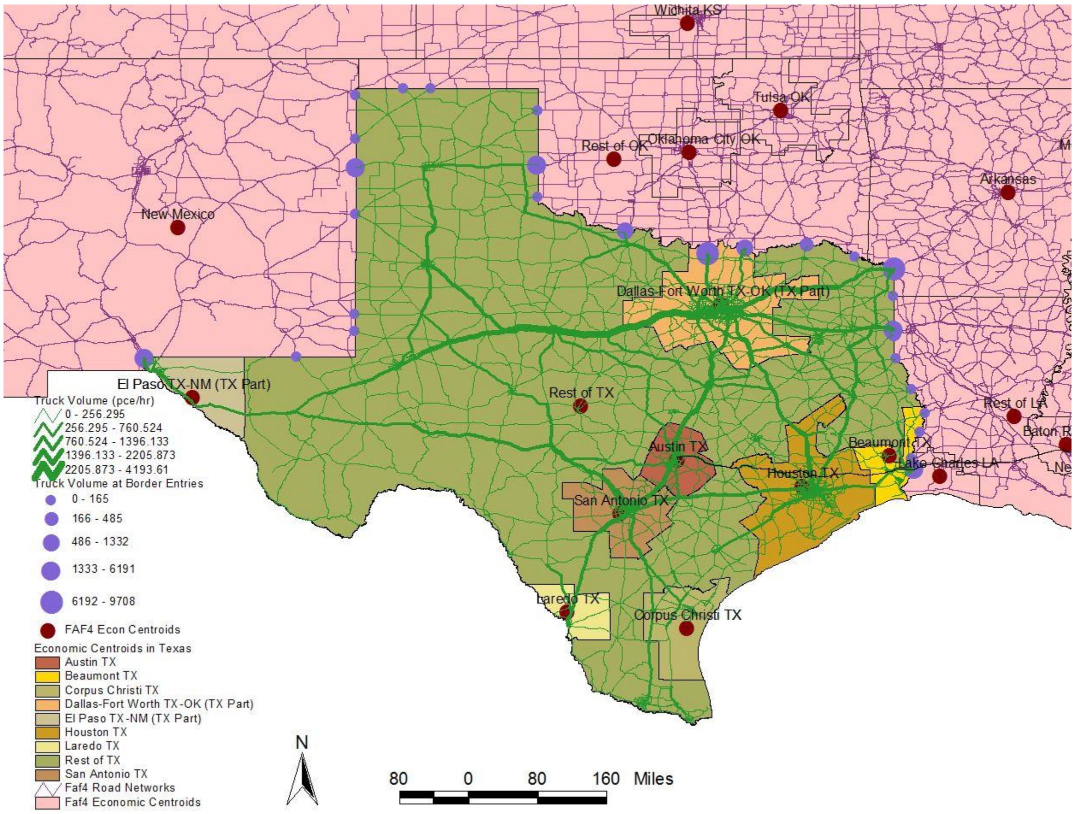
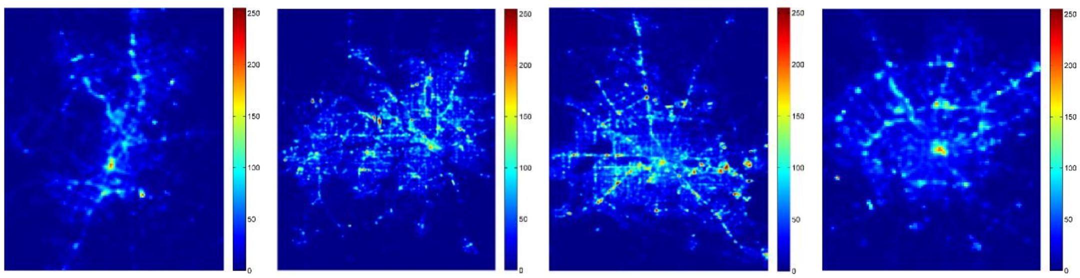


Figure 5. Truck Flows in Texas Triangle

Figure 5 clearly illustrates the strong connections between the four metropolitan areas within Texas Triangle through truck flows. It also shows the truck flows in detail within the megaregion, especially within the major metropolitan areas of the megaregion. It shows that some major metropolitan areas in Texas outside of Texas Triangle, such as El Paso, Laredo, Corpus Christi, and Beaumont, have strong connections with the major metropolitan areas in Texas Triangle through major highways. For instance, El Paso and Dallas have high volume of truck flows through Interstate Highway 20 while El Paso and San Antonio have high volume of truck flows via Interstate Highway 10.

4.2. Night time truck traffic analysis for Texas Triangle

The DMSP/OLS image is used to conduct statistical analysis over all four major cities in Texas Triangle. Although data and analytical methods are acceptable, it has a weakness in terms of spatial accuracy due to the spatial resolution of the DMSP/OLS data. Thus, the VIIRS image is applied to improve the image quality. Using the VIIRS images, we explore the relationship between nighttime lights and the freight volume for each city in 500m spatial resolution, instead of the entire area covering Texas Triangle. This procedure is problematic due to the issues of computer memory allocation. For example, computation of $(I-\rho W)-1$ is required to estimate SAR parameters. But the size of their spatial weight matrix, W, is 2,020,648×2,020,648, which generates memory problems during the computing process. To avoid this computing problem, we estimated statistical parameters over each city. Figure 6 represents nighttime lights seen from over each city. This study superimposes freight volumes, land use types, and road length on each image cell. Data overlaid on uniform grids makes it possible to combine these varying input datasets, and to create a unique database, which provides the inputs to statistical models.



(a) Austin (b) Dallas (c) Houston (d) San Antonio

Figure 6. Nighttime lights over each city

National Land Cover Data (NLCD) and the length of traffic network are utilized to enhance the model performance for each city. First, NLCD measures urban land use patterns to overcome a fundamental limitation of VIIRS images regarding land use metrics. Although it is usually classified into 16 land cover classes with a spatial resolution of 30 meters by 30 meters, Texas contains only 10 classifications. Second, realistic transportation networks offer road paths that accommodate truck flows. Particularly the Freight Analysis Framework (FAF) 4 network was employed to estimate the total length of truck flows within a given cell equal to the spatial resolution of VIIRS image. Third, FAF4 truck flow data has been integrated into FAF4 network to get estimated truck volume in 2012 (AADTT) and travel speed as a proxy for freight mobility. Given the spatial unit, all the information is aggregated into the cells in the VIIRS image. This process makes it possible to combine various input datasets into a unique database for statistical analysis.

The relationship between the nighttime lights obtained from DMSP/OLS datasets and the freight volumes provided by FAF4 is estimated using spatial lag model (SAR) and spatial error model (SEM). The results of statistical analysis are summarized in Table 1. The spatial lag (ρ) and spatial error (λ) terms are positive and statistically significant at the 99% level. The ρ value points to similar neighborhood interactions in terms of the amount of freight volume. Likewise, the λ values are also similar pointing to similar spatial autocorrelations for the error term. The coefficients of DMSP/OLS values are significant at 1 percent level in both models, indicating that it is desirable to estimate freight volume using nighttime lights. This approach can be employed to understand spatial pattern of freight movement over a large study area, such as megaregions.

Table 1. Summary of Statistical Analysis using DMSP/OLS datasets

	SAR		SEM	
	Coeff.	t-value	Coeff.	t-value
Const	263.49***	14.51	1,379***	18.24
DMSP/OLS value	7.53**	16.27	29.31***	15.58
Spatial lag (ρ)	0.78***	282.91		
Spatial error (λ)			0.78***	283.655
Log-likelihood	-307,529		-307,538	
R^2	0.71		0.71	
N	33,689		33,689	

**p<0.1; **p<0.05; ***p<0.01*

Tables 2 to 5 summarize the results of statistical analysis using the VIIRS images for the four major cities in Texas Triangle. First, they report that the spatial lag coefficients (ρ) of all the four cities are statistically significant positive at 99% level, indicating that AADTT has spatial dependence structures. In Houston and San Antonio, nighttime lights have statistically significant correlation with AADTT. However, VIIRS in Austin and Dallas was not statistically significant at 90% level. SAR explains the positive effects of developed land use (LUs) on AADTT, except low intensity for both Austin and San Antonio, and medium intensity for Houston. The predictive power measured by R^2 is more than four times higher than the old one when adding total road length.

Without the variable of total road length, all SEM models have higher R^2 than the SAR models, ranging from 0.35 to 0.43. This implies that the adjustment of the spatially correlated error (λ) increases goodness of fit, which is appropriate when explaining the relationships between AADTT and urban characteristics derived from the remotely sensed data. The SEM outputs provide evidence that nighttime lights extracted from the VIIRS image have significantly positive relationship with the increase of AADTT in Austin and Houston, but their relationship is significantly negative in San Antonio and insignificant in Dallas. It also shows that the nighttime lights play an important role in understanding the spatial pattern of AADTT in some but not all cities in the megaregion. Most coefficients of developed LUs are statistically significant at 90% level, except for the low intensity in San Antonio. As expected, developed LUs lead to high AADTT in most cases. However, the correlations between AADTT and non-developed LUs, such as barren, forest, Shrubland+Herbaceous, and Planted/Cultivated land, are insignificant and weak in almost all cases except for the Shrubland+Herbaceous LUs in Dallas, which has significantly positive effects on AADTT at 99% level.

Table 1. Summary of Statistical Analysis: City of Austin

	SAR		SAR		SEM		SEM	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Const	-417.65***	-11.84	-711.43***	-28.64	-978.59***	-19.79	-1003.01***	-35.59
VIIRS	0.05	0.14	-0.27	-1.29	3.15***	6.10	1.31***	5.01
Developed, Open Space	5.42×10^{-4}**	2.13	2.44×10^{-4}	1.53	6.32×10^{-4}**	1.91	4.59×10^{-4}**	2.35
Developed, Low Intensity	-5.73×10^{-4}*	-1.75	-2.61×10^{-4}	-1.28	-6.64×10^{-4}*	-1.60	-2.41×10^{-4}	-0.98
Developed, Medium Intensity	19.8×10^{-4}***	6.39	7.94×10^{-4}***	4.10	27.95×10^{-4}***	7.15	10.25×10^{-4}***	4.41
Developed, High Intensity	33.97×10^{-4}***	9.87	12.36×10^{-4}***	5.70	39.88×10^{-4}***	9.76	14.97×10^{-4}***	5.98
Barren	-10.36×10^{-4}	-0.78	-1.54×10^{-4}	-0.18	-5.35×10^{-4}	-0.36	-4.90×10^{-4}	-0.53
Forest	3.36×10^{-4}	1.56	1.12×10^{-4}	0.83	2.61×10^{-4}	0.88	1.30×10^{-4}	0.76
Shrubland+Herbaceous	2.39×10^{-4}	0.97	1.64×10^{-4}	1.08	4.73×10^{-4}	1.42	1.52×10^{-4}	0.79
Planted/Cultivated	1.65×10^{-4}	0.48	1.15×10^{-4}	0.53	0.12×10^{-4}	0.02	-0.20×10^{-4}	-0.07
Total road length (km)			1578.17***	88.95			1629.96***	87.64
Spatial lag (ρ)	0.62***	402.01	0.31***	26.98				
Spatial error (λ)					0.63***	59.31	0.36***	31.49
Log-likelihood	-33361.96		-30932.61		-33329.97		-31085.25	
R^2	0.17		0.76		0.43		0.75	
N	4813		4813		4813		4813	

*$p<0.1$; **$p<0.05$; ***$p<0.01$*

Table 2. Summary of Statistical Analysis: City of Dallas

	SAR		SAR		SEM		SEM	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Const	-427.59***	-34.40	-511.49***	-47.26	-427.59***	-34.40	-511.49***	-47.26
VIIRS	0.09	0.58	-0.02	-0.16	0.09	0.58	-0.02	-0.16
Developed, Open Space	3.13×10^{-4}***	2.61	1.06×10^{-4}	1.01	3.13×10^{-4}***	2.61	1.06×10^{-4}	1.01
Developed, Low Intensity	1.29×10^{-4}	1.13	0.53×10^{-4}	0.53	1.29×10^{-4}	1.13	0.53×10^{-4}	0.53
Developed, Medium Intensity	5.22×10^{-4}***	4.34	4.01×10^{-4}***	3.82	5.22×10^{-4}***	4.34	4.01×10^{-4}***	3.82
Developed, High Intensity	28.54×10^{-4}***	18.80	21.07×10^{-4}***	15.82	28.54×10^{-4}***	18.80	21.07×10^{-4}***	15.82
Barren	13.73×10^{-4}	1.56	10.41×10^{-4}	1.35	13.73×10^{-4}	1.56	10.41×10^{-4}	1.35
Forest	2.73×10^{-4}*	1.87	1.02×10^{-4}	0.92	2.73×10^{-4}*	1.87	1.02×10^{-4}	0.92
Shrubland+Herbaceous	3.97×10^{-4}***	2.99	3.32×10^{-4}***	2.87	3.97×10^{-4}***	2.99	3.32×10^{-4}***	2.87
Planted/Cultivated	0.03×10^{-4}	0.01	0.10×10^{-4}	0.07	0.03×10^{-4}	0.01	0.10×10^{-4}	0.07
Total road length (km)			611.65***	68.44			611.65***	68.44
Spatial lag (ρ)	0.56***	625.97	0.48***	557.07	0.56***	625.97	0.48***	557.07
Spatial error (λ)								
Log-likelihood	-93420.35		-91448.18		-93420.35		-91448.18	
R^2	0.10		0.41		0.10		0.41	
N	13360		13360		13360		13360	

*$p<0.1$; **$p<0.05$; ***$p<0.01$*

Table 3. Summary of Statistical Analysis: City of Houston

	SAR		SAR		SEM		SEM	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Const	-421.21***	-31.78	-714.49***	-68.95	-961.19***	-43.51	-981.62***	-94.12
VIIRS	-0.13***	-0.91	-0.26***	-3.10	1.39***	6.81	0.28***	2.78
Developed, Open Space	3.83×10^{-4}***	2.91	0.50×10^{-4}	0.63	5.38×10^{-4}***	2.97	1.76×10^{-4}*	1.84
Developed, Low Intensity	1.11×10^{-4}	0.82	0.78×10^{-4}	0.97	3.01×10^{-4}*	1.59	1.29×10^{-4}	1.30
Developed, Medium Intensity	0.34×10^{-4}	0.28	-0.83×10^{-4}	-1.18	3.05×10^{-4}*	1.82	0.77×10^{-4}	0.88
Developed, High Intensity	30.70×10^{-4}***	22.06	10.02×10^{-4}***	11.83	41.16×10^{-4}***	23.19	14.68×10^{-4}***	14.84
Barren	-1.48×10^{-4}	-0.32	0.56×10^{-4}	0.21	-2.92×10^{-4}	-0.57	1.86×10^{-4}	0.61
Forest	2.04×10^{-4}	1.40	0.47×10^{-4}	0.54	2.62×10^{-4}	1.32	0.91×10^{-4}	0.85
Shrubland+Herbaceous	0.28×10^{-4}	0.14	0.10×10^{-4}	0.08	-1.11×10^{-4}	-0.44	1.42×10^{-4}	1.04
Planted/Cultivated	2.49×10^{-4}*	1.80	0.04×10^{-4}	0.04	1.36×10^{-4}	0.65	1.53×10^{-4}	1.47
Total road length (km)			1,654.47***	153.07			1,703.22***	151.25
Spatial lag (ρ)	0.57***	607.01	0.28***	40.61				
Spatial error (λ)					0.61***	67.17	0.311***	45.81
Log-likelihood	-86,964.02		-80177.35		-86,844.79		-80540.40	
R^2	0.12		0.76		0.37		0.76	
N	12460		12460		12460		12460	

**p<0.1; **p<0.05; ***p<0.01*

Table 4. Summary of Statistical Analysis: City of San Antonio

	SAR		SAR		SEM		SEM	
	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value	Coeff.	t-value
Const	-429.61***	-12.94	-745.75***	-36.78	-429.61***	-12.94	-745.75***	-36.78
VIIRS	-0.53**	-2.16	-0.41***	-2.88	-0.53**	-2.16	-0.41***	-2.88
Developed, Open Space	6.87×10^{-4}***	3.27	2.02×10^{-4}*	1.68	6.87×10^{-4}***	3.27	2.02×10^{-4}*	1.68
Developed, Low Intensity	-5.02×10^{-4}**	-2.18	-1.51×10^{-4}	-1.15	-5.02×10^{-4}**	-2.18	-1.51×10^{-4}	-1.15
Developed, Medium Intensity	11.84×10^{-4}***	4.61	3.46×10^{-4}**	2.36	11.84×10^{-4}***	4.61	3.46×10^{-4}**	2.36
Developed, High Intensity	41.56×10^{-4}***	15.83	12.61×10^{-4}***	8.32	41.56×10^{-4}***	15.83	12.61×10^{-4}***	8.32
Barren	3.27×10-4	0.94	-0.23×10^{-4}	-0.10	3.27×10-4	0.94	-0.23×10^{-4}	-0.10
Forest	0.37×10-4	0.19	0.37×10^{-4}	0.33	0.37×10-4	0.19	0.37×10^{-4}	0.33
Shrubland+Herbaceous	3.39×10-4*	1.64	0.55×10^{-4}	0.46	3.39×10-4*	1.64	0.55×10^{-4}	0.46
Planted/Cultivated	1.39×10-4	0.63	0.54×10^{-4}	0.43	1.39×10-4	0.63	0.54×10^{-4}	0.43
Total road length (km)			1,774.09***	135.61			1,774.09***	135.61
Spatial lag (ρ)	0.57***	505.25	0.26***	32.21	0.57***	505.25	0.26***	32.21
Spatial error (λ)								
Log-likelihood	-59,279.92		-54,243.42		-59,279.92		-54,243.42	
R^2	0.15		0.79		0.15		0.79	
N	8547		8547		8547		8547	

**p<0.1; **p<0.05; ***p<0.01*

5. Conclusions

Megaregions have been of increasing interest planners and decision makers as a spatial and socio-economic domain, offering effective contributions and alternative mechanisms to the resolution problems that cannot be easily resolved by individual metropolitan areas or cities -- including congestion and pollution caused by truck movement (Harrison et al. 2012). This study describes an analytical framework for developing a megaregion truck model. A regional freight transportation model developed in our previous studies has been extended to estimate megaregion truck flows. An equilibrium function with capacity constraints has been incorporated into the traffic assignment model.

Our approach employs an analytical framework to estimate truck flows in the Texas Triangle, a notable megaregion completely within the state of Texas. The OD database and highway network links have been obtained from FAF 2012 datasets. Due to the limited number of economic centroids, this study identifies network nodes or so-called network centroids as freight external points like seaports, airports, rail yards, and highway intersections to fine-tune megaregion truck movements, especially those within the metropolitan areas of the megaregion. The results of link level truck flows in the megaregion can help to enhance the understating of megaregional truck flows and also facilitate the improvement of freight mobility.

One limitation of the study on the spatial patterns of megaregion truck traffic is the missing counts of pass-through truck flows. The analytical model developed for the megaregion truck flows only accounts for the trucks having their origin or destination within a megaregion but ignores those having both origin and destination outside of a megaregion.

Another limitation is the intra-metropolitan truck flows are disaggregated through network centroids that have uniform characteristics within an economic centroid. The megaregion truck model can be improved by incorporating additional information from local metropolitan planning organization (MPO) or other transportation planning agencies to estimate the truck flows handled by the freight facilities of the network centroids. These limitations will be considered in our future work.

To understand the temporal patterns of megaregion truck flows, this study focused on examining the nighttime truck flows, especially how they are estimated using nighttime light data and how they are affected by land use and road length. The results of the statistical analysis provide evidence to support the hypotheses that nighttime lights are associated with truck traffic. However, several limitations should be taken into account in order to achieve better statistical results in future studies. First, a downscaling technique should be developed for nighttime lights to reveal human activity over each land use at night. We expect that this may suggest accurate resources for understanding the impacts of nighttime metropolitan freight logistics. Second, it is hard to obtain statistical relationships between AADTT and the geospatial characteristics of the road networks in advanced statistical analysis that covers Texas Triangle due to our limited computational capabilities. Third, we need to include traffic analysis zones (TAZs) as spatial units to utilize diverse variables for transportation analysis, which may increase model efficacy.

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