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Testing the 'Freight Landscape' Concept for Paris

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ABSTRACT

The concept of "Freight Landscape," the basis for a modeling approach for urban freight traffic estimation using commonly available datasets, was proposed by Giuliano et al., 2015, applying it to the Los Angeles metropolitan area. To extend the scope of their research, we conduct another case study, using data from the Paris region, France. We estimate spatial lag models using population, employment or establishment, transportation accessibilities as explanatory variables and network-based truck traffic as the dependent variable, modifying Giuliano et al.'s approach. We identify similarities and differences between the case studies of Los Angeles and Paris. For Paris, the estimated models highlight the most important factors that characterize urban freight traffic in the region, including the distance to autoroutes (controlled-access highways) and jobs in trade, manufacturing of electrical products and machines, and the transportation industry. While the models estimated for the Paris region give us beneficial insights on the relations between Freight Landscape indicators and urban freight traffic, the model validation underlines the needs of further research for a modeling framework that enables unbiased estimation of urban freight traffic.

INTRODUCTION

In many cities around the world, the scarcity of data for urban freight is a long-lasting issue that hampers the analysis of urban freight flows and impacts. The complexity and heterogeneity of urban freight activities make data collection costly and challenging to implement. Only a limited number of cities implement surveys for urban freight. Even where survey data exists, the scope is often limited. On the other hand, the growth in population and economic activities in cities around the world enhances urban freight activities. Policy design requires urban freight traffic analysis. Therefore, the methodology for using the secondary data to characterize urban freight traffic is an important research subject. Finding robust yet simple secondary data to estimate urban freight traffic demand could be a solution to overcome the lack of the resource for urban freight data collection.

The objective of this research is methodological first. Following the research work from Giuliano et al. (*1*), we explore the use of available secondary data to estimate urban freight traffic. Can urban freight flows' spatial patterns be accurately generated "using simple measures of population, employment and transport access" (*1*)? The authors define the concept of 'freight landscape' as "a description of freight activity imputed from population, employment and transport network characteristics," with the hypothesis that "freight flows depend systematically on the spatial organization of freight suppliers and demanders as well as on the transportation facilities within the metropolitan areas." To test the hypothesis, they analyze the relationship between the distributions of population, employment, and transportation supply, and truck flow using the data from Los Angeles. The estimation of spatial regression models indicates the systematic relationship between those factors and truck traffic. In this line of work, as suggested by Giuliano et al. (*1*) in their conclusion, we add another case study from Paris, which is the largest urban cluster in terms of population and business activities in France, and one of the largest in Europe.

The rest of this paper is structured in the following six sections: 1) a belief literature review that focuses on urban form - urban freight relationship is provided; 2) freight features and freight data collection in the Paris region are explained; 3) analytical framework and data sources are detailed; 4) the estimated models are discussed; and 5) the conclusion of this research is provided.

LITERATURE REVIEW: THE RELATIONSHIP BETWEEN URBAN FORMS AND URBAN FREIGHT

"Freight landscape," i.e. a systematic relationship between easily accessible socio-economic indicators and goods transport activity, is an important concept, as the relationship between freight and urban forms, a broad category which encompasses the distribution of various indicators of human activities in an area (*2*), is generally understudied in the literature (*3-4*).

Past studies on urban freight modeling developed various types of freight trip generation methods since, at least, the 1970s (*5*). Existing papers, including Routhier and Gonzalez-Feliu (*6*), Taniguchi et al. (*7*), and Holguín-Veras et al. (*8*), attempt to inventory the variety of urban freight modeling efforts. Most models try to estimate freight trips generated from the economic establishments of an urban area. Even though spatial distribution plays no part in the generation of freight trips at the establishment level, other studies (*9-10*) emphasize the possibility that space can explain operational characteristics of deliveries/pick-ups such as the type of vehicle, type of parking, duration of parking.

The studies of the relationship between freight flows and urban forms are emerging at a theoretical level. Researchers recognize, for example, the links between density and inefficiency of deliveries. Dense urban centers bring about efficiency on goods transport activity, namely the shorter distances between delivery points and, therefore, the higher potential for consolidated urban freight tours. On the other hand, high density leads to inefficiency related to the operation of freight vehicles in narrow streets (*11*), the use of small vehicles due to local or national regulations (*12*), traffic congestion (*13*), and the lack of supply of parking spaces for freight vehicles (*14*-*16*).

FREIGHT TRANSPORTATION AND DATA COLLECTION IN THE PARIS REGION

The Paris region's Freight transportation in the Paris region

The Paris region (i.e. Ile-de-France) is by far the richest, most productive French region, concentrating about one fifth of the nation's population and employment as well as roughly 30% of its GDP in only 2% of the surface for 2012. The region is also a highly attractive tourist destination. As for freight tonnage, the Paris region displays a slight imbalance between inflows and outflows. 55% of the tons of transported goods are internal, 25% are inflows and 20% are outflows (*17*). 31% of the tons of goods moved in the Paris region are finished products, and 9% are food products (*17*). The Paris region requires a very efficient logistics network of freight terminals to provide high frequencies and variety of small deliveries. That is why, alongside its national economic prominence, the Paris region holds about 17% of the surface of warehouses (*18*) and 26% of the French workforce in the logistics sector (*19*), while it only represents 10.5% of France' tonnage of transported goods (*17*). It is estimated that through-traffic represents about 20% of the total truck traffic in the Paris region (*17*), even though the Paris region is the most congested French region (*20*) and one of the most congested urban areas in Europe (*21*).

The Paris region relies mostly on the road network to transport goods (*17*); in total, 88.6% of the tons of goods transported in, to or from the Paris region are transported on roads. About 6.3% of tons are transported through waterway system, 60% of which are construction materials, and about 4.5% are transported by rail, which are mainly construction materials and finished products shipped over long distances. Despite policy attempts designed to reduce the Truck-Kilometers Traveled (TKT), road transportation has increased its share for moving products. Last mile freight movements highly depend on small vehicles: according to the Paris Urban Goods Movement Survey, about 60% of operations of deliveries/pick-ups are made using light goods vehicles of 3.5 tons gross vehicle weight and less (*22*).

Truck traffic data collection efforts

French local authorities have jurisdiction over large portions of the road network and conduct counts and cordon surveys frequently, although at irregular intervals. The national government has jurisdiction over the highway network (autoroutes), and produces yearly data on the vehicle flows obtained through automatic counts (most of the national network are equipped with traffic sensors that can distinguish between small and large vehicles). The results of these surveys are often aggregated at the regional level. Other data collection efforts focus on freight flows to produce OD matrices, which can then be used in traffic assignment models. The national government conducts a yearly mandatory survey on heavy goods vehicles' users (vehicles > 3.5 tons in grow weight) called the TRM survey (Transport Routier de Marchandises - Freight Road Transport), which is used to produce freight flow matrices at the departmental and regional levels (*23*). Those data on vehicle counts and flows allows regional agencies to produce regular reports on the state of Ile-de-

France's mobility and traffic conditions, including truck traffic (*17*, *24*), which can be used for policy implementation (*25*). This paper relies heavily on data from counts (automatic or not), which are calibrated using the data from the TRM survey, to obtain truck traffic in the Paris region.

METHODOLOGY AND DATA

Methodology

The Paris region consists of 1,281 local municipalities, with an average size of 9.3 km^2. A 'municipality' is the most detailed unit for analysis for which population, employment and establishment data are fully available. This spatial unit also matches the availability of the road network and truck traffic data, which do not include the municipal road network. It is still required to exclude 262 municipalities from the analysis, which have no truck traffic data as the road network and truck traffic data do not cover those municipalities.

The purpose of this research is to test whether widely available socio-economic indicators, such as population, employment and establishments, and transportation accessibility, can describe freight traffic with the level of accuracy that warrants the use of such indicators for urban freight traffic analysis. We develop regression models for estimating TKT per square km, which represents truck traffic demand. The model development is conducted in four steps, using the following groups of indicators for independent variables: (i) population and employment indicators, (ii) population and establishment indicators, (iii) transportation accessibility indicators, and (iv) population, employment or establishment, and transportation accessibility indicators. Employment and establishment indicators are not used at the same time for regression analysis due to the expected high correlations between the two indicators.

As the spatial auto-correlation becomes an issue in this type of analysis in which the effects from neighboring municipality influence truck traffic demand (*1*, *26*-*29*), we use a spatial lag model which formula is shown below.

$$y_m = \alpha + \sum_i \beta_i x_{m,i} + \rho \sum_{n \neq m} w_{mn} y_n + \varepsilon_m \tag{1}$$

where:

- y_m: TKT per km^2 (dependent variable) in municipality *m*
- $x_{m,i}$: an indicator (independent variable) *i* for municipality *m*
- w_{mn}: the spatial weight for the pair of municipality *m* and *n*
- ε_m: a randomly distributed unobserved component
- α, β, ρ: parameters to be estimated; ρ is the autoregressive lag coefficient

The spatial lag model requires spatial weight matrix. We tested various formulas including Radial Distance Weights, Power Distance Weights, Exponential Distance Weights, and Queen Contiguity Weights, and found that the Power Distance Weights provide the highest fits for the tested models. Weight matrix is calculated using the formula below. We tested $k = 0.5, 1, 2, 3, 4$ and $k = 3$ gives the best results.

$$w_{mn} = d_{mn}^{-k} \tag{2}$$

where:

- d_{mn}: Network distance between municipality *m* and *n*

□ : a positive exponent

For the analysis mentioned above, all variables, including independent and dependent variables, are log-transformed as it gives higher Pseudo R^2 and AIC. “Spdep” package in R, the software environment for statistical computing, is used for estimating models, applying the maximum-likelihood method. The model estimations are conducted in the way to find statistically significant independent variables and minimize AIC.

Data

We use population, employment, and the number of establishments at the municipal level in the Paris region as the independent variables. To measure population density and employment density, we use the data provided by the French National Institute for Statistics (INSEE) for the year 2014. The Paris region is a monocentric metropolitan area. Population, employment and establishments (especially the latter two) are concentrated in the center of the region, the city of Paris, and the first ring of suburban municipalities (Figure 1).

The source for detailed employment and establishment patterns is the “Local Knowledge of the Productive System” (CLAP) database provided by INSEE. This database uses the European NACE classification (Statistical Classification of Economic Activities in the European Community), which provides similar categories with the North American Industry Classification System (NAICS). The NACE classification only considers the main purpose of each building so that the other functions in the establishment may not be recognized. In this analysis, we use aggregated version of the CLAP database that groups the NACE classes into 17 categories (Table 1).

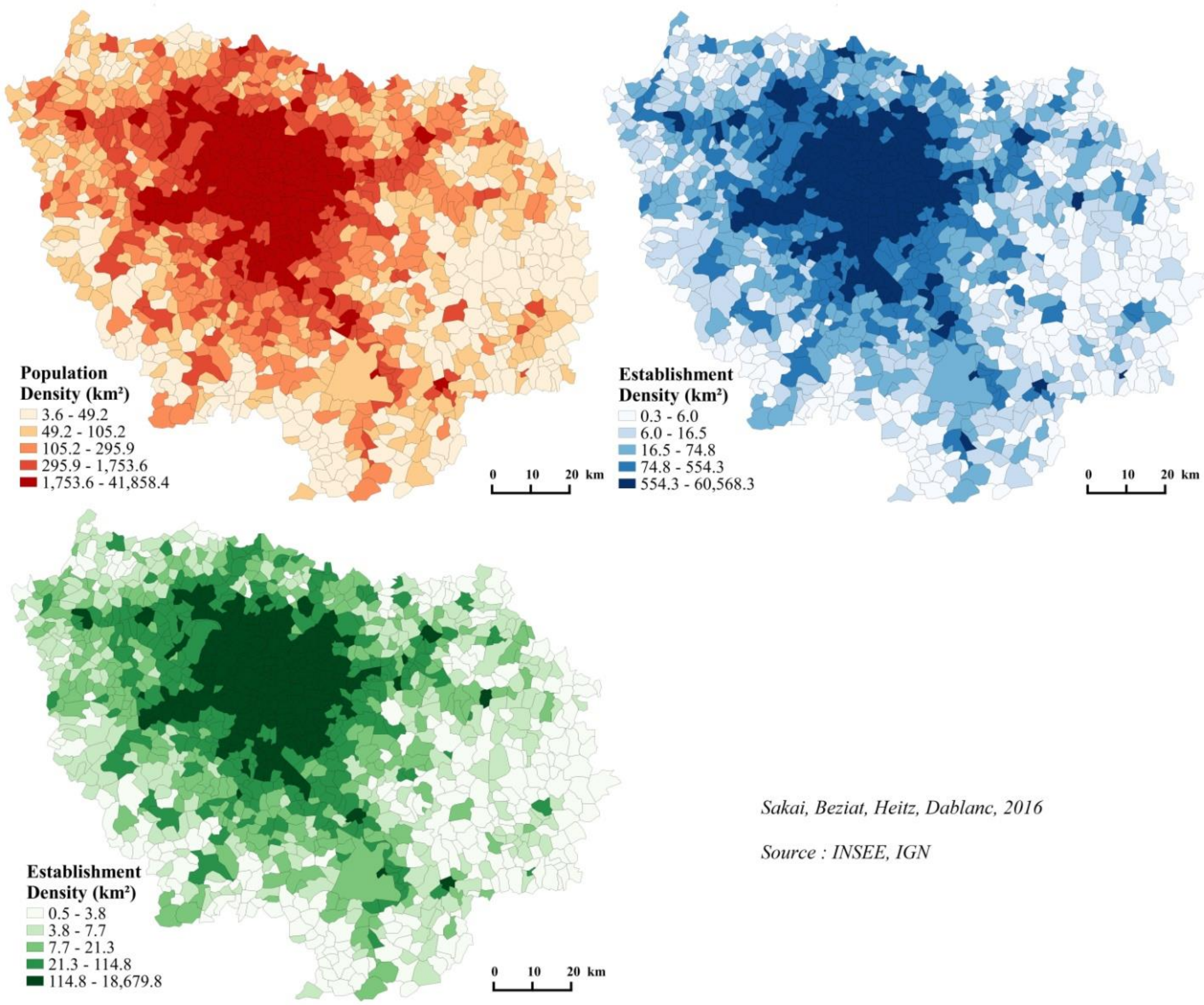

FIGURE 1 Density of population, employment and establishments in the Paris region

TABLE 1 Industry Category Based on NACE Classification (17 Categories)

Code	Industry	% of employment in the Paris region (total=100)
AZ	Agriculture, forestry and fishing	0.08
BE	Mining, energy, water, waste management and Remediation activities	1.57
C1	Manufacture of food products, beverages and tobacco products	0.88
C2	Coke and refined petroleum	0.02
C3	Manufacture of electrical equipment, electronic, computer& manufacturing machines	1.39
C4	Manufacture of transport equipment	1.43
C5	Manufacture of other industrial products	3.33
FZ	Construction	5.08
GZ	Trade & automobile and motorcycle repairs	12.90
HZ	Transportation and storage	6.80
IZ	Accommodation and food	5.17
JZ	Information and communication	6.99
KZ	Financial and insurance activities	6.14
LZ	Real estate activities	1.44
MN	Scientific and technical activities & Administrative and support services	16.76
OQ	public administration, education, human health and social work	25.44
RU	Other service activities	4.41

The list of infrastructures (roads) in the Paris region was provided by the French Institute for Geography (IGN). We use the Route 120® database which gave us all the roads and highways as well as road nodes and intersections to calculate the road accessibilities to logistics infrastructures, for the year of 2015. The database of logistics infrastructures is the product of our own compilation from HAROPA (Ports of Paris) and SNCF (French National Railway Company) information. Those infrastructures are widespread, with some located within the inner suburban areas, while others stretching from the north to the east, and in the southeast (Figure 2). This has led to the development of the areas close to the infrastructures and the ports of Gennevilliers and Bonneuil or the Charles de Gaulle and Orly airports.

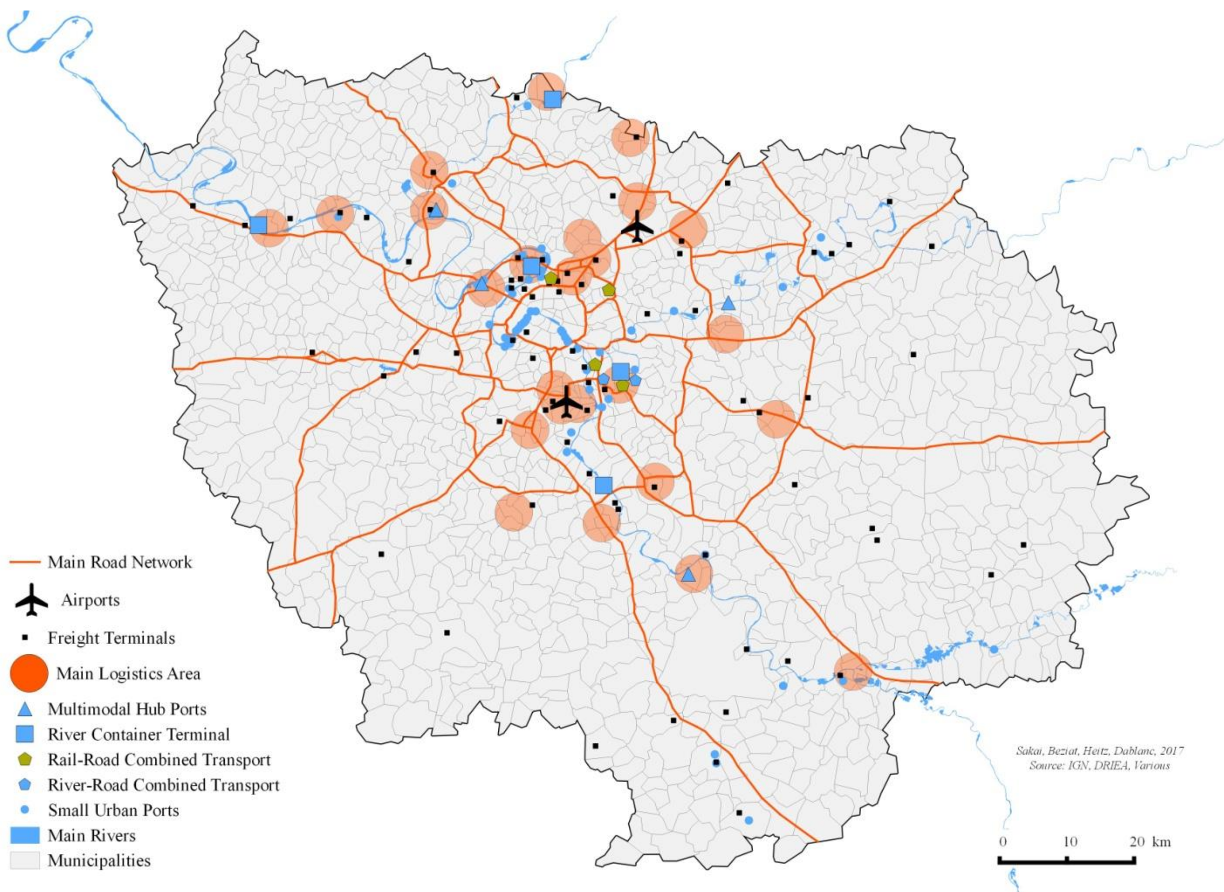

FIGURE 2 Main logistics infrastructures in the Paris region

Truck traffic data was provided by the Regional bureau of infrastructures and urban planning for the Paris region (DRIEA). We use the hourly average truck traffic volume of morning rush hours on the road network in the Paris region in 2009 that were estimated based on the samples collected by each Department (equivalent to county) of the Paris region (Figure 3). It should be noted that the data do not contain light commercial vehicles (i.e. commercial vehicles of 3.5 tons gross weight or less), which account for 57% of freight flows for deliveries according to the urban freight survey conducted in 2012 for the Paris region (22). The summary of the variables is shown in Table 2.

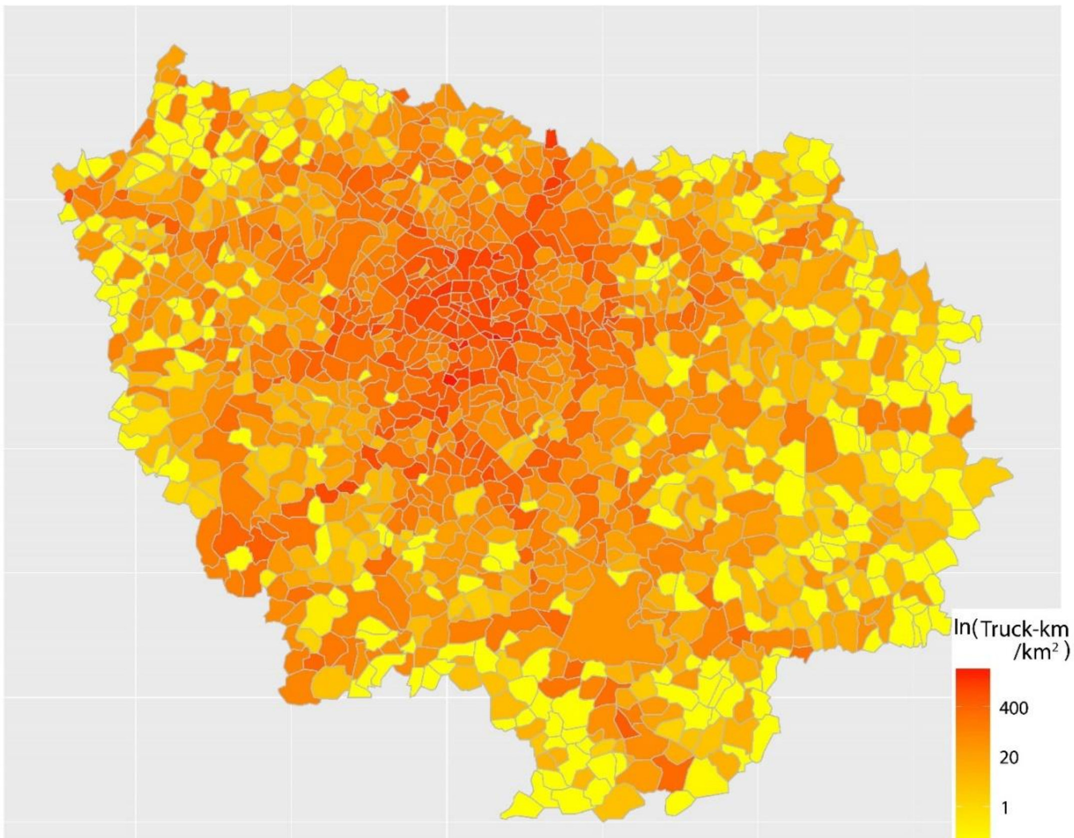

FIGURE 3 Truck-kilometer density (log-transformed)

TABLE 2 Summary of Variables (before Log-Transformation)

Variables	Annotation	Mean	Median	S.D.	Min	Max
TKT per km^2	-	180.7	48.4	363.6	0.0	4089.2
Population density (/sq. km)	Pop.	2094.8	263.9	4688.6	3.6	41858.5
Employment density (/sq. km)	Emp.	1110.0	56.4	4528.4	0.2	68238.4
Establishment density (/sq. km)	Estt.	262.3	19.1	1187.4	0.5	18679.8
Distance to *autoroutes* (km)	Dist. to *autoroutes*	9.0	6.6	8.2	0.0	51.4
Distance to airports (km)	Dist. to airports	36.9	33.7	20.0	0.9	94.4
Distance to freight terminal (km)	Dist. to freight terminal	7.9	7.1	5.0	0.0	29.7
Distance to main logistics area (km)	Dist. to main logistics area	15.0	11.2	10.9	0.0	51.3
Distance to multimodal hub port (km)	Dist. to multimodal hub port	25.8	23.7	13.6	0.9	69.4
Distance to river container terminal (km)	Dist. to river container terminal	28.6	24.6	16.7	0.0	83.9
Distance to rail-road intermodal terminal (km)	Dist. to rail-road intermodal terminal	34.6	32.7	19.6	0.8	85.0
Distance to river-road intermodal terminal (km)	Dist. to river-road intermodal terminal	34.5	32.5	19.0	1.8	84.2
Distance to urban port (km)	Dist. to urban port	15.4	12.5	11.4	0.0	54.4

Note: The breakdowns of employment density and establishment density by industry type are omitted from the table.

ANALYSIS AND RESULTS

In the following sections, the results are discussed for (i) the models with population and employment variables, (ii) the models with population and establishment variables, (iii) the models with accessibility variables, and (iv) the models with the combinations of population, employment/establishment, and accessibility variables. These models underline the set of indicators that contribute to the truck traffic estimation in each category or among all available variables.

Models with population and employment data

The three models that apply population and employment variables are shown in Table 3. For the first model (left in Table 3), only total population and total employment are used; the second model (center in Table 3) is estimated using total population and employment for 17 industrial categories; for the third model (right in Table 3), independent variables are reduced to population and only statistically significant employment variables, which show the p-values of less than 0.10.

TABLE 3 Estimated Spatial Lag Models with Population and Employment Variables

	1. Total pop. and total emp.			2. Total pop. and emp. by industry group			3. Total pop. and significant emp. variables.		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	1.453	0.214	0.000**	1.869	0.329	0.000**	2.122	0.230	0.000**
Pop.	-0.080	0.065	0.220	0.017	0.087	0.842	-0.073	0.051	0.154
Emp.	0.386	0.051	0.000**						
Emp. (AZ)				-0.036	0.101	0.725			
Emp. (BE)				-0.036	0.043	0.402			
Emp. (C1)				-0.129	0.075	0.087*			
Emp. (C2)				-0.130	0.182	0.475			
Emp. (C3)				0.075	0.048	0.120	0.083	0.043	0.054*
Emp. (C4)				0.053	0.044	0.235			
Emp. (C5)				0.010	0.050	0.847			
Emp. (FZ)				0.036	0.065	0.584			
Emp. (GZ)				0.256	0.063	0.000**	0.314	0.053	0.000**
Emp. (HZ)				0.095	0.047	0.042**	0.117	0.044	0.007**
Emp. (IZ)				0.152	0.075	0.042**			
Emp. (JZ)				-0.092	0.055	0.094*			
Emp. (KZ)				0.181	0.076	0.017**			
Emp. (LZ)				0.043	0.081	0.599			
Emp. (MN)				0.054	0.057	0.345			
Emp. (OQ)				-0.117	0.069	0.091*			
Emp. (RU)				-0.136	0.083	0.102			
Autoregressive lag coefficient	0.316	0.037	0.000**	0.286	0.037	0.000**	0.288	0.037	0.000**
Pseudo R^2	0.403			0.440			0.429		
AIC	3611.2			3576.0			3568.9		
AIC for liner regression model	3678.5			3630.2			3624.9		

*: Significant at 90% confidence level; **: significant at 95% confidence level.
Note: Dependent variable is TKT per sq. km; all independent variables are in log-transformed density (per sq. km); “pop” stands for population and “emp” stands for employment; refer to Table 1 for the codes of industrial category (AZ~RU).

“Population” is insignificant for all three models; population is highly correlated with employment so that its contribution for estimating truck traffic demand is limited. The second model shows the heterogeneity on the impacts of employment by industry type. Coefficients of some employment variables are negative, which are likely due to the multicollinearity problem, i.e. the correlations among independent variables result in the biased estimated coefficients.

To find the variables that are highly related to truck traffic demand, the insignificant employment variables and those with negative coefficients are removed and, thus, the third model is obtained. Emp. (IZ) and Emp. (KZ) are removed in the process as these variables turn to be insignificant when some other variables are omitted. Among various industrial categories, GZ (trade; automobile and motorcycle repair) shows the largest effect on truck traffic demand, followed by HZ (transportation and storage), and C3 (manufacture of electrical equipment, electronic, computer; manufacturing machines). Autoregressive lag coefficients are significant for all three models and the comparison between AIC and AIC for liner regression model indicates that the spatial auto-regressive effects are non-trivial.

Similarly, three models that apply population and establishment, instead of employment, variables are shown in Table 4. Compared with the models in Table 3, Pseudo R^2 is slightly lower and AIC is higher for each step, which indicates that employment variables are likely to be better indicators for predicting truck traffic demand.

Only GZ (trade; automobile and motorcycle repair) is the significant establishment variable that remains in the third model, and autoregressive lag coefficient is, again, significant in all the three models.

TABLE 4 Estimated Spatial Lag Models with Population and Establishment Variables

	1. Total pop. and total estt.			2. Total pop. and estt. by industry group			3. Total pop. and significant estt. variables		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	1.935	0.293	0.000**	1.892	0.456	0.000**	2.387	0.317	0.000**
Pop.	-0.304	0.105	0.004**	0.012	0.126	0.924	-0.182	0.077	0.017**
Estt.	0.728	0.111	0.000**						
Estt. (AZ)				-0.305	0.147	0.038**			
Estt. (BE)				-0.063	0.139	0.650			
Estt. (C1)				-0.522	0.236	0.027**			
Estt. (C2)				-0.224	0.753	0.766			
Estt.(C3)				0.498	0.207	0.016**			
Estt.(C4)				-0.204	0.374	0.586			
Estt.(C5)				-0.090	0.179	0.615			
Estt.(FZ)				-0.236	0.157	0.134			
Estt.(GZ)				0.699	0.176	0.000**	0.683	0.090	0.000**
Estt.(HZ)				0.266	0.140	0.058*			
Estt.(IZ)				0.344	0.202	0.089*			
Estt.(JZ)				-0.363	0.172	0.035**			
Estt.(KZ)				0.408	0.190	0.031**			
Estt.(LZ)				-0.122	0.202	0.546			
Estt.(MN)				0.418	0.185	0.024**			
Estt.(OQ)				-0.624	0.191	0.001**			
Estt.(RU)				-0.046	0.233	0.844			
Autoregressive lag coefficient	0.316	0.037	0.000**	0.286	0.038	0.000**	0.309	0.037	0.000**
Pseudo R^2	0.396			0.439			0.404		
AIC	3622.8			3578.1			3609.0		
AIC for liner regression model	3688.8			3630.8			3672.7		

*: Significant at 90% confidence level; **: significant at 95% confidence level.

Note: Dependent variable is TKT per sq. km; all independent variables are in log-transformed density (per sq. km); “pop” stands for population and “estt” stands for number of establishments; refer to Table 1 for the codes of industrial category (AZ~RU).

Models with accessibility indicators

Next, the models are estimated using nine accessibility variables. All variables are used in the first model and, in the second model, non-significant variables and the variables with positive coefficients are excluded and only three variables remain. Among all accessibility variables considered, the distance to autoroutes is most important for truck traffic prediction. This is likely due to the simple fact that a large volume of trucks use autoroutes. Also, the locations near autoroutes’ interchanges and exits are efficient for logistics activities.

The distance to rail-road intermodal terminals is also significant and its effect on truck traffic demand is strong. Two municipalities, Gennevilliers and Bonneuil, accommodate two of the region's main rail-road intermodal terminals, as well as the two main river ports in the Paris region. The other two main intermodal terminals are in Valenton and Noisy. They are all located in the fringes of the Paris urban area. The other variable which is statistically significant is the distance to freight terminals, though the effect is smaller than the two accessibility variables mentioned above.

Comparison of the models in Table 5 with Table 3 and 4 shows that accessibility indicators tend to produce more reliable models than the models with only population and employment/establishment variables. The autoregressive lag coefficient is significant but its effects are smaller in the models with accessibility variables, which indicates that the accessibility variables could capture a part of spatial auto-correlation effect.

TABLE 5 Estimated Spatial Lag Models with Accessibility Variables

	1. All accessibility variables			**2. Significant accessibility variables**		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	6.481	0.480	0.000**	6.732	0.386	0.000**
Dist. to autoroutes	-0.791	0.071	0.000**	-0.732	0.066	0.000**
Dist. to airports	-0.077	0.122	0.531			
Dist. to freight terminal	-0.226	0.079	0.004**	-0.193	0.073	0.008**
Dist. to main logistics area	-0.071	0.095	0.455			
Dist. to multimodal hub port	0.173	0.101	0.087*			
Dist. to river container terminal	0.146	0.089	0.103			
Dist. to rail-road intermodal terminal	-0.450	0.227	0.048**	-0.553	0.078	0.000**
Dist. to river-road intermodal terminal	-0.212	0.232	0.359			
Dist. to urban port	0.111	0.078	0.157			
Autoregressive lag coefficient	0.204	0.041	0.000**	0.214	0.041	0.000**
Pseudo R^2	0.446			0.441		
AIC	3547.7			3545.6		
AIC for liner regression model	3571.2			3572.2		

*: Significant at 90% confidence level; **: significant at 95% confidence level.
Note: Dependent variable is TKT per sq. km; all independent variables are in log-transformed.

Models with population employment/establishment, and accessibility indicators

The first two models (1 and 2) in Table 6 are those using population, employment, and accessibility variables. We use the three accessibility variables that are statistically significant in the earlier analysis ("dist. to autoroutes", "dist. to freight terminal", and "dist. to rail-road combined terminal") (see the second model in Table 5). The first model in Table 6 uses the total employment and the second model uses, instead, the categories of the employment that are significant in the earlier model estimation (see the third model in Table 3).

When population, employment and accessibility are included in the model, the contribution of autoregressive lag coefficient to AIC is small (i.e. the gap between AIC and AIC for linear regression model is small), although autoregressive lag coefficient is still statistically significant. Interestingly, the effect of population becomes significant when the accessibility variables are included in the models. The effect of population density is masked if accessibility variables are not adequately considered. All employment categories considered (Emp. C3, Emp. GZ, and Emp. HZ) remain significant in the second model. On the other hand, the distance to freight terminals becomes insignificant in both models and, therefore, was removed. The second model generates the highest Pseudo R^2 and the lowest AIC, which indicates the model is superior to the other models tested in this section.

The next two models (3 and 4) in Table 6 shows the models that apply the number of establishments, instead of employment. Again, the distance to freight terminals is insignificant in the models. Also, when estt. GZ are included, the distance to rail-road terminals is insignificant, because the location of the establishments in GZ (trade; automobile and motorcycle repair) is highly correlated to the distance to rail-road terminals.

TABLE 6 Estimated Spatial Lag Models with Total Population, Employment/Establishment and Accessibility Variables

	1. Total pop. and emp. and accessibility variables			2. Total pop. and significant emp and accessibility variables.			3. Total pop. and estt. and accessibility variables			4. Total pop. and significant estt. and accessibility variables.		
	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value	Coef.	S.E.	P-value
Intercept	5.017	0.561	0.00**	5.305	0.556	0.00**	5.714	0.577	0.00**	5.226	0.384	0.00**
Pop.	-0.169	0.065	0.01**	-0.169	0.052	0.00**	-0.491	0.099	0.00**	-0.323	0.073	0.00**
Emp.	0.320	0.049	0.00**									
Emp. (C3)				0.078	0.041	0.06*						
Emp. (GZ)				0.279	0.051	0.00**						
Emp. (HZ)				0.101	0.042	0.02**						
Estt.							0.758	0.105	0.00**			
Estt.(GZ)										0.716	0.084	0.00**
Dist. to *autoroutes*	-0.673	0.064	0.00**	-0.670	0.063	0.00**	-0.740	0.064	0.00**	-0.749	0.063	0.00**
Dist. to rail-road intermodal terminal	-0.246	0.096	0.01**	-0.176	0.096	0.07*	-0.189	0.096	0.05**			
Autoregressive lag coefficient	0.164	0.041	0.00**	0.142	0.041	0.00**	0.146	0.041	0.00**	0.159	0.040	0.00**
Pseudo R^2	0.471			0.493			0.476			0.481		
AIC	3489.7			3448.7			3480.0			3468.6		
AIC for liner regression model	3504.5			3459.3			3491.0			3483.3		

*: Significant at 90% confidence level; **: significant at 95% confidence level.
Note: Dependent variable is TKT per sq. km; all independent variables are in log-transformed; "pop" stands for population, "emp" stands for employment in density (per sq. km) and "estt" stands for number of establishments in density (per sq. km); refer to Table 1 for the codes of industrial category.

We also test the models using income level (i.e. median income) as an independent variable; however, the income level is always insignificant, unlike the case of Los Angeles metropolitan region (*1*). As discussed by De Lara (*30*), logistics activities may be associated with low-income neighborhoods in L.A. but that is not the case in the Paris region (*31*).

Taking one step further, we compare the actual TKT per km^2 and those estimated using the best model (the second model in Table 6). The result highlights the difficulty to obtain highly accurate estimations. Overall, truck traffic demand is under-estimated for the municipalities that have high truck traffic demand in reality, while it is over-estimated for the municipalities that have low truck traffic demand (the correlation between actual and estimated TKT per km^2 is 0.63).

While the modeling approach used for the L.A. and Paris regions works for identifying the factors for truck traffic and the locations where truck traffic concentrates, the approach still has difficulty to estimate accurate truck traffic volume.

CONCLUSION

In this paper, we use the concept of 'freight landscape' and applied the modeling approach of Giuliano et al. (*1*) with some refinements for the Paris region. The concept hypothesizes that urban freight patterns can be predicted from simple indicators of population, employment, and the accessibility to transportation infrastructure, which are generally available. For the Los Angeles case, the results mostly validate the hypothesis with nuances. Giuliano et al. find that there is a systematic relationship between density and truck traffic. In L.A., truck volume goes together with employment density, especially for services, manufacturing, and trade. Their analysis also shows that transportation supply and highway access are good indicators explaining truck traffic, although the accessibility to major freight generators (airports and seaports) is not. The intensity of truck activity is strongly and negatively associated with population density and household income.

We develop and test models using TKT per km^2 on the Paris region's road network as a dependent variable for finding the approach to estimate urban freight traffic with an adequate level of accuracy. As for independent variables, we test various demographic, economic and accessibility indicators that are usually available, such as population density, employment density, and the accessibility indicators to transportation system. Main results are the following:

(i) In the Paris region, the distributions of the residential population and employment are monocentric and quite similar, i.e. population and employment are located close together. Thus, the contribution of population for estimating truck traffic demand is limited when employment variables are also in the model. However, the addition of accessibility variables highlights the significant negative effect of population to truck traffic.
(ii) Employment is a better business activity indicator for estimating truck traffic than establishments.
(iii) The following activities: trade & automobile and motorcycle repair; transportation and storage; and manufacture of electrical equipment, electronic, computer & manufacturing machines show the largest effects on truck traffic demand.
(iv) Among all accessibility variables, the distance to autoroutes is most important for truck traffic demand prediction.
(v) Distance to rail-road intermodal terminals is also significant and its effect on truck traffic demand is strong.
(vi) The highest fit of the model is achieved by the set of the variables including population, employment in the three industrial categories mentioned earlier, the distances to autoroutes and rail-road intermodal terminals; and
(vii) The income level is always insignificant.

We identify the relationship between population, employment and accessibilities, and truck traffic demand in the Paris region, similarly to the L.A. case, but with a lot of differences. It is not surprising, as the urban structure of the Paris region is monocentric and different types of activities are located close to one another, while in L.A., the urban area spreads widely with a more evenly distributed road network.

The analysis presented in this research has shortcomings. One of them is that we did not consider van traffic, which represents more than half of the vehicles used for deliveries and pick-ups in the Paris region. The updating of the analysis using comprehensive freight traffic flow data is a future research task. Also, the methodology to improve the predictive performance of the models using the secondary data need to be further studied for making the models of use in urban freight planning practices.

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