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Freight Transport and Land Use Interaction: an Analysis Approach Based on Floating Car Data

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Abstract

Freight transport in urban areas affects city liveability and, in turn, it is affected by the territorial characteristics and by the location of firms, factories and production activities. Therefore, the relationship between freight flow and land use must be investigated, combining knowledge derived from the analysis of data on freight transport and territorial attributes. This work considers a dataset of floating car data (i.e., a sample of freight vehicles moving in the study area) and a dataset of territorial data (e.g., number of activities and employees) in order to calibrate a model able to foresee the production of tours from each zone of the study area. In particular, a linear and a spatial autoregressive model are calibrated considering aggregated data related to the commercial activities in the study area.

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Keywords: city logistics; land use; Moran index; floating car data; urban freight transport; spatial correlation.

1. Introduction

The location of factories, industries and production activities greatly affects their competitiveness, so the aim is to optimise it, also trying to maximize market coverage and to reduce distribution costs. Furthermore, the cost of land plays a key-role in this decision-making. As an example, accessibility (both active and passive; Cascetta, 2009) is a fundamental location factor influencing both freight distribution and supply (crucial for the just-in-time strategies), which needs to be balanced with the costs for renting, the building and, in general, the space to perform own activities.

Studies on land use (and related effects) range from the spatial effects of activity relocation (Hounwanou et al.,

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2018; Pinheiro et al., 2023) to environmental impacts (Foley et al., 2005) and planning (in terms of spatial distribution of urban freight facilities; Nuzzolo et al., 2014). A typical analysis relies with the study of the relation between land use and urban freight operations mainly considering the loading and/or parking facilities for freight vehicles (de Abreu e Silva and Alho, 2017; Comi and Polimeni, 2021). Other studies take into account how policy procedures on land use affect the costs associated with the freight transport (Holguin-Veras et al., 2021; Di Gangi et al., 2023; Belcore et al., 2023). Another aspect that emerges is that different use of the land are, in most cases, conflictual, highlighting the different needs of the actors involved. The result is that, sometimes, the location of a production activity is not optimal with respect to the demand or with respect to the resources (e.g., raw materials or semi-finished products). Then, stakeholders have to adapt their product distribution and material acquisition plans. This implies an impact on freight production and distribution (Russo et al., 2010; Allen et al., 2012). Thus, a flow of vehicles is generated/attracted from/to the production activities and the correlation between this freight flow and the land use seems worthy of investigation, combining knowledge coming from the analysis of data on freight transport and territorial attributes (secondary data). Therefore, the proposed approach considers the production activities in the study area as the generator/attractor of the freight trips, with the aim of relating the freight trips with territorial attributes.

In this work, the data related to freight transport (e.g., vehicle tours/trip chains) are obtained, rather than using the classic interviews with operators, by analysing the global positioning system (GPS) traces, which are available on a large scale for such uses as fleet management or vehicle insurance, while the territorial attributes come from census data (secondary data). In fact, such GPS data, known also as floating car data (FCD), were largely used for investigating delivery tours, as well as for setting up methodology for demand forecasting (Alho et al., 2019; Napoli et al., 2021; Comi et al., 2021), but few studies pointed out their use for linking vehicle operations with socio-economic attributes of the area. Usually, such a type of data could represent specific operators (e.g., if they come from some given operators that use them for fleet management), or to a specific freight market (e.g., from the retail or wholesale sector). In this study, the data comes from an external provider that has a significant penetration rate and, as shown from previous studies by the authors, it can be assumed that they are quite representative of freight vehicles moving within the area investigated (Comi et al., 2021; Comi et al., 2022; Comi and Polimeni, 2022). The provider operates in developing and producing telematics devices and manages a consistent FCD database powered by information systems for real-time data collection, detected (and transmitted) by specific onboard units. Usually, the spatial autocorrelation is based on a measure on the interaction between two spatial units (e.g., traffic zones), expressed by a weight matrix (in the simplest case, this matrix is a transformation of the distance, but other specifications, such as travel time or accessibility, are possible) and a representative attribute related to the spatial units (e.g., number of employees, economic entities). The task of the weight matrix is to relate the value of attributes observed in a zone to those observed in the other zones. The indicator (Dhulipala and Patil, 2022) used to quantify spatial correlation is the Moran index ($I \in [-1, 1]$).

The paper is structured as follows. The Section 2 presents the literature review, Section 3 describes the methodology developed. The Section 4 provides a description of the study area and the database used for implementing the proposed methodology. In the Section 5, the results of such an application to a real case study are discussed. Finally, the conclusions and the possible further developments are presented in Section 6.

2. The background

In the literature, as introduced earlier, some authors analysed the relationship between land use and freight transport characteristics, others developed models linking the tours generated/attracted with the study area attributes and the freight characteristics (e.g., Holguín-Veras et al., 2011; Comi et al., 2021). Without presuming to be exhaustive, the following literature review considers these two aspects.

The distribution on the territory of factories, industries, and production activities (and their interactions) impact freight demand both in terms of production and consumption (Aljohani and Thompson, 2016). In relation to this aspect, Allen et al. (2012) explored relationships between freight transport, city characteristics, land use, activity location and logistics chain management demonstrating that land use affects the distances over which freight is transported. Nuzzolo et al. (2014) focused on the distribution of urban freight facilities, the choices of types of retail and the travel mode used by end consumers travelling for shopping, and assessed some land-use strategies related to relocation of retail outlets and warehouses in terms of traffic impacts. Musolino (2019) analysed the relationships between land prices and freight transport costs at the urban level with the aim of obtaining information to support decision makers in the location of freight transport facilities. Similarly (but at regional level), Tsekeris (2022) investigated the effects of urban form and land use on freight transport costs, the goal was to identify the actions to implement in order to improve land use-freight transport interaction. The influence of the location of logistics facilities was analysed by Sakai et al. (2017), who demonstrated that the decentralisation of logistics facilities to the outskirts of the city caused an increase in vehicle payload (and, consequently, an increase in efficiency). When considering that the location of logistics facilities causes externalities, Sakai et al. (2019) proposed an approach to analyse the impacts of urban freight distribution in relation to the logistics facility locations, the logistics chain, and the flow of freight vehicles. Similarly, de Sousa and de Oliveira (2020) analysed the logistics sprawl caused by the location of logistic facilities in the suburbs, identifying this phenomenon as the main cause of the externalities associated with urban freight transport. Lindsey et al. (2014) examined the relationship between freight transportation and industrial space demand (the spatial level is the metropolitan area), identifying a significant association between freight movements and levels of industrial space demand.

In terms of trip generation/attraction forecasting, Ducret et al. (2015) used spatial analysis to explain urban delivery structures and to added some spatial descriptors in urban freight simulation. Alho and de Abreu de Silva (2015) proposed some alternative approaches to calibrate models to foresee the number of trips generated/produced, by considering cross classification and multiple classification analysis, regression trees and generalised linear models. The effect of land-use variables in models for trip generation/attraction was analysed in De Bakshi et al. (2020) concluding that the structure of the city is a fundamental element in freight trip forecasting.

In the papers reviewed above, the influence of the land use variables in model calibration is considered, but the possible spatial correlation among them is not deeply taken into consideration. In Dhulipala and Patil (2022), a spatial autoregression model was proposed in order to overcome this aspect. After the identification of the spatial interaction, the spatial regression model is calibrated for areas where spatial autocorrelation has been detected. Sánchez-Díaz et al. (2016) analysed the relationship between the trip attraction and a set of attributes that contain, among the others, land use attributes and the facility locations. They proposed a set of models to foresee the attracted trips. Ni et al. (2016) proposed a spatial correlation model in order to foresee the origin-destination freight vehicles flows. Among the predictors, they used attributes related to the urbanization level (e.g., urban road density). Therefore, the significant effects that the spatial correlation can have in analysing transport and land use interaction need to be further investigated. A methodology that contributes to this topic and exploits the opportunity offered by telematics is presented in the next section.

3. Proposed methodology

Spatial analysis (Figure 1), in general, consists of three main tasks: *visualisation*, *exploration* and *modelling* (Pfeiffer et al., 2008). Partitioning the study area into zones and associating at each zone a set of attributes, visualisation allows us to check if there is a trend (*pattern*) of the attributes in the study area and to identify any biases; exploration is aimed at providing statistical *analyses* of data (e.g., in order to individualise correlation among zones); modelling consists of the estimation of *forecasting* models.

Focussing on the exploration task, the goal is to evaluate if spatial autocorrelation exists. Considering a study area composed of N zones, the spatial autocorrelation refers to the relationship between attributes related to each zone taking into consideration their reciprocal distance through an impedance (weight) calculated for all $N(N-1)$ couple of zones (Hubert et al., 1981). The indicator chosen to evaluate the spatial correlation is the Moran Index (eq. 1):

$$I = \left(N \Big/ \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} \right) \cdot \left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right) \Big/ \sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 \right) \tag{1}$$

where:

- N is the number of zones of the study area,
- w_{ij} is the weight value associated to zone i and zone j,
- x_i is the value of the reference variable (e.g., number of employees or activities) in the zone i,
- $\bar{x}$ is the average value of the reference variable in the study area.

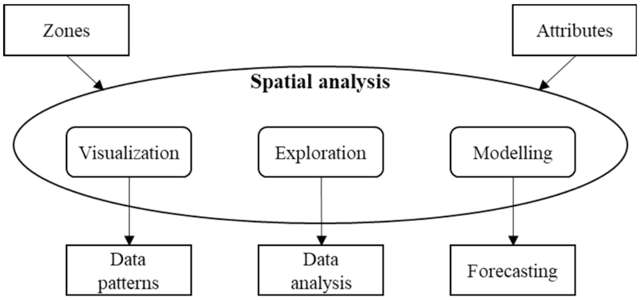


Figure 1. Framework of spatial analysis

In relation to the value of I, a positive autocorrelation is possible when I is greater than zero, while negative autocorrelation is possible when I is less than zero. A value of I equal to zero indicates the absence of spatial correlation. The Moran's I is an inferential statistic, then a null hypothesis H_0 must be made to interpret the results. In this case, the null hypothesis is the absence of autocorrelation (the analysed attribute is randomly distributed in the study area). The test is performed by considering the *p-value* and the *z-score* related to I. Small values of the *p-value* associated with high (in absolute value) of *z-score* fall in the tails of the normal distribution and, in this case, the null hypothesis can be rejected (also in relation to the value of the significance of the test). The value of the *Z-score* is:

$$Z[I] = (\ )\, I - E[I] \big/ \sqrt{\mathrm{var}(I)} \tag{2}$$

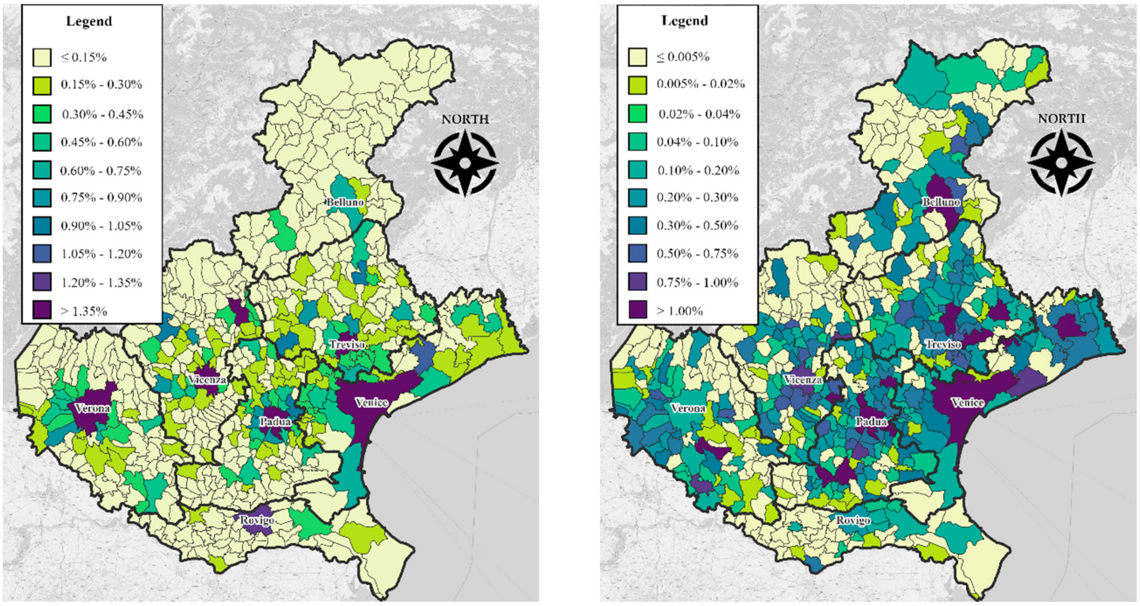
where:

- $E[I] = -1/(N-1)$ is the expected value of the Moran Index under the null hypothesis,
- *var[I]* is the variance of the Moran's Index.

4. Study area and data analysis

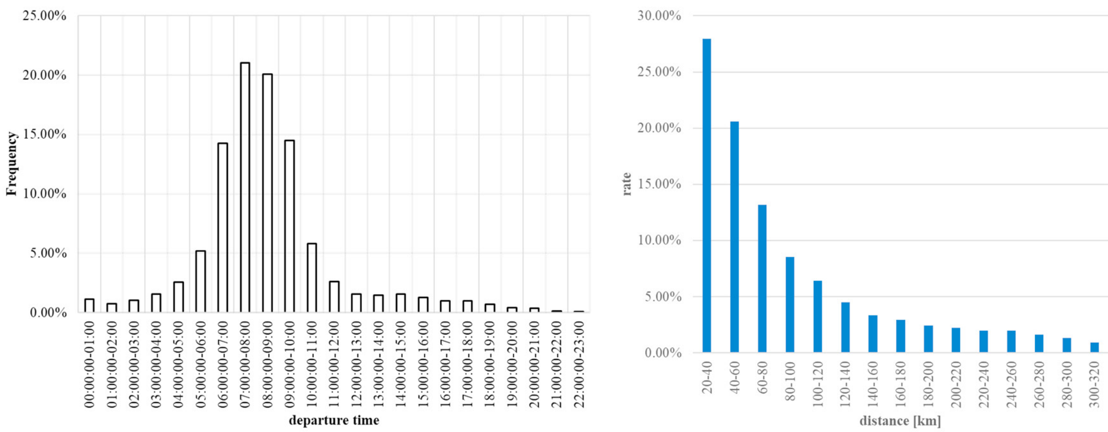
The study area is the Veneto region, a region of the northern Italy with about 5 million of inhabitants and a highly developed production establishments. The territory is divided into seven provinces and, according to the scope of this paper, in the study area 581 zones were identified. The available FCD relates to light freight vehicles (laden weight less than 3.5 tons), collected for a reference period of 60 working days (from January to June 2018). Each record contains information on the vehicle (e.g., mode, gross weight, model), the position (latitude and longitude), the time, on the travel (e.g., speed, type of road). Note that, in the reference period, the same vehicle may have been registered several times. At the end, the database consists of about 23,000 tours performed by 1,579 light freight vehicles. Unlike data collected in a traditional way, for example through interviews with operators (with high expenditure of time and costs), the FCD are cheaper, more reliable and have a higher degree of detail. However, there may be limitations, linked both to technology and to the number of vehicles equipped with on-board units. Despite this, as shown in the literature (Ehmeke et al., 2012; Alho et al., 2019; Comi and Polimeni, 2021), such sample size should be allowed to have a significant figure of the freight flow patterns. The analysis of these data on tours allows one to identify, among other things, the origin zone of each tour (depot). Figure 2a reports the rate of tours generated by zone. Because the number of generated tours is the dependent variable used in the analyses described below, the focus is on the origin of each tour.

For each zone, some secondary data considered for the land use analysis are available (ISTAT, 2022). In this case study, the data used are related to commercial activities (wholesale and retail) and employees in these sectors, identified by the ATECO codes (461-469 for wholesale activities and 471-479 for retail activities). Figure 2a shows the spatial distribution of the wholesale activities in the study area, it is possible to highlight that the distribution is scattered over the study area with peaks in some zones (e.g., Verona and Venice). Figure 2b reports the rate of produced/generated tours by zone. The focus is on the origin given that the number of generated tours is the dependent variable used in the further analyses reported below. The comparison between these two maps gives an initial idea of the correlation between the wholesale activities and the generated/produced tours. This analysis (see the next section) allowed us to verify the existence of spatial correlation from generated tours (from FCD) and secondary data. Figure 3 reports some analyses on the tours database. In particular, Figure 3a shows the distribution of the departure times from origins (it can be approximated to a normal distribution) while in Figure 3b the distribution of tour lengths is reported. For further information on tour analysis, refer to Nuzzolo et al. (2020) and Comi and Polimeni (2021).



(a) (b)

Figure 2. Wholesale activities (a) and generated tours by zone (b)



(a) (b)

Figure 3. Departure time (a) and length (b) of the generated tours.

5. Application results

The application aims to understand whether the attributes considered relevant in the tour generation are spatially correlated. Table 1 reports the results obtained by performing a Moran's I test under randomisation (one-sided). From the values obtained, it emerges that, for all attributes, the p-value is less than 0.01 and the Z-score is greater than 1.96, indicating that the null hypothesis can be rejected with a significance level of 95% (note that, excluding the attribute *retail activities*, the null hypothesis can be rejected with a significance level of 99%). It follows that the attributes are spatially autocorrelated with a positive autocorrelation (being the Moran's I greater than zero). Since from the results on Moran's I it emerges that an autocorrelation among attributes exists, a traditional regression model may not properly describe the phenomenon. In this case, the use of a spatial regression model considers the spatial lag to take the correlation effects into account. Figure 4 shows the Moran's I for wholesale activities and for generated tours. It is a visualisation of the degree of spatial autocorrelation (*SA*): on the horizontal axis are the reported the wholesale activities (part (a) of the Figure 4) and the generated tours (part (b) of the Figure 4) while the vertical axis represents the mean neighbouring value. The Moran's I, as reported in Table 1, is 0.125 for wholesale activities and 0.102 for tours. The expected value of the Moran's I without spatial autocorrelation is $-1/(N-1) = -0.002$. The quadrants of the Moran plot are helpful for classifying observations. The first (top right) quadrant represents zones with above-average values that are also surrounded by above-average values. The third (bottom left) quadrant contains low values surrounded by low values. The points in these quadrants contribute positively to the Moran's I and they represent a positive spatial autocorrelation. The second (top left) and fourth quadrants represent negative spatial autocorrelation, since they contain spatial outliers, i.e., high (or low) values surrounded by dissimilar values.

Table 2 reports the preliminary results of the model calibration, both for linear regression and spatial regression. *** The attributes used in the model are related to wholesale activities and retail activities (in this phase at the aggregate level, that is, without distinguishing the particular ATECO sector). In some cases present in the literature, vehicle tours are related to the number of employees (e.g., Gonzalez-Feliu and Sánchez-Díaz, 2019; Comi and Polimeni, 2021). However, in the case study presented in this paper, the best result was found by relating the number of activities to the generated tours given that the analysis refers to a given vehicle type (i.e., light goods vehicles) and, further, the spatial correlation takes into account possible homogeneity in warehouse dimension. Besides, a location variable (*city centre*) is considered to take into account if the origin belongs to the city centre or not. The rate of tours departing from zone i with respect to the total tours departing within the study area, Y_i, is expressed as follows:

$$Y_i = \psi\left(\mathbf{X}_i, \rho\right) \tag{3}$$

where $\boldsymbol{X}_i$ is the vector of socio-economic data related of zone i (e.g., number of wholesalers, of retailers) and ρ is the spatial lag value of the dependent variable. The parameters are correct in terms of signs and statistically significant (the parameter related to the wholesale activities is on the border of the significance interval). The spatial lag value (ρ) of the dependent variable (Y) defines the spatial dependence existing in the sample data, it is a measure of the (average) influence on observations by their neighbouring observations. As in Table 2, the effect of the spatial lag is positive and significant. The result is that the spatial model fit improved, as demonstrated by the R-squared value.

Table 1. Moran's Index (I)

Attribute	I	Z(I)	p-value
Wholesale activities	0.125	4.130	1.816E-05
Retail activities	0.068	2.333	9.825E-03
Wholesale employees	0.127	4.273	9.629E-06
Retail employees	0.077	2.671	3.777E-03
Tours	0.102	2.795	2.599E-03

Table 2. Tour production/generation: calibrated models

Variable	Regression model	Spatial regression model
Intercept	1.017e-03	5.421e-04
t-student	*(2.951)*	*(2.347)*
Wholesale activities (*number*)	5.025e-06	3.831e-06
t-student	*(1.927)*	*(1.989)*
Retail activities (*number*)	5.534e-06	5.885e-06
t-student	*(2.617)*	*(2.839)*
City centre (*dummy variable*)	1.970e-02	2.078e-02
t-student	*(5.662)*	*(6.065)*
Lagrange multiplier test for residual autocorrelation	-	0.0115
p-value	-	*[0.745]*
R-Square	*0.425*	*0.542*
Adj. R-Square	*0.420*	-
Spatial regression lag (ρ)	-	*0.155*

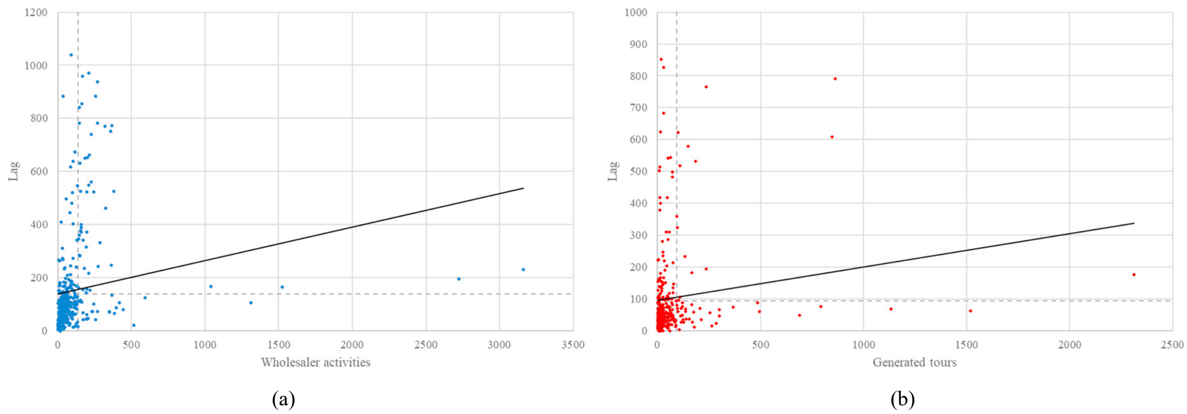


Figure 4. Moran's Index for wholesale activities and generated/produced tours.

6. Conclusion

The paper proposed a methodology for estimating freight tour production taking spatial correlation into account. The observed data on the number of tours comes from a set of floating car data, which contains information on vehicle movements. Before calibrating the model, an analysis was performed to understand the benefits of calibrating a spatial autocorrelation model instead of a traditional regression model. The spatial autocorrelation considered some potential attributes usable for calibration and points out their spatial correlation through the evaluation of the Moran index. The approach was applied to a real case study, where the vehicle tours and the attributes were available. From the spatial autocorrelation analysis it emerged that, for all considered attributes, a spatial positive autocorrelation exists, and then significant improvement can be obtained if a spatial model is calibrated. A preliminary calibration was developed, and the results address further developments.

To date, more and more vehicles are equipped with on board units, this makes it easy to analyse trips, and the estimate the number of freight trips. In addition, increasing the penetration of such a technology can allow the procedure to be replicated in other contexts. Thus, further developments foresee the extension of the database of the vehicle tours and model calibration for different ATECO sectors and different classes of freight vehicles. Besides, the procedure can be extended in order to estimate a model for trip attraction, however previous tour activities need to be determined in order to identify tour composition (i.e., number and location of each stop).

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