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Mapping Logistics Development in the Netherlands

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Abstract. The increasing demand for logistics real estate calls for a better understanding of the location dynamics of logistics firms. Previous empirical studies have largely focused on describing the spatial patterns of logistics but not on explaining the factors that lead to them. To fill this void, we develop a unique dataset of logistics buildings in the Netherlands and employ it in a multinomial logistic regression model to study the impact of key spatial factors on logistics development in the Netherlands during the period 1990-2020. In general, we find a positive influence of highway accessibility on logistics development. Contrary to previous studies in the US, we find a positive influence of rail accessibility and a negative influence of accessibility to airports. The effect of port accessibility and other factors varies with the type of logistics development. Finally, we also present probability maps that illustrate the combined effect of these factors.

Keywords. Logistics, Location, Land-use change, Spatial analysis, The Netherlands

1 Introduction

The logistics sector has a key role to play in modern supply chains. The increasing spatial separation between production and consumption has led to an increase in the demand for freight transport and logistics. Growth of the logistics industry is not only associated with positive economic effects but also negative societal effects like urban sprawl, congestion, air and noise pollution and landscape transformation (Aljohani & Thompson, 2016). Therefore, it is crucial for stakeholders in the spatial planning process to understand the location dynamics of logistics companies.

Empirical research into understanding the location dynamics of logistics is underrepresented in the economic geography stream (Hesse & Rodrigue, 2004) in spite of the increasing demand for logistics floorspace. Few prior studies have focused on quantifying logistics location patterns (Heitz *et al.*, 2020; van den Heuvel *et al.*, 2013), but not on analysing the factors leading to these patterns. The key spatial factors believed to influence logistics location are accessibility to transport infrastructure, proximity to urban areas and to consumer and labour markets, land availability, and proximity to other logistics firms (Onstein *et al.*, 2018). However, the few empirical studies that exist have only focused on the role of accessibility to transport infrastructure (Bowen, 2008; Holl & Mariotti, 2018; Verhetsel *et al.*, 2015). Their results suggest that air and road accessibility have a strong effect while rail accessibility has little to no effect on logistics location. The importance of seaport access only emerged in the case of a few European studies (Holl & Mariotti, 2018; Verhetsel *et al.*, 2015).

In this study, we aim to contribute to this literature by developing a comprehensive dataset of logistics buildings in the Netherlands and using it to empirically investigate the effect of important spatial factors (including, but not limited to, accessibility measures) on logistics development. Logistics is classified into three categories to analyse whether preferences for location characteristics vary with logistics function. We perform the analysis at a spatially detailed 100 m grid cell level. Our empirical approach involves a combination of Geographic Information System (GIS) and econometric techniques to model logistics development as a land-use change process. Specifically, we use a multinomial logit model with logistics change (during the period 1990-2020) as the dependent variable and a range of spatial drivers as the explanatory variables.

2 Method

2.1 Empirical Design

Discrete choice analysis provides a spatially explicit framework to model the effect of various factors on land-use change (Irwin & Geoghegan, 2001). In this study, we model logistics development as a land-use change process using multinomial logistic regression. The dependent variable can assume four values corresponding to four possible outcomes (described in more detail later), each of which represents a discrete land-use change process and one of which is chosen as the reference. The analysis is performed at the individual 100 m x 100 m grid cell level. The multinomial logit model is specified as shown below in Eq. (1).

$$\ln \frac{P_{c,i}}{P_{c,j}} = \alpha_i + \beta_i A_c + \delta_i L_c + \Upsilon_i P_c \tag{1}$$

In the equation above, the probability of occurrence of process *i* in cell *c* is given by $P_{c,i}$, while $P_{c,j}$ denotes the probability of occurrence of the reference process *j* in cell *c*. The ratio of these two probabilities represents the odds of occurrence of process *i* in cell *c* relative to the reference process. A_c , L_c , and P_c are vectors of explanatory variables related to accessibility, location, and spatial policy factors, respectively. The regression coefficients to be estimated are denoted by β, δ, and Υ while α gives the intercept. The parameters estimated through the model can be used to compute the probability of occurrence of process *i* in cell *c* using the expression shown below in Eq. (2), where k represents the four land-use change processes.

$$P_{c,j} = \frac{e^{\alpha_j + \beta_j A_c + \delta_j L_c + \Upsilon_j P_c}}{\sum_k e^{\alpha_k + \beta_k A_c + \delta_k L_c + \Upsilon_k P_c}} \tag{2}$$

2.2 Data and Software Availability

The primary dataset used in this study is an open access geodata of logistics buildings in the Netherlands between 1980 and 2021. The geodata contains information on attributes such as building function, footprint, construction year, employment density, etc. of all logistics buildings in the Netherlands. The dataset is compiled using various available sources, such as the Basic Registration Addresses and Buildings (BAG) dataset, the Dutch database on business estates (IBIS), a database containing microdata on employment locations in the Netherlands (LISA), and Open Street Map (OSM) data.

The methodology used to compile the geodata is briefly described as follows. Using OSM and IBIS datasets, all buildings larger than 500 m^2 that lie within a business estate were selected. Similarly, a selection was made in the LISA data based on the company type. For this purpose, a rather broad definition of logistics was employed to include trade, import, and export companies (including e-commerce), transportation and warehousing companies, and retail (excluding e-commerce). Manufacturing and recycling facilities were not included. The buildings selected using OSM and IBIS datasets were then spatially joined to company information from the selected LISA data. This led to a final selection of buildings larger than 500 m^2 that lie on business estates and have one of the four types of logistics function, namely: trade, import, and export; transport and logistics; retail; and logistics co-activity. Buildings with a logistics co-activity function are multitenant buildings with >33% logistics employment of the first three types of logistics.

The resulting set of buildings lacked firm identification (LISA) for about one-third. This can be explained by incomplete firm data, due to firms being registered in other buildings, or due to very recent constructions that are not present yet in the data. To assess the possible logistics function of this subset, an additional selection of large buildings (>2,500 m^2) from OSM data were processed through manual verification in Google Earth and Streetview and assigned an appropriate logistics function, if any. Inclusive criteria here were the existence of company logos on the façade (transporter, trade or retail firms), and large numbers of loading docks. Exclusive criteria were the absence of such docks, and the storage of machines and materials on terrains around the building, which is typical for building contractors, industries and other non-logistics firms. Buildings which were not assigned any logistics function were removed from the dataset. The resulting dataset of buildings with a logistics function was spatially joined to the BAG and OSM datasets to incorporate attributes such as construction year and building footprint.

The final data consist of ca. 26,000 buildings, ca. 9,600 of which are larger than 2,500 m^2. Ca. 9 out of 10 buildings are new greenfield developments, while 1 out of 10 is developed on an existing business site (brownfield development). There are also functional grey areas: some buildings clearly have a logistics typology and activity, but, according to business microdata, fall in another category, for example automobile assembly and service, or production of food. An interactive map of this data set and a more detailed description is available elsewhere (http://mertennefs.eu/landscapes-of-trade/; Nefs, 2022).

Buildings with the following three types of logistics function are used in this study:

- Transport and logistics services (*Transport & Logistics*)
- Trading companies, both import and export including e-commerce (*Trade, Import & Export*)
- Large-scale retail excluding e-commerce (*Large Retail)*

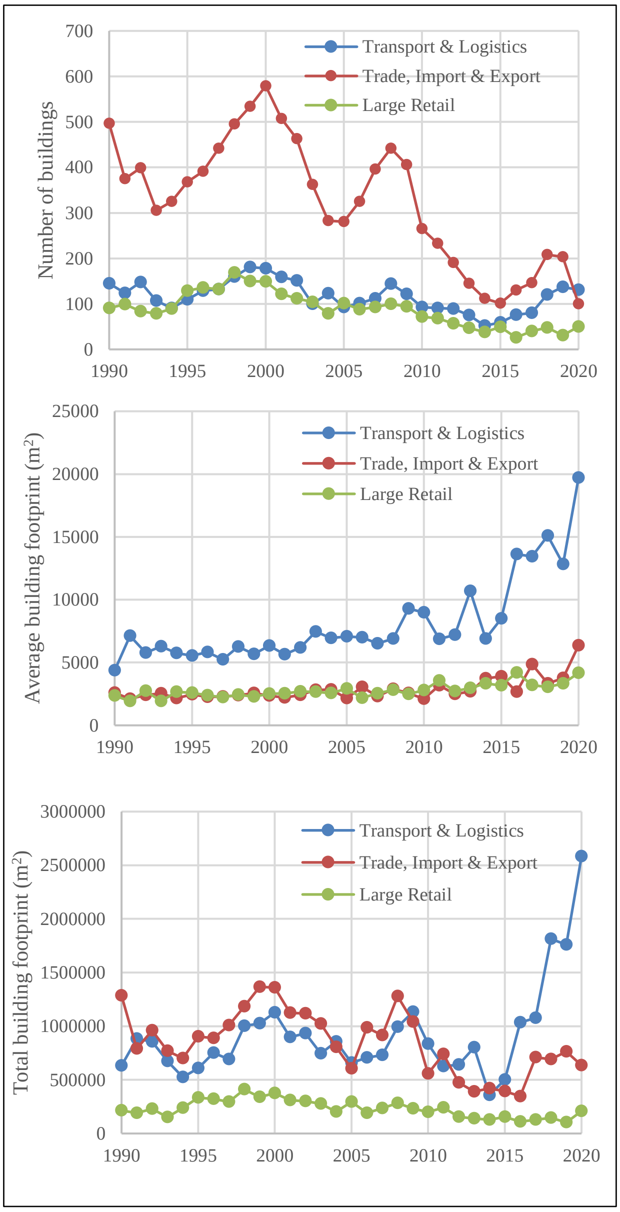

Figure 1. Trends in the growth of logistics footprint in the Netherlands during 1990-2020.

Fig. 1 illustrates a few general trends with respect to the three types of logistics buildings for the study period spanning three decades between 1990-2020. The number of new buildings added annually has largely declined since the year 2000. However, the same is not true for the total building footprint per year which has not declined as much. This indicates that the average footprint of new buildings has increased over time, as is clear from the graph showing average building footprint per year. This increase has been most evident for Transport & Logistics buildings and more so in recent years. On the other hand, most new buildings added every year belong to the Trade, Import & Export category. But due to the higher average footprint of Transport & Logistics, the annual addition in the total footprint of Trade, Import & Export buildings is similar to that of Transport & Logistics.

Logistics development is modelled as a discrete process in this study. For this purpose, the vector dataset of logistics buildings was rasterised to a 100 m resolution in such a way that every 100 m x 100 m grid cell represents the dominant logistics function in that cell. The dependent variable in our logistic regression model denotes logistics land-use change between 1990 and 2020 and has four possible outcomes/categories. The reference/base category represents the outcome of 'no change' which implies no logistics development. The remaining three categories represent land-use changes to the three logistics functional classes, respectively. Interconversions between the classes are excluded from the analysis.

We include a range of accessibility, location, and policy factors as explanatory variables in our model. Local as well as regional accessibility measures are employed. Local accessibility measures include several distance variables representing accessibility by air, road, rail, and sea. Accessibility to freight terminals is also included. Regional accessibility is measured by the least possible network-based travel time required to reach 100,000 inhabitants. Location factors include land value as measured by a residential hedonic price index (de Groot *et al*., 2010), presence of urban amenities as measured by an urban attractiveness index (Broitman & Koomen, 2015), proximity to urban areas, and land-use composition of the surroundings including the shares of nature and residential use, available space and logistics. Lastly, a policy variable, in the form of a dummy, is also included which takes on a value of 1 if a grid cell lies within the spatial policy zone, and 0 otherwise. The spatial datasets of explanatory variables are as close as possible to the base year of 1990, subject to data availability. All datasets were processed to a 100 m resolution and spatially joined to the raster representing logistics land-use change between 1990-2020. The spatial analysis was performed in ArcMap 10.7 while the subsequent regression analysis was performed in Stata 17.

3 Results and Discussion

Tab. 1 presents the results of the multinomial logistic regression for analysing the effect of various spatial factors on logistics development. In a multinomial logit model, the regression coefficients are interpreted as a change in the log-odds of a chosen land-use change category relative to the base category corresponding to a marginal change in the predictor variable in question. For ease of interpretation, this can be understood as a change in the likelihood of a specific land-use change for a marginal change in the explanatory variable.

Table 1. Multinomial logit estimates of logistics land-use change – Pseudo R^2: 0.232.

Explanatory variables	Transport & Logistics	Trade, Import & Export	Large Retail
Accessibility			
Ln (distance to nearest highway access/exit)	-0.238***	-0.246***	-0.284***
Ln (distance to nearest seaport)	-0.231***	-0.0729***	0.0197
Ln (distance to nearest airport)	-0.0107	0.260***	0.379***
Ln (distance to nearest freight terminal)	-0.415***	-0.120***	0.0210
Ln (distance to nearest train station)	-0.103***	-0.144***	-0.297***
Ln (travel time to nearest 100,000 inhabitants)	-1.343***	-1.314***	-1.013***
Location			
Ln (distance to urban area)	-0.288***	-0.345***	-0.310***
Ln (hedonic land price, residential, 2007 Euros)	-0.117***	0.226***	0.525***
Urban attractiveness index	-5.105***	-2.748***	1.552***
Share of nature land-use in cell	-2.970***	-3.197***	-3.397***
Share of residential land-use in cell	-7.364***	-5.264***	-3.572***
Share of available land in cell	1.319***	1.482***	0.967***
Initial share of logistics (within 500 m)	38.83***	42.15***	44.04***
Within Logistics Top Sector region	0.303***	-0.209***	-0.853***
Constant	-0.594**	-3.735***	-7.418***

Notes: Province fixed effects are included. 3,449,149 observations. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Additionally, the regression coefficients in Tab. 1 can be used to compute the probability of logistics development in every grid cell according to Eq. (2). The probability maps for the province of North Brabant, a fast-growing logistics region in the Netherlands, are shown in Fig. 2. In addition to interpreting the individual coefficients, these maps help us to visualise how the different spatial factors in our model work in combination.

3.1 Effect of accessibility and location factors

Many of the spatial factors in our model have a similar effect on all three logistics types. For example, locations closer to highway exits and train stations have a higher likelihood of development of all three logistics classes. On the other hand, locations closer to airports generally experience a lower likelihood of logistics development (except for Transport & Logistics, in which case the coefficient is insignificant). The model shows a higher likelihood of logistics development for locations with better regional accessibility. This suggests that proximity to consumers is important for the development of logistics. Proximity to urban areas has a similar effect.

Land-use composition and availability of land in the vicinity also affects the likelihood of logistics development. For instance, a higher share of nature and residential land-use is associated with a decrease in likelihood of logistics development. To the contrary, as the share of available land increases, likelihood of development of logistics also increases, as would be expected. Additionally, the results are also suggestive of positive agglomeration effects since for a higher share of logistics in the neighbourhood the model shows an increased attractiveness of development.

3.2 Varying effects across logistics categories

Some of the spatial factors in our model have different effects on different types of logistics development. Proximity to seaports, for instance, has a greater positive effect on the likelihood of Transport & Logistics development as compared to the development of Trade, Import & Export, while there is no significant effect on the development of Large Retail. This is in line with expectation since a lot of transport and shipping companies depend on port accessibility and are therefore located close to the harbour. The effect of accessibility to freight terminals follows a similar trend across the logistics classes as accessibility to seaports.

Land price and urban attractiveness both serve as measures of the degree to which a location is closer to the city centre and their effects follow comparable trends. Locations with a higher land value and urban attractiveness experience a higher likelihood of development of Large Retail and a lower likelihood of development of Transport & Logistics. The effect on Trade, Import & Export is somewhere in-between such that a higher land price has a positive effect while urban attractiveness has an opposite effect. These trends suggest that locations which are relatively more central are preferred more for Large Retail development and less so for the other two types of logistics. Finally, the model shows that being within a ‘Logistics Top Sector’ zone is associated with an increase in likelihood of Transport & Logistics development and a decrease in likelihood of development of the other two categories of logistics.

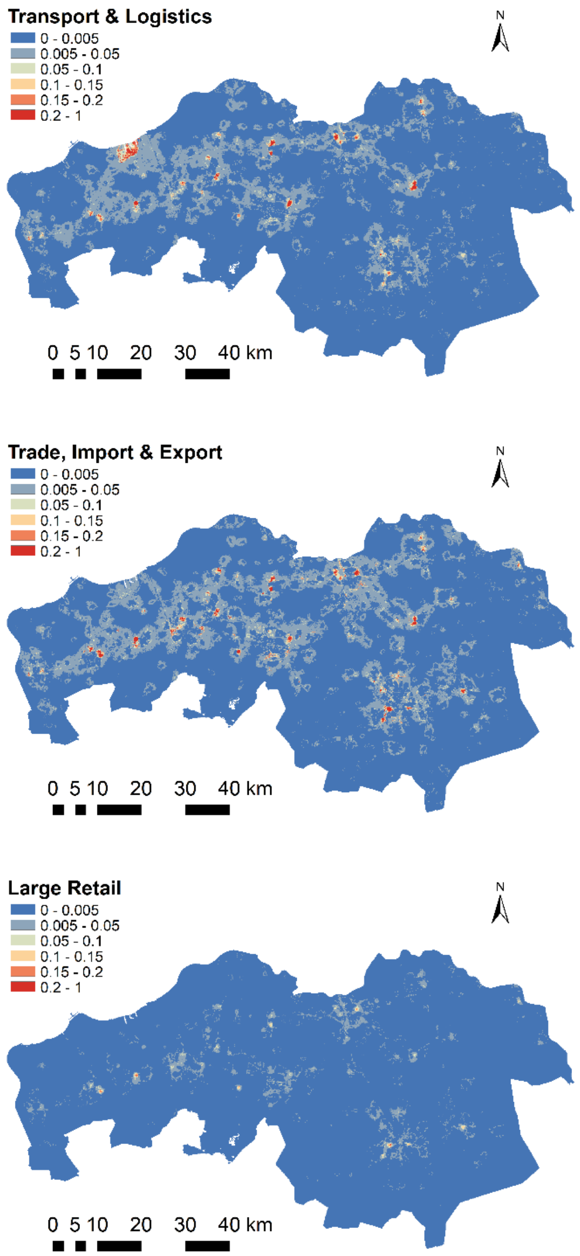

Figure 2. Predicted probabilities of development of three different logistics classes in North Brabant province.

4 Conclusion

With a view to better understand the location dynamics of logistics firms, a spatial dataset of logistics buildings in the Netherlands is developed which helps to establish a comprehensive timeline of logistics growth in the Netherlands. This dataset is further employed to model logistics development as a land-use change process using a multinomial logistic regression approach. This approach allows us to empirically assess the effect of various spatial factors on logistics development.

In most of the previous studies, the geographic scope of analysis was limited to a specific metropolitan area or region. Though the studies by Bowen (2008) and Holl & Mariotti (2018) were performed at the national level, the spatial resolution was limited to county level and municipality level, respectively. In this study, however, we extend the geographic scope of analysis to the national level while maintaining a fine spatial resolution of 100 m. We find that while certain spatial factors such as highway and rail accessibility have a positive effect on all types of logistics development, the effects of other factors such as seaport and freight terminal accessibility vary with logistics function. The probability maps computed for one of the provinces help illustrate the combined effect of all these spatial factors.

We must be cautious in inferring causality from the relationships observed between logistics development and the spatial factors considered in this study since further research is needed to address concerns of endogeneity, especially, in the locations of transport infrastructure potentially leading to reverse causality. Also, the model is not currently tested for spatial autocorrelation in the residuals and further research would be required to address these concerns as well. Additionally, if historical time-series data become available for the spatial variables used in our model, it would also provide an opportunity to test for temporal variability in the effects of these variables.

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