Journal of Transport Geography 131 (2026) 104529

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Logistics facilities location choice modeling: Effects of environmental constraints

Caterina Malandri[a,*], Luca Mantecchini[a], Francesco Paolo Nanni Costa[b], Valentina Rizzello[a]

[a] Department of Civil, Chemical, Environmental and Materials Engineering (DICAM), University of Bologna, Viale del Risorgimento 2, Bologna 40136, Italy
[b] ITL Foundation, Viale Aldo Moro 38, 40127 Bologna, Italy

ARTICLE INFO

Keywords:
Logistics facilities
Discrete choice model
Conditional logit model
Natural disasters risk
Environmental constraints

ABSTRACT

The selection of logistics facility locations is a critical decision that influences supply chain efficiency, cost structures and operational resilience. While previous studies have extensively examined the role of transport accessibility in location choices, the interplay between socio-demographic, transport-related and environmental constraints remain partially underexplored. This study addresses this gap by developing a conditional logit model to assess the impact of these factors on logistics facility location decisions, using the Emilia-Romagna region (Italy) as a case study. The model incorporates key determinants of location choice, including proximity to transport infrastructure (highways, freight terminals, rail stations), population density, environmental risks (flooding and seismic hazards) and land-use restrictions (protected natural areas). Results confirm that transport accessibility is the primary driver of logistics location choices and that socio-demographic factors, particularly population, also influence location preferences. Conversely, environmental constraints exert a negative effect on site selection, reducing the likelihood of a location being chosen. These findings bring significant policy implications. Investments in logistics-oriented transport infrastructure – such as enhanced highway connectivity, intermodal terminals and advanced congestion management systems – remains essential for strengthening regional logistics competitiveness. Moreover, implementing risk mitigation measures in location choice process analysis, including flood-resilient warehousing and seismic-resistant facilities, can enable firms to operate in moderate-risk areas without undermining operational resilience. Finally, integrated transport and land-use planning that harmonizes industrial expansion with environmental sustainability, through initiatives like eco-industrial parks, can support the development of resilient and efficient logistics systems.

1. Introduction

In recent decades, as economic globalization has expanded, the demand for logistics has grown rapidly on a global scale, becoming increasingly extensive and driving significant changes in freight transportation processes and operations (MacCarthy et al., 2016; Dablanc and Rodrigue, 2017). In 2023, global logistics costs were estimated to represent about 10–11 % of the world's GDP, underscoring the increasing economic significance of the logistics sector (Armstrong and Associates, 2025). As global trade expands, companies are facing increasing pressure to enhance their logistics networks to remain competitive and quickly adapt to shifting customer expectations (Burity, 2021). The rapid growth of e-commerce has further intensified this pressure by increasing the demand for faster, more reliable delivery services and driving the widespread adoption of last-mile logistics solutions and real-time tracking systems (Feng and Ye, 2021; Akıl and Ungan, 2022). At the same time, rising consumer concerns about sustainability have pushed companies to prioritize and adopt greener and more environmentally friendly logistics practices (Wan et al., 2022; Piecyk and Björklund, 2015).

Evolving supply chain practices are also reshaping the functions and locations of logistics facilities (Xiao et al., 2021). Logistic facilities are specialized sites, such as distribution centers, cross-docking terminals and fulfilment centers, designed to efficiently manage, store and move goods within the supply chain (Mangan and Lalwani, 2016). They perform essential functions including warehousing, distribution, inventory management and packaging, while being strategically located to optimize product flow, potentially reducing transit times and costs. Driven by the growing demand for faster deliveries and sustainable operations, companies are increasingly prioritizing facility location

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* Corresponding author.
E-mail address: caterina.malandri2@unibo.it (C. Malandri).

https://doi.org/10.1016/j.jtrangeo.2025.104529
Received 17 April 2025; Received in revised form 31 October 2025; Accepted 12 December 2025
Available online 17 December 2025

strategies that enhance delivery efficiency, minimize environmental impact and ensure compliance with regulatory standards (Sakai et al., 2023).

The selection of logistics facility location is therefore a critical decision in operations management, as it directly influences supply chain efficiency, cost management and service quality (Ivanov et al., 2019; Tajbakhsh and Shamsi, 2019). An effective location strategy, while being essential for ensuring efficient operations and long-term operational and managerial success (Kumar and Kumanan, 2012), is a complex process that involves relevant investments and requires a balance between economic, logistical, environmental and social factors (Wang and Liu, 2007; Rao et al., 2015). As a result, logistics developers face increasing decision-making challenges in selecting the most suitable sites for their facilities, since a range of factors should be carefully considered.

When selecting logistics facility location, the primary focus is typically on accessibility to transportation infrastructure and hubs – such as major road networks, ports, railway stations and airports – as it directly affects transportation costs, delivery times and the ability to meet customer demand and expectations (Saldanha-da-Gama, 2022; Targa et al., 2006). Economic factors are equally important, including land prices, labor costs, operational expenses, taxes and potential incentives and subsidies (Samani et al., 2023; Jakubicek and Woudsma, 2011). Other relevant aspects include access to markets and suppliers, labor availability, infrastructure quality, local regulatory context and even elements like quality of life (Rao et al., 2015; Sakai et al., 2020; Heizer and Render, 2004). Political stability also plays an important role, along with the alignment of logistics activities with local development goals, to ensure long-term sustainability and compatibility with broader corporate strategies (Kayikci, 2010; Essaadi et al., 2016).

Additionally, as companies and governments place greater emphasis on sustainable practices and resilience against environmental risks, site environmental constraints are becoming equally important in the decision-making process (Klibi et al., 2010). This involves not only local environmental regulations – such as zoning and land-use regulations, air quality and noise pollution standards – but also broader sustainability considerations. For instance, the risk of extreme weather events or natural disasters is becoming an increasingly important factor to consider, especially as climate change effect intensifies. Facilities located in areas prone to natural hazards – such as earthquakes, landslides, floods and hurricanes – are exposed to risks of operational disruptions, potential damage and safety concerns (Ulutaş et al., 2020). The literature highlights that major natural disasters often prompt companies to relocate facilities to safer sites and adjust their logistics operations to avoid high-risk areas, with the aim of minimizing operational interruptions and ensuring greater resilience for their networks (Lin et al., 2012; Orhan, 2017). Therefore, ignoring environmental risks and regulations can result in significant setbacks, costly relocations and also reputational damage, making it beneficial for companies to consider these factors when selecting logistics facility locations (Rao et al., 2015). By assessing environmental risks, businesses can choose safer, lower-risk locations, which not only minimizes potential disruptions but also reduces downtime, repair and insurance costs, while enhancing long-term operational stability. Considerations on environmental dimensions also include proximity to protected natural areas, where stricter requirements on emissions, waste management and noise pollution can impact both operational costs and efficiency. Companies choosing to establish facilities near these zones must understand and comply with local regulations, which often require investments in environmental impact assessments, sustainable technologies and pollution control measures. While these requirements may increase operational expenses, locating facilities near protected natural areas can demonstrate a commitment to environmental stewardship (Zhu et al., 2014). This, in turn, may enhance a company's reputation for environmental responsibility, attract eco-conscious customers and investors, improve brand perception and foster long-term business growth (Rodrigue et al., 2001). However, land-use restrictions in ecologically sensitive zones may at the same time limit future expansion opportunities. Therefore, the inclusion of environmental constraints into the decision-making process involves balancing the potential benefits and challenges, as the long-term advantages may be offset by immediate costs or limitations. Given the complexities and varying impacts of environmental factors on site selection, it is not always straightforward to assess their influence on the final decision.

The objective of this paper is to examine logistics facilities location choices, with a particular focus on the effect of environmental constraints. Specifically, it explores how socio-demographic characteristics, transportation network accessibility and environmental factors – including flood risk, seismic hazard and the presence of protected natural areas – shape these decisions. While several studies in the literature have analyzed the spatial distribution of logistics facilities, focusing mainly on their accessibility to transportation infrastructure (Verhetsel et al., 2015; Sakai et al., 2020), environmental constraints have received comparatively little attention as integral factors in facility location planning. To the best of our knowledge, no studies have examined how environmental factors, alongside key logistical and demographic locational characteristics, influence the establishment of logistics facilities. This represents an important research gap, particularly in understanding how land-use limitations, natural hazards and regulatory constraints interact with socio-demographic and logistical criteria shape logistics facility planning and development. By integrating environmental considerations into the location selection process, this study addresses aspects that have been overlooked in prior research, providing a more comprehensive understanding of the challenges and criteria involved in developing resilient and sustainable logistics networks.

To address the research objective, this study adopts a conditional logit modeling framework to investigate the determinants of logistics facility location choices. The analysis explicitly incorporates three primary categories of explanatory variables, each reflecting a distinct choice dimension: (a) socio-demographic factors, including population and employment, included to account for the potential demand for logistics services as well as the availability of labor resources; (b) transportation accessibility to key infrastructure, such as highways, rail terminals and intermodal freight facilities, which is crucial to ensure efficient logistics operations; (c) environmental factors, encompassing natural hazard risks (floods and earthquakes) and ecological constraints (presence of protected natural areas) that may impose regulatory limitations, increase construction and insurance costs, or pose direct threats to operational continuity, thereby influencing facility location decisions. Furthermore, this study examines the relative importance of these factors by analyzing how variations in certain factors influence the probability of selecting a specific location for a logistics facility. The Emilia-Romagna region serves as an ideal case study for this research, given its well-developed logistics infrastructure, the pressure of significant environmental challenges, including flooding and seismic risks and the presence of extensive natural protected areas that impose territorial constraints (Emilia-Romagna Region, 2024; Zanella et al., 2024). By drawing on the insights generated through this case study, the research provides valuable guidance for managers, policymakers and urban planners engaged in the strategic planning of logistics facilities. By identifying key factors influencing logistics facility location choices and examining their interaction with transportation networks, socio-demographic conditions and the considered environmental factors, this study contributes to the development of land-use policies that align logistics facility establishment with broader urban planning goals and environmental objectives.

The rest of the paper is organized as follows: Section 2 presents a short literature review, focusing on recent studies related to the spatial distribution of logistics facilities and the quantitative methods used to identify the key factors influencing logistics facility location choices. Section 3 outlines the proposed methodology, detailing the conditional logit model and the variables considered in the analysis. Section 4 introduces the case study of the Emilia Romagna region, describing its logistics landscape and highlighting the specific environmental challenges that impact logistics facility location decisions. The main conclusions and findings and their implications for land-use policy and logistics planning in the region are described in Section 5.

2. Literature review

The location of logistics facilities has been a critical topic of research, given its influence on supply chain efficiency, cost optimization and transport planning issues (Melo et al., 2009). Several studies have explored the various factors that shape the spatial distribution of logistics facilities, aiming to uncover the key drivers behind location decisions and the literature highlights that these influencing factors are diverse and interrelated (Onstein et al., 2019). This review synthesizes the current state of knowledge, focusing on the most extensively studied factors that influence logistics facilities location decisions, as well as the methodologies used to analyze them.

2.1. Location factors of logistics facilities

Among the most widely analyzed factors are those related to the socio-economic characteristics of the location site, including demographic and market features. Several studies identify socio-economic elements such as land availability, labor costs and market proximity as key determinants in the location choice for logistics facilities. Market proximity in particular stands out as a critical factor, often measured in the literature as a function of the population living within a given territory (Nachum et al., 2008). Logistics facilities are often strategically located near suppliers and customers to minimize transportation costs and enhance service efficiency (Durmuş and Turk, 2014; Lean et al., 2014). Moreover, proximity to consumer basins becomes increasingly important with the rise of e-commerce and the growing demand for rapid deliveries, with urban logistics hubs and warehouses located in high-density areas playing a crucial role in meeting the demand for last-mile deliveries (Fried and Goodchild, 2023; Jaller and Pahwa, 2020). Labor cost and availability also emerge as significant factors in location decisions, as companies prefer to establish logistic facilities in areas with a large, cost-effective labor force (Jakubicek and Woudsma, 2011; Demirel et al., 2010). However, as logistics operations become more automated, the dependence on low-skilled labor decreases (Dekhne et al., 2019) and the focus shifts toward workers capable of managing complex systems (Bowen Jr, 2008). A study by Sakai et al. (2020) reveals also that the size of the facilities may influence location choices, with smaller facilities typically being more influenced by the proximity to wholesale jobs and population density. Land availability and cost are other relevant socio-economic factors influencing logistics facility location decisions. Logistics operations are highly sensitive to land rents (Yuan and Zhu, 2019); as a result, many logistics companies tend to establish their facilities in peripheral or suburban areas, where land cost is lower and more affordable (Kang, 2020). For instance, studies by Verhetsel et al. (2015) and Giuliano and Kang (2018) analyze the relocation of logistics activities from dense urban areas to suburban zones and find that rising land rents in urban centers drive logistics facilities to move to areas with lower land costs. This trend is particularly noticeable in metropolitan areas, where large logistics facilities are increasingly located on the outskirts (Cidell, 2010; Cidell, 2015) and is further strengthened by agglomeration economies (Van den Heuvel et al., 2014).

In addition to socio-economic factors, transportation accessibility is one of the most frequently cited elements influencing logistics facility location. According to Rose et al. (2017), a successful logistics strategy must account for freight accessibility across the entire refence area. Infrastructure networks – road/rail links and complex transport nodes such as highways, railroads, ports and airports – represent the shared physical entity supporting all logistics operations within a territory and are critical factors influencing the efficiency of logistics systems (Gonzalez-Feliu et al., 2014; Cedillo-Campos et al., 2022). Numerous studies underscore the importance of accessibility to key transportation nodes to minimize travel times and costs (Hesse and Rodrigue, 2004). Research consistently shows that logistics facilities cluster around major transport hubs to capitalize on logistical advantages. For instance, Giuliano et al. (2016) and Jakubicek and Woudsma (2011) note that logistics facilities are often situated near transportation hubs to reduce costs and improve operational efficiency. In the Netherlands, van den Heuvel et al. (2013) highlight the significance of ease of access to airports and rail terminals, while Woudsma et al. (2008) find that highway accessibility plays a critical role in logistics land use in Calgary, Canada, with traffic congestion significantly impacting operations. Similarly, Sakai et al. (2020) emphasize that highways and other transport nodes are essential for logistics facilities, especially for cross-docking and storage operations that require frequent, efficient transportation. Holl and Mariotti (2018) highlight that improvements in suburban transportation make peripheral areas more competitive for logistics facilities. Enhanced regional connectivity and reduced congestion may shift preference away from central urban locations, making suburban areas increasingly attractive. While urban cores remain desirable for last-mile delivery hubs, suburban locations are increasingly favored for regional distribution centers (Holl and Mariotti, 2018; Pan et al., 2021). Transportation accessibility is typically measured in terms of travel distance or travel time to the nearest relevant transport node (e.g. highway ramp), estimated through various methods differing in theoretical approach and complexity. Distance is commonly estimated either as an Euclidean (straight-line) or as a network distance (Verhetsel et al., 2015; Sakai et al., 2019, 2020), while time-based measures – including actual or perceived travel time estimation – are often employed for assessing network impedance (Gonzalez-Feliu et al., 2014; Sakai et al., 2015). A few approaches incorporate traffic congestion into accessibility measurements, considering simulated or observed traffic flows (Weber and Kwan, 2002; Medda, 2012). Others explicitly account for congestion effects, emphasizing the distinction between peak and off-peak conditions (Woudsma et al., 2008).

While much of the research focuses on the importance of transportation accessibility, land availability and proximity to markets, environmental and land-use factors have been less thoroughly explored. Managing activities at facility locations requires significant energy and material resources, leading to notable environmental impact that warrants careful consideration. Some studies explore these impacts, with a particular focus on greenhouse gas emissions (Yang et al., 2019; Perotti et al., 2022) and the effects caused by freight vehicle traffic (Mepparambath et al., 2021; Sahu et al., 2022). Though, factors related to environmental constraints, land-use and zoning regulations and their influence on facility location decisions are less explored in the literature. For example, Sakai et al. (2016, 2020) examine the impact of zoning regulations on logistics facility locations, revealing that strict zoning regulations can push logistics facilities to less regulated areas, often on the outskirts of urban regions. Similarly, Jakubicek and Woudsma (2011) suggest that land-use restrictions can influence the spatial distribution of logistics facilities, particularly in cities with limited available land for development.

2.2. Methods for analyzing logistics facility locations

The majority of the cited studies use quantitative methods, with discrete choice models, multi-criteria decision-making (MCDM) models and geographical information systems (GIS) being the most common approaches. Discrete choice models (DCMs) are frequently used to investigate the determinants of logistics facility location, offering a rigorous framework to model the decision-making process. These approaches typically rely either on stated preference (SP) data or on revealed preference (RP) data derived from observed facility locations and associated characteristics. For instance, Sakai et al. (2020) use discrete choice models to examine the location determinants of logistics facilities across five activity categories in the Paris region. Discrete choice models (MNL models) are also applied in other studies, such as Durmuş and Turk (2014), who use a stated preference (SP) survey to evaluate location choices for warehouses in Istanbul, and Kang (2020), who analyzes warehouse locations in Los Angeles. While SP-based models allow for the exploration of hypothetical scenarios, RP-based approaches leverage real-world data to infer preferences and provide stronger external validity, particularly when SP data are difficult or costly to collect. In addition to discrete choice models, some studies apply geospatial analysis using GIS to understand the spatial distribution of logistics facilities. For example, Yang et al. (2022) use high-resolution grid-based data to explore how transport infrastructure and urban structure influence the spatial evolution of logistics facilities in Shanghai. Their study highlights the growing importance of transport supply and land-use changes in determining logistics facility locations. Similarly, Woudsma et al. (2008) employ spatial lag models to measure how accessibility impacts logistics land use. Moreover, multi-criteria decision-making (MCDM) techniques are applied to evaluate the trade-offs between multiple factors such as cost, transportation accessibility and environmental impacts. Studies such as Onstein et al. (2019) and Żak and Węgliński (2014) employ MCDM methods to integrate both quantitative and qualitative data, allowing for more comprehensive models of location decision-making.

This study contributes to existing literature on logistics facility location decisions by integrating a novel focus on environmental variables such as natural hazard exposure and ecological restrictions. By introducing this dimension, this research offers a deeper understanding of the interplay between logistic facilities location choice and their environmental context, which remains largely underexplored in the current literature. Although several studies highlight the increasing importance of considering environmental constraints and natural risks when making location decisions, research on how factors like proximity to natural protected zones or hazardous areas (e.g. flood-prone or seismic areas) influence logistics facility positioning is still limited. While some prior studies consider natural conditions, they generally focus on supply chain optimization models rather than directly examining how these conditions affect location decisions. This research bridges this gap by explicitly incorporating environmental considerations into facility location choices~~,~~ enabling researchers to evaluate how environmental regulations and natural conditions, demographic factors and transportation infrastructure shape logistics sprawl and its consequences.

In this study, environmental variables are analyzed alongside sociodemographic and transport-related factors, in line with existing literature. By integrating these variables, the study aims to provide a comprehensive analysis of the factors influencing logistics facility location decisions. Transport-related variables are evaluated by computing the peak-hour travel time, thereby accounting for the impact of traffic congestion. While previous studies generally evaluate accessibility in terms of Euclidean distance, this method provides a more accurate representation of real-world conditions encountered by logistics facilities, enhancing the accuracy of the location analysis. Consistent with most studies in the field, a discrete choice model is employed. This methodology provides significant advantages, allowing for a detailed examination of decision-making at the individual facility level while effectively capturing the complex interdependencies among influencing factors. A discrete choice modeling approach is well-suited for analyzing the location of logistics facilities as it effectively captures the complexity of decision-making in this context. Discrete choice models provide a framework for assessing the influence of different factors on logistics facility distribution, yielding insights into spatial patterns and enabling the evaluation of the potential impact of policy interventions as well as the prediction of future developments. Moreover, discrete choice models account for the probabilistic nature of decisions and the heterogeneity of preferences across different facilities. In line with previous research (Sakai et al., 2020), the discrete choice modeling approach adopted is based on observed facility locations and spatially-referenced attributes, rather than stated preference surveys, to estimate the determinants of logistics facility location choices. The discrete choice model used in this study is described in the following section.

3. Methodology

To analyze the factors influencing the location choices of logistics facilities, discrete choice modeling is employed within the framework of random utility theory. Specifically, a conditional logit model is used (McFadden, 1974) to examine how various location attributes affect the selection of sites for logistics facilities, in order to identify key determinants shaping these location decisions.

Discrete choice models operate under the assumption that a decision-maker *i*, when making a choice, evaluates a finite number of discrete and mutually exclusive alternatives that constitute the decision-maker's choice set. In the context of this research, it is assumed that the decision-maker *i* is a logistics firm tasked with selecting the location for its facility. Specifically, a logistics firm chooses location *l* from a finite set of discrete alternative zones, where $l = 1, \dots, L$ and $l \in L$, with L representing the total number of available alternative zones.

In discrete choice modeling, the decision-maker *i* assigns a perceived utility, or "attractiveness" $U_l^i$to each alternative site *l* within the choice set and selects the option that maximizes this utility. The selection of a site can be described by an unobservable utility function U_l^i, such that zone *l* will be chosen over zone *j* ($j \in L$, $j \neq l$) if and only if $U_l^i > U_j^i$.

The utility U_l^i, which guides the selection of a location, has two components: a deterministic (systematic) one, which depends on measurable characteristics or attributes of the alternative itself and a stochastic (random) one, represented by an error term accounting for unobserved factors. Thus, the utility U^l for a logistics facility in zone *l* can be expressed as:

$$U_l(\boldsymbol{X}_l^i) = V_l(\boldsymbol{X}_l^i) + \varepsilon_l \tag{1}$$

where V_l represents the deterministic component, $\boldsymbol{X}_l^i$ is the vector of the attributes relative to alternative *l* and ε_l is a random variable that, in the framework of the logit model, is assumed to be independently and identically distributed (i.i.d.) according to a generalized extreme value type I distribution. The probability of selecting a specific alternative *l* (location) for a logistic facility is the likelihood that the perceived utility of *l* exceeds the utility of all other alternatives in the choice set. This can be expressed as follows:

$$p_l = \frac{e^{V_l}}{\sum_{j \in L, j \neq l} e^{V_j}} \tag{2}$$

where p_l is the probability of selecting location *l* and V_l is the systematic (deterministic) utility associated with location *l*.

The systematic component of the utility function V_l in the conditional logit context is modeled as a linear function of alternative-based explanatory variables (attributes) X_{kl} expressed as:

$$V_l\ (\boldsymbol{X}_l^i) = \sum\nolimits_k \beta_k X_{kl}^i = \boldsymbol{\beta}^T \boldsymbol{X}_l^i \tag{3}$$

where $\boldsymbol{X}_l^i$ represents a vector of explanatory variables (attributes) for location alternative *l* and $\boldsymbol{\beta}$ is a vector of unknown parameters (coefficients) β_k to be estimated.

The alternative-based attributes in vector $\boldsymbol{X}_l^i$ can be classified into different categories. The conditional logit model developed in this study considers three distinct groups of independent variables, each describing characteristics of the alternative (site) that may be critical in the location selection process:

- Socio-Economic attributes $\boldsymbol{X}_{l,SE}^{i}$: this group includes variables that reflect the socio-demographic attractiveness and activity system in each zone, such as data regarding population and employment. These factors are crucial for understanding the socio-economic conditions of a location and its potential to support logistics operations.
- Transport system attributes $\boldsymbol{X}_{l,TRANSPORT}^{i}$: The second group focuses on the accessibility and level of service of the transport system in each zone. These attributes reflect the connectivity and performance of the transport network, which are critical in determining the logistical efficiency and operational feasibility of a site. In the context of logistics facilities, key attributes include the distance to transport infrastructure such as highways, airports, freight terminals, river container terminals and intermodal terminals. The model uses network travel distance, rather than Euclidean distance, accounting for factors such as congestion and the conditions of the road network.
- Environmental and land attributes $\boldsymbol{X}_{l,ENVIRONMENT}^{i}$: the third group refers to the environmental constraints of the area. This includes factors such as natural disasters risk and environmental regulations that might influence the feasibility or attractiveness of a location for logistics facilities.

The systematic component of the utility function thus becomes:

$$V_l\left(\boldsymbol{X}_l^i\right) = \boldsymbol{\beta}_{SE}^T\boldsymbol{X}_{l,SE}^i + \boldsymbol{\beta}_{TRANSPORT}^T\boldsymbol{X}_{l,TRANSPORT}^i + \boldsymbol{\beta}_{ENVIRONMENT}^T\boldsymbol{X}_{l,ENVIRONMENT}^i \tag{4}$$

where $\boldsymbol{\beta}_{SE}$, $\boldsymbol{\beta}_{TRANSPORT}$ and $\boldsymbol{\beta}_{ENVIRONMENT}$ are the vectors of unknown parameters to be estimated.

To estimate the coefficients, the Maximum Likelihood Estimation (MLE) method is used. In the context of this research, the likelihood function is based on the probability of choosing a particular location l for a decision-maker i, given the observed data on location attributes and the chosen location alternative. The likelihood function for a sample of N decision-makers is given by:

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{N}\prod_{l=1}^{L} p_l^i(\boldsymbol{\beta}) \tag{5}$$

where $L(\boldsymbol{\beta})$ is the likelihood function, $\boldsymbol{\beta}$ represents the vector of parameters (coefficients) to be estimated, p_l^i is the probability of decision-maker i choosing alternative l given the parameter vector $\boldsymbol{\beta}$. The log-likelihood function is the natural logarithm of the likelihood function and the maximum likelihood estimation aims to find the values of $\boldsymbol{\beta}$ that maximize this log-likelihood function:

$$\mathrm{argmax}\ln L(\boldsymbol{\beta}) = \sum_{i=1}^{N}\sum_{l=1}^{L} y_l^i \ln p_l^i\left(\boldsymbol{X}_l^i;\boldsymbol{\beta}\right) \tag{6}$$

where $y_l^i = 1$ if decision-maker i selects alternative l, 0 otherwise.

Once the coefficients in $\boldsymbol{\beta}$ are estimated, they can be interpreted and discussed to assess the influence of explanatory variables – such as socio-economic factors, transport accessibility and environmental constraints – on the probability of selecting a given location for a logistics facility. Since discrete choice models do not directly quantify the magnitude of each attribute's impact on the location choice process, the elasticity of each location attribute is therefore calculated to assess its influence on outcome probabilities. Elasticity measures how a change in a specific attribute affects the likelihood of a particular location being chosen, providing a more nuanced understanding of the relative importance of different determinants. Finally, a sensitivity analysis is conducted to assess the variation in attribute elasticity as the accessibility thresholds of the considered locations change.

4. Case study: Emilia-Romagna region in Italy

As a case study, this paper examines the location choices of logistics facilities in Emilia-Romagna, Italy. With a population of approximately 4.5 million, the Emilia-Romagna region is a strategic logistics hub in Italy due to its location, infrastructure and industrial presence. Positioned centrally, the region is traversed by major highways which form key freight corridors connecting northern and southern Italy and linking to broader European routes. Additionally, the region's high-speed rail and extensive rail freight services offer efficient options for goods movement, while the port of Ravenna serves as a vital gateway for maritime trade, accommodating significant import and export volumes. Emilia-Romagna's robust industrial base – dominated by sectors such as automotive, food and machinery - further drives demand for efficient logistics services. Besides, Emilia-Romagna presents unique logistical challenges due to its susceptibility to natural hazards, as the region is located in a seismic zone and has many areas prone to flooding, which adds complexity to logistics planning. Additionally, the Emilia-Romagna region is characterized by numerous protected natural areas, which influence the location of logistics facilities by imposing environmental and regulatory considerations.

The choice set for the analysis is defined by using census zones as the unit of analysis. This approach was selected because it aligns with the availability of key independent variables (e.g., population data) and ensures consistency in data aggregation and analysis. Additionally, it maintains a manageable computational cost for model estimation. In total, the choice set includes 6545 potential locations (zones) for analysis, with an average size of 3.5 km^2. The considered logistics units include logistics service provider facilities, with a total of 980 facilities, based on data provided by the Emilia-Romagna Region - Institute for Transport and Logistics (ITL). Specifically, the dataset includes warehouses, distribution, logistic hubs and cross-docking centres operated by logistics service providers. Fig. 1 shows the spatial distribution of logistics facilities across the Emilia-Romagna region in 2023.

Before specifying the final set of independent variables for the deterministic component of the utility of each location alternative, multiple combinations of attributes have been evaluated, including metrics such as population density, employment density and total number of employees per zone. It is important to emphasize that the selection process was not limited to straightforward significance testing for individual variables, as the variables exhibited a complex correlation structure that required careful consideration. In particular, both population and the number of employees have been considered as potential indicators of local demand and economic activity, but their strong correlation raised multicollinearity issues in preliminary model estimations. Finally, seven variables are selected for inclusion in the deterministic component of a zone's utility, as described below. These variables are carefully chosen to yield meaningful insights into the key

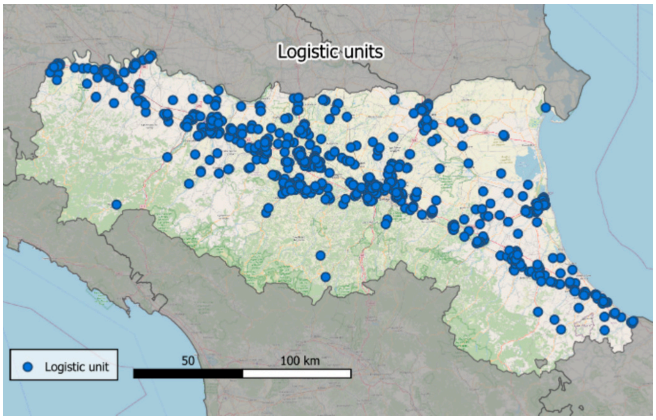


Fig. 1. Spatial distribution of logistic facilities in the Emilia-Romagna region.

factors influencing location choices, reflecting a balance between theoretical relevance, statistical robustness and the availability of up-to-date and spatially complete data. They produce coefficients with expected signs, ensuring alignment with theoretical expectations, while maintaining low correlations among variables. Additionally, their inclusion contributes to achieving strong model fits, enhancing both the robustness and interpretability of the results.

Population by zone is considered a key socio-demographic indicator in the analysis, given its significant role in assessing market potential and local demand. As previously noted, population is an important determinant of factors such as the potential customer base, workforce availability and overall economic activity, all of which can shape location decisions and enhance the attractiveness of a given zone. The population data used in this analysis is sourced from Italian National Statistical Institute (ISTAT) recent census (2021). Fig. 2a illustrates the distribution of the population across the different zones within the study area. As variables related to the transportation system, this study considers the impedance (in terms of travel time) of each zone to key transportation nodes such as the nearest highway entrances and freight terminals (Fig. 2b). Among the freight terminals considered, the Ravenna terminal in particular operates in close functional connection with the Port of Ravenna, the region's largest seaport, enabling the model to capture the influence of major port-related logistics infrastructure on location decisions. Airports were not included as explicit variables due to the relatively limited role of air freight in Emilia-Romagna's logistics network compared to road and sea transport. The computed impedance values can be interpreted as a measure of a zone's accessibility to the transport system (Cheng et al., 2018; Sun and Zacharias, 2020), from the perspective of a logistics firm. To calculate the paths between each zone and critical transport nodes, the Here Routing API (https://www.here.com/platform/routing) is used, with the geometric centroid of each zone serving as the origin for distance calculations. The Here Routing API calculates travel routes, durations and distances based on real-time and historical traffic data, considering factors such as road conditions, traffic congestion and time-of-day variations to provide accurate results. It provides reliable travel times and routes and effectively accounts for factors such as traffic congestion, improving the precision of the accessibility analysis and offering more realistic estimates compared to less refined and measures such as Euclidean distances. The analysis specifically focuses on morning peak hour (7:30–8:30), when congestion is most likely to impact travel times. By concentrating on this time frame, the study aims to capture real-world accessibility conditions during periods of intense traffic. The model sets trucks as the transportation mode, reflecting the primary mode of transport for logistics facilities: this ensures that only routes suitable for heavy vehicles are considered and the travel times are calculated accordingly. The results are presented in Figs. 2c-2e. Additionally, among the transportation-related variables, pedestrian distance from rail passenger stations is considered, as proximity to public transport can enhance worker accessibility and, consequently, the attractiveness of a location. The distances, measured in kilometers, are calculated based on the shortest path using OpenStreetMap (https://www.openstreetmap.org). Table 1 presents summary statistics for the transportation-related variables used in the analysis, where *HWY* and *FREIGHT* represent truck travel times (in minutes) from the nearest highway entrance and freight terminal, respectively, and *RAIL* indicates the distance (in kilometers) from the nearest rail station.

Regarding environmental factors, three variables are considered in the analysis. The first is seismic risk, which plays a crucial role in location selection due to its direct impact on the structural safety and operational continuity of logistics facilities. Seismic hazard data, obtained from the Emilia-Romagna region, include detailed risk maps that categorize zones into high, medium and low seismic hazard levels, as illustrated in Fig. 2f. To incorporate this factor into the analysis, a dummy variable is introduced to represent the seismic risk level of each zone. This variable takes the value of 1 if the zone's seismic risk is classified as greater than the regional average – corresponding to areas classified as green, yellow, orange or red in Fig. 2f. Conversely, it takes the value of 0 for zones with a lower seismic risk. The metric used to assess the risk level is the Hazard from seismic microzonation parameter (H_{SM}), that represents the expected ground shaking expressed in terms of a percentage of the acceleration due to the gravity, as shown in Fig. 2f.

The second environmental factor considered is flood risk, which plays a critical aspect in location selection, as flooding can disrupt supply chains and incur significant repair and downtime costs. Flood risk data are obtained from hazard maps provided by the *Po River District Authority* (https://webgis.adbpo.it/catalogue/uuid/3d0edd80-cfa2-11ec-b5d0-0242c0a8200). These maps classify zones into high (50-year return period), medium (200-year return period) and low-risk areas (500-year return period), as shown in Fig. 2g. For our analysis, a dummy variable is introduced to represent the flood risk level of each zone. Specifically, this variable is assigned a value of 1 if the flood risk is classified as average or high; conversely, it is assigned a value of 0 for zones classified as low flood risk.

The third variable analyzed involves the presence of protected natural areas, addressing the regulatory and ecological factors that may influence the attractiveness or feasibility of zones for logistics facility development. Data for these areas are sourced from the "Natura 2000" network, a European initiative aimed at preserving habitats and species of high ecological value (Italian Ministry of Environment and Energy Security - MASE, https://www.mase.gov.it/pagina/rete-natura-2000). This network includes areas classified as Special Areas of Conservation (SACs) and Special Protection Areas (SPAs), as illustrated in Fig. 2h. Also in this case, a dummy variable is used to indicate whether a zone is located within these protected areas. Specifically, the variable is assigned a value of 1 if the zone intersects with any "Natura 2000" site and 0 otherwise.

It is important to emphasize that the decision to treat seismic risk as a dummy variable is based on modeling considerations. Alternative models have been also explored, considering variables such as the surface area at risk or the percentage of protected areas per zone. However, the most effective results were obtained by using dummy variables and for this reason the model presented here adopts this approach.

Finally, the deterministic component of the utility for a potential location *l* of a logistics facility is represented as the linear combination of the selected attributes and their coefficients:

$$\begin{aligned} V_l = {} & \beta_{POP} POP_l + \beta_{HWY} HWY_l + \beta_{FREIGHT} FREIGHT_l + \beta_{RAIL} RAIL_l \\ & + \beta_{SEISMIC} SEISMIC_l + \beta_{FLOOD} FLOOD_l + \beta_{NATURE} NATURE_l \end{aligned} \tag{6}$$

where POP_l represents the population of the zone; HWY_l, $FREIGHT_l$ and $RAIL_l$ are the distances to the nearest highway entrance, to freight terminals and to rail stations, respectively; $SEISMIC_l$ and $FLOOD_l$ are the dummy variables for the seismic and flood risk; $NATURE_l$ indicates whether the zone falls within a protected natural area and betas are the coefficients to be estimated. A summary of the variables used in the model is presented in Table 2.

5. Results

The results from the calibration of the conditional logit model, presented in Table 3, provide valuable insights into the determinants of logistics facility location choices. The findings highlight the complex nature of these decisions, influenced by a combination of socio-economic factors, transport network accessibility and environmental considerations. The model exhibits good statistical fit, as indicated by the pseudo R-squared value of 0.412, suggesting that the independent variables explain a substantial proportion of the variation in logistics facility location choices. Additionally, the Likelihood Ratio (LR) test produces a highly significant value ($\chi^2 = 2364.7$, $p < 0.01$), confirming that the set of explanatory variables significantly improves the model compared to a null (intercept-only) model.

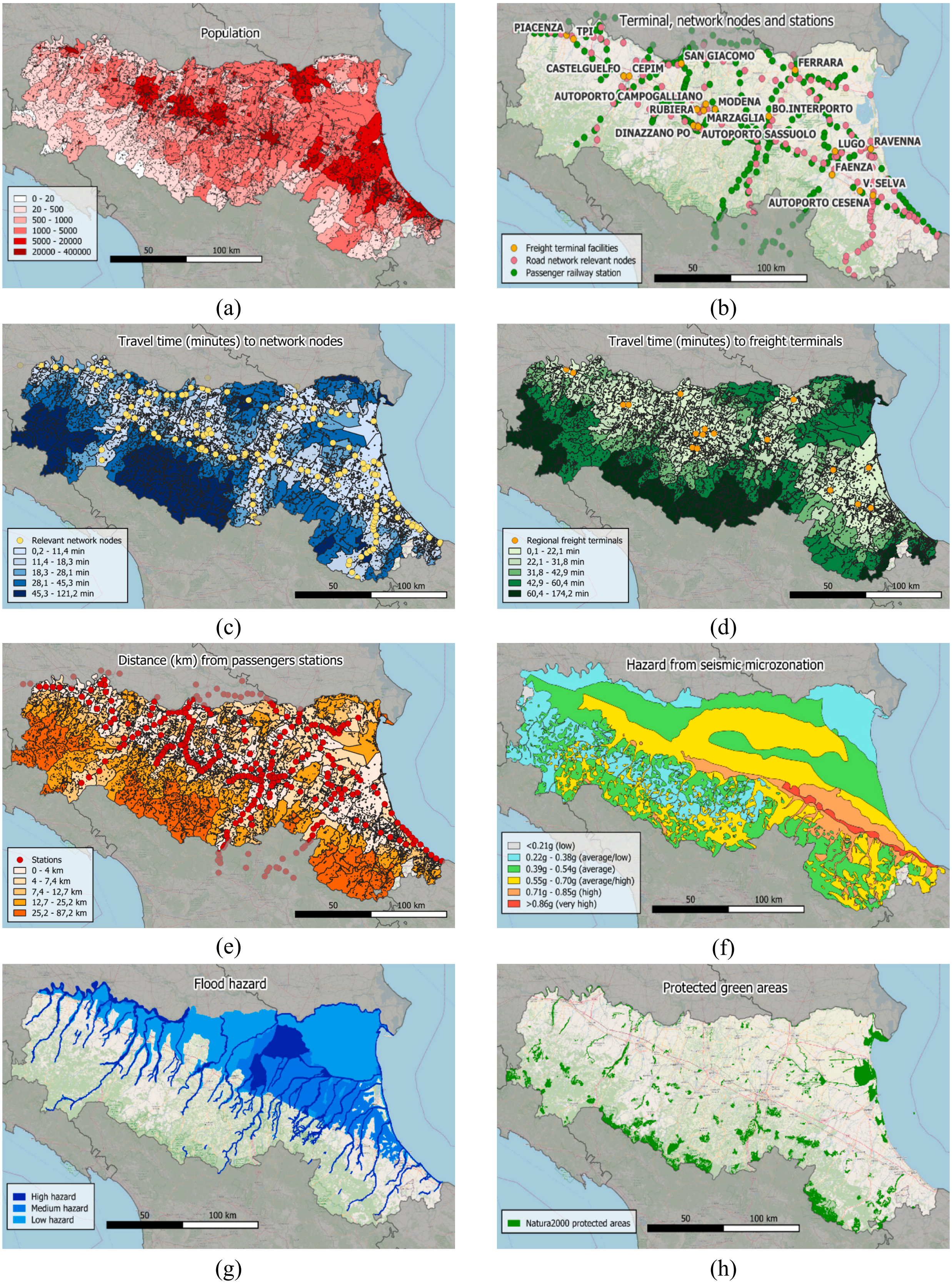


Fig. 2. (a) Population; (b) Key transport nodes; (c) Travel time to highway entrance; (d) Travel time to main freight terminal; (e) Distance to rail stations; (f) Seismic hazard; (g) Flood hazard; (h) Protected green areas, in the Emilia-Romagna region. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Descriptive statistics of transport-related variables among the zones of the study area.

	Mean	St. Dev.	Min.	Max.
HWY (minutes)	27.27	20.86	0.23	121.20
FREIGHT (minutes)	39.54	24.23	0.07	174.18
RAIL (kilometers)	13.91	14.22	0.03	87.15

Table 2
Variables included in the logistics facilities location choice model.

Type	Name	Description	Source
X_{SE}	*POP*	Number of inhabitants (population)	ISTAT (2021)
$X_{TRANSPORT}$	*HWY*	Truck travel time during the morning peak hour (7:30–8:30) between the zone centroid and the nearest relevant node of the transport network (in minutes)	HERE Routing API
$X_{TRANSPORT}$	*FREIGHT*	Truck travel time during the morning peak hour (7:30–8:30 am) between the zone centroid and the nearest freight terminal facility (in minutes)	HERE Routing API
$X_{TRANSPORT}$	*RAIL*	Walking distance between the zone centroid and the nearest passenger rail station (in km)	OpenStreetMap
$X_{ENVIRONMENT}$	*FLOOD*	Flood hazard within the area (0/1)	Po River District Authority
$X_{ENVIRONMENT}$	*SEISMIC*	Hazard from seismic microzonation within the area (0/1)	Data provided by Emilia-Romagna Region
$X_{ENVIRONMENT}$	*NATURE*	Presence of protected natural areas (0/1)	MASE

Table 3
Estimation results.

Variable	Estimate (Std. Error)	z-value	Pr(>|z|)
(Intercept)	1.665*** (0.295)	5.649	1.612E-08
POP	0.312*** (0.017)	18.293	< 2.2E-16
HWY	−0.058*** (0.007)	−8.886	< 2.2E-16
FREIGHT	−0.054*** (0.004)	−14.003	< 2.2E-16
RAIL	−0.011*** (0.001)	−10.455	< 2.2E-16
FLOOD	−0.739*** (0.115)	−6.404	1.516E-10
SEISMIC	−0.922*** (0.099)	−9.311	< 2.2E-16
NATURE	−0.626*** (0.215)	−2.916	0.003
Observations: 7259		Log Likelihood: −1690.7	
Pseudo-R^2: 0.412		LR Test: 2364.7*** (df = 8)	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

The population variable (*POP*) is positively associated with the probability of selecting a given location, underscoring the attractiveness of areas with higher population densities. This likely translates into easier access to labor markets and end consumers, as well as better integration into urban distribution networks. The strength of this effect aligns with existing literature and emphasizes the critical role of population density in shaping logistics demand and supply chain networks. It is worth noting that highly populated areas may also be proxies for higher land costs, as indicated by prior studies such as Sakai et al. (2020) and this factor could potentially discourage the selection of locations with high property prices. However, despite the potential disadvantage of elevated land prices, our findings show that the population still exerts a positive influence on location decisions. This suggests that the strategic benefits of the proximity to labor markets and end consumers may be greater than the economic challenges posed by higher land costs.

All the transport-related attributes in this study are statistically significant and align with previous research (De Bok and Van Oort, 2011). The negative coefficients for travel time to highway nodes (*HWY*) and freight terminals (*FREIGHT*) confirm that shorter travel times to these key nodes significantly increase a zone's attractiveness. The distance to rail stations (*RAIL*) also has a negative effect, suggesting that also rail accessibility may play an important role in determining location choices. These findings underscore the need for efficient, well-connected transport networks to support logistics operations.

Environmental risk factors, including flood (*FLOOD*) and seismic (*SEISMIC*) hazards, have a negative influence on location decisions. The high statistical significance of the coefficients suggests that decision-makers prioritize safety and operational continuity, avoiding areas prone to natural disasters. Protected natural areas (*NATURE*) also show a significant negative effect on location choices, indicating that regulatory restrictions and ecological considerations remain a meaningful constraint in site selection.

For the calibrated discrete choice model, direct elasticity is used to measure the effect of a percentage change in an explanatory variable on the probability of choosing a particular location. Elasticity quantifies how the probability of selecting a site for a logistics facility changes in response to a percentage change in a specific attribute, while other attributes remain constant (Train, 2009). The direct elasticity of a variable X_k with respect to the probability of selecting location l is calculated as:

$$E_{X_k} = \frac{\partial p_l}{\partial X_k}\frac{X_k}{p_l} \tag{7}$$

where the first term of the product is the partial derivative of the probability of selecting a location with respect to an explanatory variable X_k and the second term represents the percentage change in the variable of interest. Considering the conditional logit model specification, the elasticity can be derived as:

$$E_{X_k} = \beta_n(1 - p_l)\frac{X_k}{p_l} \tag{8}$$

This formula can be employed to quantify the effect of a change in X_k on the probability of selecting a particular logistics facility location. The elasticity derived from Eq. 8 applies only to continuous variables. For non-continuous (discrete) variables, the formula for elasticity must be adjusted, since these variables assume distinct, finite values rather than continuous ones. For discrete variables, the elasticity formula is:

$$E_{X_k} = \frac{\Delta p_l}{\Delta X_k}\frac{X_k}{p_l} \tag{9}$$

where Δp_l is the change in the probability of selecting location l due to a small change ΔX_k in the discrete variable X_k, p_l is the probability of selecting location l. This adjustment accounts for the fact that discrete variables – such as categorical attributes – cannot be differentiated infinitesimally like continuous ones. As a result, the change in probability is typically computed by comparing the model outcomes when the variable takes different levels or values (e.g., 0/1). Calculating and interpreting elasticities provides valuable insights into the extent to which site-specific characteristics influence the location decision of a logistics facility. A high elasticity indicates that even a small change in an explanatory variable will result in a significant change in the probability of selecting a site. Conversely, a low elasticity implies that the variable has a less substantial impact on the location decision. For example, if the elasticity associated with the distance to an intermodal terminal is high, then even a modest increase or decrease in that distance can strongly affect the probability of a location to be selected. Thus, elasticities help understanding how changes in key variables can affect the attractiveness of potential locations.

The results of the elasticity analysis are summarized in Table 4. The positive elasticity for population (1.05) suggests that an increase in the number of inhabitants in a zone increases the probability of it being

Table 4
Elasticities.

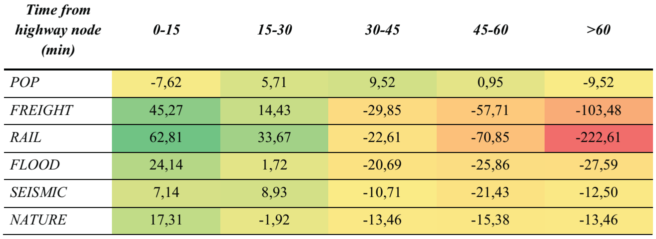
Variable	*Elasticity*
POP	1.05
HWY	−1.50
FREIGHT	−2.01
RAIL	−1.99
FLOOD	−0.58
SEISMIC	−0.56
NATURE	−0.52

chosen as a logistics facility location, confirming the tendency to locate such facilities in areas with easier access to markets and consumers. The negative elasticities for transport-related variables highlight the importance of accessibility in determining logistics facility locations. The most significant effect is observed for freight terminal accessibility elasticity (−2.01), followed closely by rail station accessibility elasticity (−1.99) and highway accessibility elasticity (−1.50). These results indicate that the probability of a location being chosen decreases significantly as travel time to these critical transport nodes increases. This is consistent with expectations, as logistics operations rely heavily on efficient transportation networks to minimize costs and delivery times. Among the three, the highest elasticity – in absolute terms – is observed for freight terminals, suggesting that logistics facilities are particularly sensitive to proximity to freight hubs. This might be due to the increasing importance of intermodal transport in supply chain management, where logistics centers require close integration with freight terminals for efficient movement of goods.

Environmental aspects exhibit negative elasticities, indicating that logistics facilities tend – as expected – to avoid locations exposed to flood and seismic risks, as well as areas located within protected natural zones. The absolute values of these elasticities are lower than those of transport-related variables, implying that while environmental risks influence location decisions, their impact is less pronounced compared to transport accessibility factors. Among the environmental variables, flood risk (−0.58) has the largest absolute elasticity, followed by seismic risk (−0.56) and protected natural areas (−0.52). This suggests that the risk of flooding is perceived as a slightly greater deterrent than seismic activity when selecting logistics facility locations. One possible explanation is that flood events tend to have more immediate and disruptive impacts on supply chains compared to seismic hazards, which may have a lower probability of occurrence but potentially more severe consequences. Similarly, the negative elasticity for protected natural areas (−0.52) indicates that logistics developers tend to avoid sites within ecological protection zones. This is likely due to strict regulatory constraints, higher compliance costs and restrictions on infrastructure expansion. However, the relatively smaller magnitude of this elasticity suggests that even if environmental protection is a consideration, it is not as decisive as factors related to transport accessibility or socio-demographic factors.

Table 5 reports the percentage variations in elasticities as a function of road travel time during the morning peak hour (7:30–8:30) between a zone and the nearest relevant node of the transport network (in minutes). As observed, the elasticities of the transport-related variables tend to increase when travel time is below 30 min, whereas they decrease markedly significantly for longer travel times. This confirms that as road impedance increases, the adverse effect of limited accessibility to major transport nodes becomes progressively more pronounced and widespread, thereby reducing the probability of a zone being selected for logistics facility location. Conversely, the sensitivity of environmental variables follows a distinctly different pattern. While a slight reduction in their associated elasticities can be observed as road impedance increases, the behavior of individual variables varies. Specifically, for *SEISMIC* and *NATURE*, the maximum decrease in elasticity occurs within the 45–60-min travel time range, after which a subsequent increase is observed. In contrast, the *FLOOD* variable exhibits a decline that stabilizes at levels below 30 %, even for road travel times exceeding 60 min.

Table 5
Elasticities sensitivity (% variation of elasticity).



Time from highway node (min)	***0-15***	***15-30***	***30-45***	***45-60***	***>60***
POP	-7,62	5,71	9,52	0,95	-9,52
FREIGHT	45,27	14,43	-29,85	-57,71	-103,48
RAIL	62,81	33,67	-22,61	-70,85	-222,61
FLOOD	24,14	1,72	-20,69	-25,86	-27,59
SEISMIC	7,14	8,93	-10,71	-21,43	-12,50
NATURE	17,31	-1,92	-13,46	-15,38	-13,46

Overall, these results suggest that the relative effect of environmental variables on logistics facility location choices remains largely stable, despite variations in a key accessibility attribute. This finding supports the hypothesis of a generalized perception of risk associated with the considered environmental effects, which exerts a relatively uniform influence on location decisions regardless of changes in transport accessibility conditions.

These findings also highlight the importance of the spatial characterization of natural hazard variables. In this study, both flood and seismic risks were included as binary variables, indicating exposure above regionally defined thresholds. However, the spatial dynamics and underlying mechanisms of the two hazards differ substantially, which has important implications for their interpretation. Flood risk is typically characterized by high spatial variability and flood hazard maps provide detailed, high-resolution delineation of flooded zones, allowing for relatively precise identification of high-risk locations even within small regional contexts. Consequently, modeling flood risk at the census zone level (average area $\approx 3.5\ \text{km}^2$) aligns well with the spatial resolution of available data and the potential for fine-grained locational differentiation in firm decision-making. In contrast, seismic hazard presents distinct challenges. Although the Emilia-Romagna region benefits from advanced seismic microzonation studies, seismic risk is influenced by multiple factors – ground motion propagation, subsurface geology, depth of the seismic event and structural amplification effects - that are difficult to resolve at very localized scales. The stochastic and temporally uncertain nature of seismic events further complicates their integration into predictive models of location choice. In this context, while the use of a binary seismic risk variable captures general regional-level exposure, it may oversimplify the complex spatial and physical processes underlying seismic hazard distribution. Nonetheless, even a relatively rough representation of seismic risk remains relevant for logistics location decisions, since the consequences of a seismic event can propagate beyond the immediate epicentral area, affecting regional transport infrastructure and supply chain continuity. From a logistics standpoint, such systemic disruptions can have spatially diffuse impacts, meaning that firms may perceive seismic exposure in a broader territorial sense, rather than strictly localized terms. This perception is corroborated by the elasticity analysis, which suggests that the deterrent effect of seismic risk is significant and comparable in magnitude to that of flood risk, despite the differing nature of the two hazards.

6. Discussion and policy implications

The findings of this study confirm that transport accessibility remains the most influential factor in logistics facility location choice, followed by socio-demographic characteristics and environmental constraints. However, the coexistence of high accessibility and environmental risk across territories of the Emilia-Romagna region underscores a relevant challenge for both logistics operators and policymakers: reconciling economic efficiency with environmental resilience.

A spatial examination of the study area reveals that many of the zones with the highest probability of hosting logistics facilities are located near major transport corridors, where accessibility to both highway and freight terminals is maximized. These same corridors, however, intersect areas of medium to high flood hazard, particularly in the lower Po River basin and the coastal plain surrounding Ravenna. Similarly, parts of the central and northern provinces (e.g., Modena, Reggio Emilia, Ferrara) are classified as medium seismic hazard zones. This geographical overlap highlights an intrinsic vulnerability of logistics systems that depend on infrastructures exposed to natural hazards. The analysis thus points to a risk-accessibility trade-off: firms tend to favor locations offering strong connectivity and market access, even when these areas are characterized by moderate hazard exposure. This behavior suggests that risk mitigation costs are often perceived as secondary to the operational advantages associated with accessibility. Nonetheless, as recent extreme events have demonstrated – such as the 2012 Emilia earthquake and the 2023 and 2024 floods – disruptions in transport networks can rapidly propagate across supply chains, leading to significant economic losses and temporary isolation of logistics nodes and facilities. These events highlight the systemic nature of logistics vulnerability, which extends beyond individual facilities to affect regional mobility and supply continuity.

Emilia-Romagna is among the Italian regions most affected by natural hazards. According to the Italian Institute for Environmental Protection and Research (Trigila et al., 2025), over 45 % of the regional territory is classified as having medium-to-high seismic or flood risk. The May 2023 floods, for example, caused widespread infrastructural disruptions and temporary closures of several road network elements and industrial facilities, particularly in the Ravenna and Bologna provinces. During the 1–3 May 2023 an area of approximately 58 km^2 was flooded (Cremonini et al., 2024); similarly, the 2012 Emilia earthquake damaged over 13,000 industrial buildings and warehouses (Dolce and Di Bucci, 2014), demonstrating the vulnerability of logistics assets in the region.

From a policy perspective, the findings of this study underline the need for integrated spatial and risk-aware transportation and logistics planning. In particular, in light of recent events that affected the Emilia-Romagna region, national regulation and decrees issued by the Po River District Authority impose, through urban planning regulatory guidelines, prohibition on new construction in areas flooded during 2023 flooding events. In terms of resilience and mitigation of the effects of climate change on human society and the environment, the land use regional law already requires municipal plans to include a strategy that provides infrastructures aimed at reducing seismic, hydrogeological, hydraulic, and flood risks. For instance, logistics operators located in flood-prone areas could be required to adopt specific preventive-adaptive measures, such as elevated loading docks, waterproof materials, or dedicated emergency drainage infrastructure. Similarly, for facilities in seismic areas, building codes could incorporate performance-based criteria and mandatory structural retrofitting for large-scale warehouses.

Another implication concerns the integration of hazard information into strategic logistics planning. Regional governments could enhance decision-support systems by coupling established transport accessibility metrics with high-resolution hazard maps and network vulnerability assessments. Such an approach would enable the identification of “resilient accessibility corridors,” where high transport performance coexists with low hazard exposure. These areas could be prioritized for new logistics development, while more vulnerable locations could be targeted for retrofitting or gradual relocation of sensitive facilities. In addition, economic incentives could be adopted to promote private investment in resilient and sustainable logistics infrastructures. Examples include tax reductions or grants for firms that apply resilience standards, locate within designated low-risk logistics parks, or invest in green technologies (e.g., photovoltaic roofing, on-site water retention). Finally, the findings highlight the importance of policy coordination between transport, environmental, and economic planning authorities. Ensuring that logistics location decisions align with broader climate adaptation and land-use strategies requires a cross-sectoral governance approach. Collaborative planning involving regional governments, municipal authorities, and private stakeholders can help balance infrastructure efficiency, territorial safety, and environmental protection. Such coordination is particularly relevant in regions like Emilia-Romagna, where logistics infrastructure plays a key role in national supply chains but is increasingly exposed to the cumulative effects of climate change.

7. Conclusions

This study provides a comprehensive analysis of logistics facility location choices by integrating socio-economic, transport accessibility and environmental factors into a conditional logit model. The empirical results confirm that transport accessibility remains the dominant factor influencing location decisions, while socio-economic conditions and environmental constraints also play significant roles. The findings offer valuable insights into the spatial distribution of logistics infrastructure and its relationship with key determinants, with implications for both private-sector decision-making and public policy formulation. The main contribution of this work is the inclusion within the research framework of factors pertaining to both key locational characteristics and factors related to environmental and natural hazards, addressing a literature gap. With the growing incidence of natural hazards and the emphasis on preserving natural environments, this subject is likely to become even more relevant and demanding.

The results indicate that proximity to road network key nodes and freight terminals is a significant determinant of logistics facility location. This aligns with existing literature emphasizing that logistics operations rely heavily on efficient and well-connected transport networks to optimize costs and delivery performance. The elasticities associated with travel times to major transport nodes suggest that even relatively small increases in transport accessibility considerably reduce a location’s attractiveness, highlighting the importance of enhancing accessibility, particularly in areas that are currently underserved by major logistics corridors. The role of socio-demographic factors, particularly population density, is also evident in the results. The results of the calibration confirm that high-density areas tend to be more attractive for logistics facilities, likely due to greater labor availability and proximity to consumer markets. However, this effect appears to be secondary to transport accessibility, as confirmed by the elasticity value of this variable. Conversely, environmental constraints exhibit a deterrent effect on location choices, with flood risk, seismic hazard and proximity to protected natural areas all reducing the likelihood of a location being selected. While these effects are statistically significant, their magnitude is lower than that of transport-related factors, as indicated by the elasticities. This suggests that, although environmental risks are taken into account, logistics firms are often willing to accept a certain level of risk when balanced against accessibility advantages. Moreover, the elasticity analysis reveals that the influence of environmental factors remains relatively stable across different levels of transport impedance, indicating that these risks are perceived in a broad rather than context-dependent manner.

The findings of this study have potentially relevant implications for policymakers, urban planners and logistics operators, particularly in the context of balancing economic efficiency, sustainability and risk mitigation. The results confirm that improvements in highway connectivity, intermodal transport facilities and congestion management can significantly enhance a region’s attractiveness for logistics development. While environmental risks negatively affect logistics site selection, their relative influence is weaker than that of transport-related factors. This suggests that implementing targeted risk mitigation measures, rather than excluding high-risk areas, may be a viable policy strategy. Governments could incentivize logistics firms to invest in flood-resistant and seismic-proof infrastructure in higher-risk areas, thereby reducing vulnerabilities without compromising site selection opportunities. Additionally, incorporating climate resilience and disaster preparedness into urban planning frameworks can help reduce long-term disruptions. Moreover, the findings highlight the need to reconcile logistics expansion with environmental protection goals. The significant negative effect of proximity to protected natural areas suggests that regulatory restrictions influence location site selection, indicating that even if regulations are essential for environmental preservation, policymakers should explore zoning strategies that accommodate logistics growth while safeguarding ecologically sensitive areas.

From a policy perspective, the findings underscore the need for a holistic approach that balances economic efficiency, environmental sustainability and regional development. Investments in transport infrastructure, climate resilience and sustainable logistics solutions will be key to fostering a robust and adaptive logistics network in the face of evolving economic and environmental challenges. Ultimately, by integrating infrastructure planning, regulatory frameworks and technological innovations, policymakers and industry stakeholders can create logistics ecosystems that are both efficient and resilient, supporting long-term economic growth while mitigating environmental and social impacts.

While this study provides valuable insights into logistics facility location choices, some limitations should be acknowledged. First, the use of dummy variables for environmental risks may oversimplify the complex impact of these factors. Future research could explore continuous measures, such as flood probability or seismic intensity, to capture more detailed effects. Furthermore, while the current model focuses on static attributes, incorporating dynamic factors such as economic growth or infrastructure expansion could provide a more comprehensive understanding of location decisions over time. Moreover, the model provides a static view of logistics location preferences, even if regulatory shifts, climate change policies and infrastructure developments could alter location attractiveness over time. Longitudinal analyses incorporating policy simulations and scenario modeling could provide more forward-looking insights. Additionally, spatial effects – such as clustering tendencies and potential spatial autocorrelation among zones - have not been explicitly addressed in the present model. Future research could incorporate spatial econometric extensions, such as spatial lag or spatial error structures (e.g., Nguyen and Sano, 2010), to capture interdependencies in location patterns. Regarding environmental hazards, while flood risk can be spatially delineated at fine resolution, seismic risk classification is more generalized. The use of regional microzonation data allows for risk differentiation; however, its granularity may not fully capture localized vulnerability. Furthermore, population was used as a proxy for land prices due to the lack of comprehensive, consistent land value data across the study area. While previous studies (e.g., Cidell, 2010; Sakai et al., 2020) have adopted similar approaches to reflect urban pressure and competition for space, this substitution only partially captures the complexity and spatial variability of land markets. Specifically, population levels may not reflect local land value dynamics accurately, as some industrial or logistics zones can have relatively low population but high land costs driven by strategic location, infrastructure accessibility or regulatory constraints. Acknowledging these limitations, future research would benefit from incorporating detailed and spatially disaggregated land price data to better represent cost-related locational trade-offs. Finally, future research could benefit from a more granular differentiation of logistics facilities by function or physical scale. Distinguishing between small-scale urban logistics hubs and larger regional distribution centers, for example, may reveal distinct location patterns driven by varying operational requirements. These aspects represent promising avenues for further analysis.

In summary, the empirical evidence suggests that logistics competitiveness and environmental resilience should not be treated as conflicting objectives but as complementary dimensions of sustainable territorial development. Incorporating risk mitigation and adaptive design into logistics planning can simultaneously strengthen supply chain reliability and reduce long-term economic vulnerability, supporting the transition toward a more efficient and climate-resilient logistics and transportation systems.

CRediT authorship contribution statement

Caterina Malandri: Validation, Software, Methodology, Investigation, Data curation, Conceptualization, Writing – review & editing, Writing – original draft. **Luca Mantecchini:** Supervision, Methodology, Formal analysis, Conceptualization, Writing – review & editing, Writing – original draft. **Francesco Paolo Nanni Costa:** Visualization, Software, Resources, Data curation. **Valentina Rizzello:** Visualization, Software, Investigation, Formal analysis, Data curation, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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